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Article *in* Journal of Intelligent Manufacturing · August 2020

DOI: 10.1007/s10845-019-01512-w

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To cite this paper: Lim, K.Y.H., Zheng, P. & Chen, C. A state-of-the-art survey of Digital Twin: techniques, engineering product lifecycle management and business innovation perspectives. *J Intell Manuf* **31,** 1313–1337 (2020). https://doi.org/10.1007/s10845-019-01512-w

A State-of-the-Art Survey of Digital Twin: Techniques, Engineering Product Lifecycle Management and Business Innovation Perspectives

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Abstract. With the rapid advancement of cyber-physical systems, Digital Twin (DT) is gaining ever-increasing attention owing to its great capabilities to realize Industry 4.0. Enterprises from different fields are taking advantage of its ability to simulate real-time working conditions and perform intelligent decision-making, where a cost-effective solution can be readily delivered to meet individual stakeholder demands. As a hot topic, many approaches have been designed and implemented to date. However, most approaches today lack a comprehensive review to examine DT benefits by considering both engineering product lifecycle management and business innovation as a whole. To fill this gap, this work conducts a state-of-the art survey of DT by selecting 123 representative items together with 22 supplementary works to address those two perspectives, while considering technical aspects as a fundamental. The systematic review further identifies eight future perspectives for DT, including modular DT, modeling consistency and accuracy, incorporation of Big Data analytics in DT models, DT simulation improvements, VR integration into DT, expansion of DT domains, efficient mapping of cyber-physical data and cloud/edge computing integration. This work sets out to be a guide to the status of DT development and application in today's academic and industrial environment.

Keywords: digital twin; cyber-physical system; business model; product lifecycle management; review

Nomenclature

AMQP	Advanced Message Queuing Protocol
BMs	Business Models
CoAP	Constrained Application Protocol
CPS	Cyber Physical Systems
DMFEA	Design Failure Mode and Effects Analysis
DT	Digital Twin
ERP	Enterprise Resource Planning
FEM	Finite Element Method
LabVIEW	Laboratory Virtual Instrument Engineering Workbench
MES	Manufacturing Execution System
MQTT	Message Queuing Telemetry Transport
NTP	Network Time Protocol
OMPL	Open Motion Planning Library
OPC UA	Open Platform Communication Unified Architecture
OSI	Open Systems Interconnection
PHM	Prognostics and Health Management
PLC	Programmable Logic Controller
PLM	Product Lifecycle Management
PTP	Precision Time Protocol
RAMI 4.0	Reference Architecture Model Industry 4.0
SCADA	Supervisory Control And Data Acquisition

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SHDR	Simple Hierarchical Data Representation
SOAP	Simple Object Access Protocol
STEP	Standard for Exchange of Product model data
TCP/IP	Transmission Control Protocol/ Internet Protocol
UDP	User Datagram Protocol
VV&A	Verification Validation and Accreditation
WirelessHART	Wireless Highway Addressable Remote Transducer Protocol

1. Introduction

With industries advancing into the Industry 4.0 era, factories are shifting towards a smart manufacturing paradigm with multi-scale dynamic modeling, simulation and intelligent decision making to enhance production capabilities (Davis et al. 2012). DT technology is an effective tool to fulfill the requirements of smart manufacturing by reflecting the physical status of systems in a virtual space. Under the broad spectrum of CPS, the DT paradigm aligns well with a lifecycle-centered perspective (Schneider et al. 2019). DT technology is increasingly prominent as the focal point of the enhancement and evolution of global manufacturing.

As DT technology becomes more sophisticated, (J. Liu et al. 2019) described it as one of the strategic directions for manufacturing enterprises to progress. Designed to improve manufacturing efficiency, DT is a digital duplications of entities with real-time two-way communication enabled between the cyber and physical spaces (I-Scoop 2017). By providing a means to monitor, optimize and forecast processes, DT is envisioned by (El Saddik 2018) as an approach for continuous improvement towards human well-being and quality of life. The maturity of this technology has also attracted attention from a wide range of industries, including healthcare and urban planning. City planners, assisted by DT technology, are able to interact with a data-rich city simulation, laying the foundation for a smart city as seen in the case of Singapore (Dassault Systèmes 2018). Gartner, a prominent global research and advisory firm describes DT as one of the top ten strategic technology trends in 2019 (Gartner 2019). Meanwhile, Grand View Research forecasts the DT market to grow to USD $27.06 billion by 2025, an approximate tenfold increase from USD $2.26 billion back in 2017 (Research 2018). With DT technology's ability to provide new possibilities for the emergence of new services and BMs, Industry 4.0 is no longer a "future trend" and many leading organizations have made it the center of their strategic agenda. For instance, with DT simulations and optimized decision-making, new insights can be obtained to produce smart products with self-awareness (Posada et al. 2015). Enterprises that are able to capitalize on this will benefit from the competitive advantages that are available to early adopters (Ghobakhloo 2018). (Mabkhot et al. 2018) described an enormous range of benefits ranging from product design and verification, product lifecycle monitoring to shop-floor design, optimizing manufacturing processes and maintenance. (X. Xu 2017) pointed out the role of DT technology in making smart machine tools via optimal decision support and machine health awareness analysis. The versatility of DT technology allows it to form the bedrock of future technologies, for example, it has the potential to be provisioned as a cloud service in support of cloud manufacturing.

In this review paper, past and present contributions to DT are analyzed by systematically examining the state-of-the-art research articles from their engineering PLM and business innovation perspectives. The different industries and stakeholders involved with DT technology as well as tools and models utilized are investigated to provide a clear understanding on the various trends and directions this technology is heading towards. The rest of the paper is organized as follows: Section 2 outlines a literature review of DT concepts and related works including the systematic search process for relevant journal articles. Section 3 highlights the key technological tools and models used in DT creation. Section 4 describes the role of DT technology along stages of engineering PLM, while Section 5 discusses the business advantages of DT. Section 6 explores future perspectives of DT technology advancement and lastly, Section 7 summarizes the contributions of the work done.

2. Literature review

This systematic literature review specifically focuses on works related to business and engineering aspects of DT technology. According to (Cook et al. 1997), a systematic review differs from traditional general review in that a duplication of the distinct and objective process is possible. As DT technologies are progressively developed for a wider range of industries to tackle extensive corporate functions such as strategic planning, it is essential that the technical, engineering PLM and business aspects of DT technology be reviewed to investigate the collective insights on theoretical analysis of existing studies.

2.1 Methodology in research selection

A systematic literature search was conducted in the Scopus database, covering most of the peer-reviewed interdisciplinary research papers, where a broad sum of studies on DT and other related literature can be identified using the systematic review methodology. Articles collected were further refined through a three-step approach (Reim et al. 2015), as depicted in Figure 1.

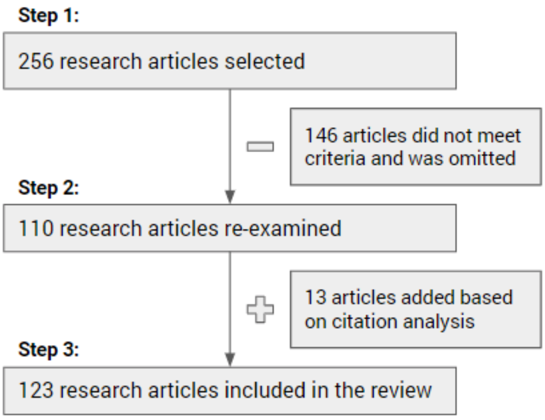

Figure 1. Systematic review flow diagram

Step 1: Publications identification and screening

The first step serves to obtain quality publications via practical screening criteria during the past five years. Conference articles, working papers and commentaries are excluded to derive quality publications (Seuring and Müller 2008). Meanwhile, several keywords closely related to DT were identified. In addition to "Digital Twin", search terms such as "cyber twin" and "virtual twin" were used, as (Oracle 2017) indicated that DT is made up of Virtual, Predictive and Projective twins. Although the differentiation represented different technological levels of DT, the purpose of these papers fit the scope of the study. The search phrase can be duplicated with the following searching sentence: "Topic = (Digital Twin OR "Virtual Twin" OR "Cyber Twin); Time Span: 2015 – 2019; Language: English; Type = "Article" (searched on 15/09/2019). This inclusive search yielded 256 relevant articles for further analysis.

Step 2: Theoretical screening process

To emphasize both engineering PLM and business perspectives, articles advancing and applying DT technology are included, regardless of present or future considerations. More specifically, the selection benchmark is shown below:

- DT applications and scenarios are selected, including using DT for situation optimizations. These studies involve conceptual and empirical discussion on DT implementations, allowing key technical aspects to be highlighted.

- DT reviews and frameworks were examined to provide a comprehensive overview of trends, business functions and technologies involved. The insights gained from these studies will aid in identifying challenges faced for the evolution of DT.

- Studies directly and indirectly involving DT concepts and challenges were examined, even those without mentioning DT in the title, keywords or abstract. This allows identification of future DT perspectives for new industrial developments.

Although various definitions exist, the core of DT remains the same. Therefore, in order to conduct a survey without any bias, DT is regarded consistently as a high fidelity virtual replica of the physical asset with real-time two-way communication for simulation purposes and decision-aiding features for product service enhancement, as depicted in Figure 2 concurring with the contrast between DT and CPS as analyzed by (Tao et al. 2019)

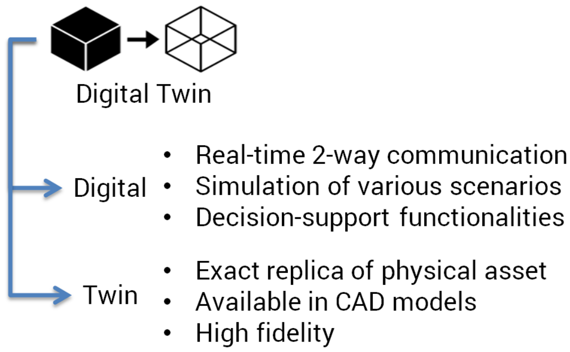

Figure 2. Definition of Digital Twin

Step 3: Reference analysis
In this last stage, cited references from the original 110 articles that met the selection benchmark were further leveraged as a secondary source for literature analysis, resulting in an identification of 13 additional articles. Hence, this systematic literature review consists of 123 articles in total. For article analysis, DT categories were created based on their association with the research focus allowing easy reference and the categories were collated to form discussion themes. Additionally, 22 supplementary references were added to the reference section to make the survey concrete.

2.2 Evolution of DT

DT was first introduced by (Grieves 2014) during his presentation of PLM in 2003. Although the initial concept was vague, a preliminary form of DT included both physical and virtual products and their interconnections. First serving as an inexpensive means to simulate varying conditions for NASA rockets, DT has since advanced technologically and expanded its scope of utilization. From the literature to date, DT-related enabling techniques have experienced exponential growth over time and its core idea has been transformed into distinctive concepts outlined in Table 1.

Table 1. Definitions of DT

Author	Definition of Digital Twin
(Grieves 2014)	*"Virtual representation of what has been produced"*
(R. Stark et al. 2017)	*"Digital representation of a unique asset that compromises its properties, condition and behavior by means of models, information and data"*
(Söderberg et al. 2017)	*"Using a digital copy of the physical system to perform real-time optimization"*
(El Saddik 2018)	"*Digital replications of living as well as non-living entities that enable data to be seamlessly transmitted between the physical and virtual worlds"*
(Zhuang et al. 2018)	*"Virtual, dynamic model in the virtual world that is fully consistent with its corresponding physical entity in the real world and can simulate its physical counterpart's characteristics, behavior, life and performance in a timely fashion"*
(Qi and Tao 2018)	*"Virtual models of physical objects are created in a digital way to simulate their behaviors in real-world environments"*
(Y. Xu et al. 2019)	*"Simulates, records and improves the production process from design to retirement, including the content of virtual space, physical space and the interaction between them"*
(Kannan and Arunachalam 2019)	"*Digital representation of the physical asset which can communicate, coordinate and cooperate the manufacturing process for an improved productivity and efficiency through knowledge sharing*"

2.3 Descriptive analysis

As sensors become cheaper to procure and communication technology advances, DT provides a means to simulate and investigate scenarios that are otherwise too costly to explore. Figure 3 illustrates an exponential increase in DT utilization over the last 5 years with an expected increase in potential DT applications.

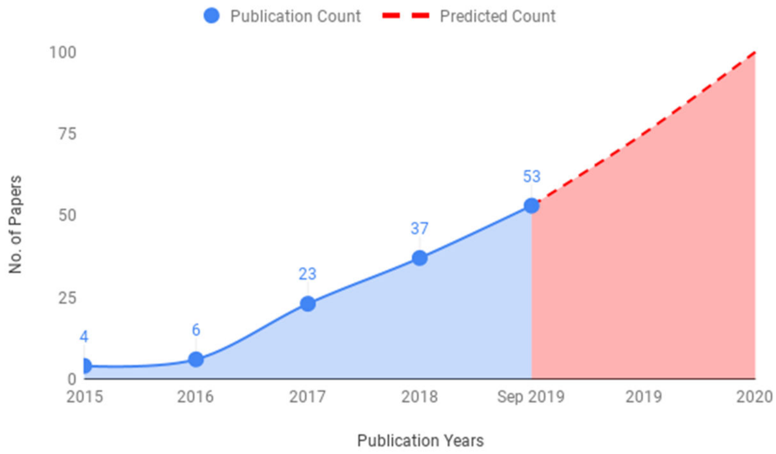

Figure 3. Number of publications over past 5 years (2015 - 2019)

Table 2 shows the top journal names published in this area. *IEEE Access* is the most dominant source, accounting for 10% of articles reviewed, followed by other journals, especially in the manufacturing or industrial engineering field. Nevertheless, a total of 61 different journals are investigated after the systematic review process conducted in Section 2.1, proving DT's versatility and hotness in many fields.

Table 2. Top journals presented in the review

Journal	Article Count
IEEE Access	12
CIRP Annals Manufacturing Technology	9
Journal of Ambient Intelligence and Humanized Computing	7
International Journal of Advanced Manufacturing Technology	6
Journal of Manufacturing systems	6
Robotics and Computer Integrated Manufacturing	6
International Journal of Production Research	5
IEEE Transactions on Industrial Informatics	4
International Journal of Computer Integrated Manufacturing	4

Many countries have proposed national strategies (B. H. Kim et al. 2016) towards Smart Manufacturing. The policies and research trends of advanced manufacturing countries such as China, USA and Germany can be summarized with headlines such as Made in China 2025, CPS-based manufacturing and Industrie 4.0 (Cheng et al. 2018). DT categorizes under Industry 4.0 and Figure 4 shows the number of DT related research to highlight the enthusiasm of nations embarking on the DT trend.

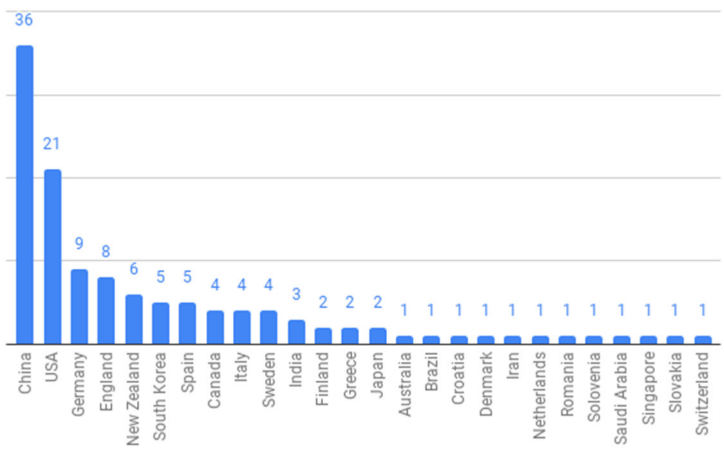

Figure 4. DT publication count categorized by countries

3. DT techniques

As new industries acquire DT in a bid to boost productivity, efficiency and competitiveness, a diverse mix of tools and methodologies are used. This section provides a comprehensive analysis on tools and models used to create DT. Figure 5 shows the technology stack for DT establishment. Starting with data management and connectivity, models for DT communication are discussed. Subsequently, data representation and storage tools, machine learning tools and analytical methodologies are summarized. Lastly, microservices used to fulfill specific DT tasks such as virtual reality shop-floor are examined. Microservices are vulnerable to cyber-attacks, which could jeopardize the safety and quality of manufacturing systems. To raise awareness to these threats, (Elhabashy et al. 2019) analyzed cyber security issues in CPS, identifying attack methods and their impacts to operations.

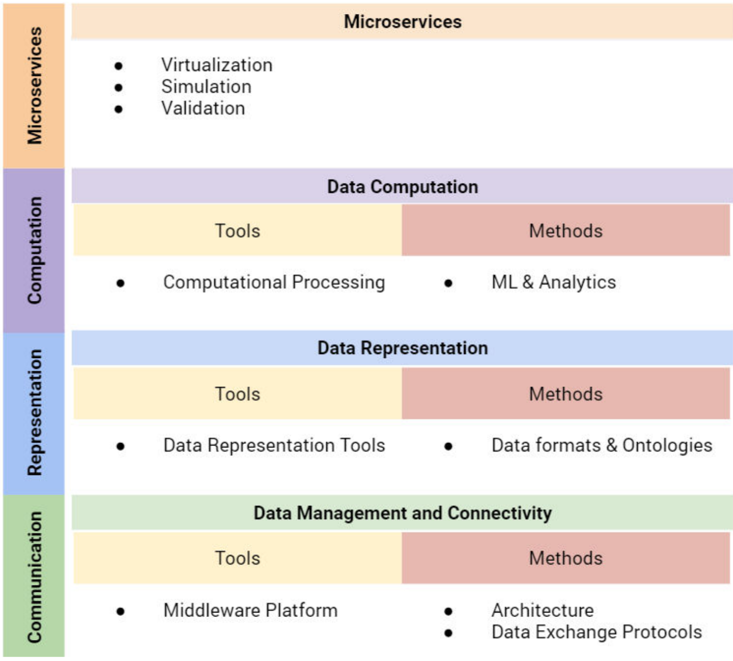

Figure 5. Technology stack for DT creation

3.1 Communication

Data acquisition and transmission are crucial in DT for real-time information flow and connectivity. This section emphasizes on key network architectures, data exchange protocols, as well as middleware platforms used in studies to facilitate information exchange and streaming processing. Network architecture involves integration of protocols and layered network interface through function blocks. Table 3 highlights the prominent architectures discussed such as multi-tier architecture and others. The OSI model, consisting of 7 layers (physical, data-link, network, transport, session, presentation, application), then establishes the concept of layered network architecture with the use of abstraction layers. These communication protocols are crucial rule sets for machine-to-machine connectivity between communicating entities. Table 4 highlights data exchange protocols in manufacturing environments used by data acquisition systems for high level DT communication. For ease of reference, the protocols are classified according to their nearest OSI model layers after which middleware platforms manage diverse software components for further development and streaming processing. (Freeman 2016) described data stream processing system as analytics and continuous queries on real-time data. Table 5 summarizes key middleware platforms to enable seamless connectivity without altering infrastructures, allowing easier DT adoption into the current manufacturing ecosystem. These data acquisition systems are crucial for DT implementation in production environments with data collected via volatile (equipment specification, bill of materials etc.) and non-volatile data capturing processes (real-time sensor-based processing systems) (Uhlemann et al. 2017).

Table 3. Network architectures for DT creation

Author	Architecture	Description

(Hao Zhang et al. 2017) (Leng et al. 2018) (Q. Liu et al. 2018)	J2EE SSH programming architecture	Platform providing functionality for developing multi-tiered and distributed Web based applications
(Arafsha et al. 2019)	Master-Slave architecture	Communication model where a device has unidirectional control
(J. H. Lee et al. 2018)	RESTFul	Software architectural style for creating web services
(Park et al. 2019)	Service Oriented architecture	Software design style where services are provided via application components, through communication protocol
(P. Zheng, Lin, et al. 2018)	Server-Client architecture	Computing model in which server manages resources consumed

Table 4. Data exchange protocols for DT creation

OSI Layers	Author	Rule	Description
Application Presentation Session	(Ardanza et al. 2019) (Neill 2016) (Bao et al. 2018) (C. Liu et al. 2019) (Luo et al. 2018) (Y. Zheng et al. 2018)	OPC UA	Machine-to-machine communication protocol for industrial automation
	(Hao Zhang et al. 2017) (J. Liu et al. 2019) (J. H. Lee et al. 2018) (Q. Liu et al. 2018)	OPC	Predecessor of OPC UA, OPC is a series of standards and specifications for industrial telecommunication
	(Haag and Anderl 2018)	MQTT	ISO standard publish-subscribe-based messaging protocol
	(C. Liu et al. 2018) (Coronado et al. 2018) (Bao et al. 2018) (Helu et al. 2018)	MTConnect	MTConnect is a protocol designed for data exchange between shop-floor equipment and software applications for monitoring and data analysis
	(Leng et al. 2018)	CoAP	Specialized internet application protocol for constrained devices
	(Park et al. 2019)	SOAP	Messaging protocol specification for exchanging structured information in the implementation of web services in networks
	(Lovas et al. 2018) (Damjanovic-Behrendt and Behrendt 2019)	AMQP	Open standard application layer protocol for message-oriented middleware
	(Nikolakis et al. 2019)	NTP	Networking protocol for clock synchronization between systems
	(H. Kim et al. 2018)	PTP	Nanosecond/ Picosecond time synchronization between systems
	(Haijun Zhang et al. 2018)	Profinet	Industry technical standard for data communication over industrial Ethernet in data collection and equipment control
	(Haijun Zhang et al. 2018)	Wireless-HART	Used in wireless sensor networking technology
Transport	(Laaki et al. 2019) (Senthilnathan and Annapoorani 2018)	TCP	Main protocol for enabling two hosts to exchange data
	(C. Liu et al. 2018) (Ardanza et al. 2019)	TCP/IP	Communication protocol suite to interconnect network devices
	(Laaki et al. 2019)	UDP	Protocol for creating low-latency and loss-tolerating connections
Data Link	(Moreno et al. 2017)	Ethernet/IP	Industrial network protocol widely used in industries including factory, hybrid and process
	(H. Kim et al. 2018)	OpenFlow	Protocol to give access to forwarding plane of network switch

Table 5. Middleware platforms for software development

Author	Tool	Description
(P. Zheng, Lin, et al. 2018)	Amazon EC2	Cloud-based environment for cloud deployable web application
(Lovas et al. 2018) (Damjanovic-Behrendt and Behrendt 2019)	Docker	Saas and Paas products that use operation system level virtualization to develop and deliver software in containers
(Damjanovic-Behrendt and Behrendt 2019)	Kubernetes	Open source container orchestration system for automating application deployment, scaling and management
(C. Liu et al. 2018) (Senthilnathan and Annapoorani 2018)	LabVIEW	System-design platform and development environment
(P. Zheng, Lin, et al. 2018)	MetaEnv sensor platform	Metawear sensor for real-time communication
(Y. Zheng et al. 2018)	MWorks software	Suite of open source applications and libraries for designing and running real-time experiments
(Lovas et al. 2018)	OpenNebula	Cloud computing platform for managing heterogeneous distributed data centre infrastructures
(He et al. 2018)	Pavatar	Real-time monitoring, decision-aiding of entire operation process
(Electric 2016)	Predix	Platform to ingest and analyse data
(Damjanovic-Behrendt and Behrendt 2019)	RabbitMQ	Open source message-broker software
(J. H. Lee et al. 2018)	Spark	General-purpose distributed data processing engine
(MacDonald et al. 2017) (Choi et al. 2017)	Thingworx	Industrial innovation platform for rapid delivery of IoT applications and AR experiences

3.2 Representation

Heterogeneous data and domain knowledge gathered from shop-floor processes need to be modeled and integrated into manufacturing systems. Highlighted in Table 6, knowledge representation tools for DT creation such as ontologies and NoSQL databases are potential choices for achieving knowledge-based systems. Ontologies are favored as they address integration and domain-specific modeling concerns as well as reusing and sharing of knowledge. Knowledge representation languages such as OWL and knowledge management models such as RDF form the bedrock for DT creation while semantic integration of sensor data is explored to create taxonomies, ontologies and standards. Table 7 shows prominent data formats used in the research articles.

Table 6. Databases and data management for DT creation

Author	Tool	Description
(Yuqian Lu and Xu 2019)	AWS DynamoDB	Fully managed proprietary NoSQL cloud database service from AWS S3
(Rodič 2017) (L. L. Liu et al. 2018)	MS SQL	Relational database management system
(Lovas et al. 2018)	MySQL	Open source relational database management system
(Nikolakis et al. 2019) (Lovas et al. 2018)	Apache Cassandra	Open source NoSQL database management system
(Coronado et al. 2018) (Helu et al. 2018)	MTConnect database	Database for all MTConnect product information
(Yuqian Lu and Xu 2018)	OntoSTEP	Plug-in of Protégé, an open source ontology editor
(Schluse et al. 2018)	Versatile Simulation database	Real-time database able to store any UML data structure
(Angrish et al. 2017) (Arafsha et al. 2019)	MongoDB	Cross-platform document-oriented NoSQL database program
(Abramovici et al. 2016)	Neo4j	ACID-compliant transactional graph database
(Schneider et al. 2019)	Ontotext	Semantic graph database with text mining,

		for unstructured data
(P. Zheng, Lin, et al. 2018)	SQLite 3	Relational database management system fitted in end programs
(Abramovici et al. 2016)	SciGraph	Open source project to represent ontological data in Neo4j
(Damjanovic-Behrendt and Behrendt 2019)	InfluxDB	Database supporting data transformation and prediction queries

Table 7. Data format and representation for DT creation

Author	Approach/ Language	Description
(Bao et al. 2018) (Sierla et al. 2018)	AutomationML	An open, XML-based and standardized data format
(C. Liu et al. 2018)	SHDR	Data format containing timestamp, identifier and item value
(Q. Liu et al. 2018)	STEP	Open format for systems to exchange design information

3.3 Computation

After selecting a storage engine, computational models are employed for batch-oriented and real-time data processing. Extracting practical knowledge from heterogeneous data is challenging and thus, determining the right methodologies and tools for querying and aggregating sensor data is crucial to DT construction. Machine learning and data processing tools provide a wide range of solutions ranging from analytics to automation and these provide DT with decision-aiding capabilities via enabling tools such as computer vision. Table 8 summarizes the computational processing tools used in this review. In Table 9, machine learning and analytics methodologies, including statistical kits for optimization are presented. Due to the overlapping nature of DT applications in manufacturing, some of the techniques involved are biased towards manufacturing operations.

Table 8. Computational processing for DT creation

Author	Tool	Description
(Yuqian Lu and Xu 2019)	AWS Elastic MapReduce	AWS tools for big data processing and analysis across Hadoop
(Damjanovic-Behrendt and Behrendt 2019)	Elastic Stack (ELK Stack)	Tool for searching, analysing and visualizing data in real-time. Comprises of Elasticsearch, Logstash and Kibana
(J. H. Lee et al. 2018)	HBase	Open source, non-relational distributed database
(MacDonald et al. 2017)	IoT EL20 Edge Computing	Analytics system developed by Hewlett-Packard Enterprise
(Denos et al. 2018) (Schluse et al. 2018)	MatLAB/ Simulink	Data processing system
(Tan et al. 2019)	MS Excel VBA	Application for editing custom scripts and automating actions
(Sierla et al. 2018)	OMPL	Software for computing motion plans via sampling algorithms
(Alam and El Saddik 2017)	QFSM	Graphical tool for designing finite state machines
(J. H. Lee et al. 2018)	Reduce	Extract feature vectors from time-series data
(Damjanovic-Behrendt and Behrendt 2019)	TensorFlow	Open source software library for dataflow and differentiable programming for machine learning applications

Table 9. Machine learning and analytics for DT creation

Author	Method/ Algorithm	Description
(J. H. Lee et al. 2018) (Park et al. 2019) (Luo et al. 2018)	Artificial Neural Network	Computing systems based on examples without task-specific rules
(Zhuang et al. 2018)	Boundary Element Method	Simulate physical functions and performance of elements
(Madni et al. 2019)	DFMEA	Identify design functions, failure modes and severity effects

(Ding et al. 2019) (Y. Xu et al. 2019)	Deep Neural Network	Part of broader machine learning methods based on Artificial Neural Networks
(Rodič 2017)	Discrete Event Simulation	Models system operation as a sequence of events in time
(P. Zheng, Lin, et al. 2018)	Discrete Fourier Transform	Calculate frequency information from periodic summation of continuous Fourier transform
(Li et al. 2017) (Alam and El Saddik 2017)	Dynamic Bayesian Network	Bayesian network relating variables over adjacent time steps
(Li et al. 2017) (Zhuang et al. 2018) (Söderberg et al. 2017) (Haag and Anderl 2018) (Tao and Zhang 2017)	FEM analysis	Numerical method to fix engineering and mathematical physics
(Denos et al. 2018) (Zhao et al. 2019)	Gaussian Filtering	Suppress and reduce noise data for data accuracy
(Ding et al. 2019) (Petkovi 2018)	Hidden Markov Model	Statistical Markov model whereby system is assumed to be a Markov process with unobservable states
(Söderberg et al. 2017)	Monte Carlo Simulation	Technique for accessing risk and uncertainty impact for visualization potential outcomes
(L. L. Liu et al. 2018) (Ding et al. 2019) (Park et al. 2019) (W. Wang et al. 2020)	NSGA-II Algorithm	Fast sorting and multi objective genetic algorithm for optimizing machine performance
(Oyekan et al. 2018)	Savitzky-Golay Filtering	Method to reduce noise and data smoothing for sensor noise
(Tao and Zhang 2017)	VV&A	Set of processes to determine accuracy of a model or simulation

3.4 Microservices

Microservices are software development tools constructed as a set of loosely coupled services. (Lewis and Fowler 2014) describes this architectural style as an enabling feature for an application to be built as a suite of relative small, consistent, isolated and autonomous services performing specific tasks.

Based on RAMI 4.0 (Rojko 2017), Table 10 provides a list of virtualization tools in modern production systems, to allow monitoring and tracing services of shop-floor assets for automated conflict resolution and performance enhancement through decision-aiding support and control. Table 11 highlights tools used in model creation and DT simulation of high fidelity asset replicas while Table 12 highlights validation tools provide support for task verification to ensure data accuracy and integrity.

Table 10. Virtualization microservices for DT creation (RAMI 4.0)

Author	**Virtualization Tool**	**Description**
(Rodič 2017) (Zhuang et al. 2018) (Neill 2016) (Oracle 2017) (Choi et al. 2017)	ERP (Layer 4)	Integrated real-time management of main business processes
(Rodič 2017) (Coronado et al. 2018) (Zhuang et al. 2018) (Neill 2016) (Haijun Zhang et al. 2018) (Hao Zhang et al. 2017) (J. H. Lee et al. 2018) (Q. Liu et al. 2018) (R. Stark et al. 2017) (Choi et al. 2017)	MES (Layer 3)	Real-time control of multiple elements of production processes
(Electric 2016) (Haijun Zhang et al. 2018) (Bao et al. 2018) (Love and Matthews 2019)	SCADA (Layer 2)	Control system architecture involving devices, networked data communications and GUI for process supervisory management

(R. Stark et al. 2017)		
(J. H. Lee et al. 2018) (Q. Liu et al. 2018) (R. Stark et al. 2017) (Schneider et al. 2019) (Y. Xu et al. 2019)	PLC (Layer 1)	Hardware architecture for monitoring and control of production processes

Table 11. Modeling and simulation microservices for DT creation

Author	Tool	Description
(Popa et al. 2018)	ANSYS Simplorer	Simplify multi-domain simulations within a design environment
(R. Lu and Brilakis 2019)	Autodesk Revit	Building information modeling software
(Datta 2017)	Avatar software	Simulation application used for mimicking operation scenarios
(Schneider et al. 2019)	Dymola	Tool for modelling and simulation by Dassault Systems
(Lovas et al. 2018)	EasySim	Simulation software for designing and simulating operations
(Sierla et al. 2018)	JMonkeyEngine 3.0	Community-centric open source 3D modelling engine
(Moreno et al. 2017)	Lantek Expert Punch	CAD/CAM nesting simulation software designed for automation of CNC punching machines
(Luo et al. 2018)	MWorks	Open source tool for designing and running real-time experiments
(J. H. Lee et al. 2018) (Ding et al. 2019)	Plant Simulation	Modelling, simulating, process and system optimization application
(Ferguson et al. 2017)	Siemens' STAR-CCM+ software	Multidisciplinary platform for simulation of designs and products
(Rodič 2017)	SIMIO	Generic flow-shop simulation model maker
(Laaki et al. 2019) (Oyekan et al. 2018) (J. H. Lee et al. 2018) (Q. Liu et al. 2018) (Omer et al. 2019) (Xie et al. 2019)	Unity3D engine	Cross-platform engine for model and simulation creation
(Popa et al. 2018)	WITNESS Horizon	Flexible process simulation software

Table 12. Validation microservices for DT creation

Author	Validation Tool	Description
(Iglesias et al. 2017)	ANSYS	Software using finite element method to solve discretized models
(Electric 2016)	GE OpFlex	Suite of solutions for analyzing and mitigating unplanned scenes
(Caputo et al. 2019) (Bilberg and Malik 2019)	Tecnomatix process simulate	Process management and PLM software tool by Siemens

4. DT perspectives on engineering PLM

DT perspectives in PLM stages are analyzed with the adoption of a generic competitive process framework proposed by (Casadesus-Masanell and Ricart 2010) that outlined DT's implementation structure and process. By adopting this framework, companies can focus on relevant PLM aspects for product enhancement. The review highlights relevant industry applications and provides an overview of DT capabilities.

In engineering, (Nasir et al. 2016) described PLM as a process of managing the product lifecycle from inception till disposal. PLM integrates people, data, processes and systems to provide product information support. Figure 6 provides a breakdown on the 54 DT papers identified to involve engineering PLM phases. Generally, an engineering PLM has 5 sequential stages (J. Stark 2016) and Table 13 outlines the various stages involved.

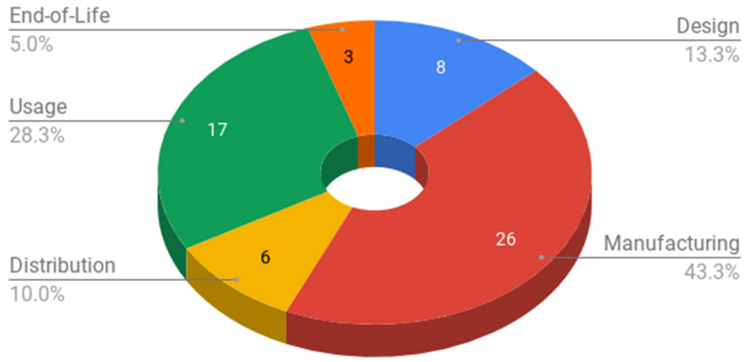

Figure 6. Overview of engineering PLM phases addressed

Table 13. Engineering product lifecycle stages

Engineering PLM stages	Description
Design Stage	Integrate, describe, innovate, analyse, validate
Manufacturing Stage	Production, modelling, optimization, individualization
Distribution Stage	Collaboration, delivery, location tracking
Usage Stage	Evaluate, operate, reconfiguration, maintain, support
End-of-Life Stage	Phase-out, recover, recycle, disposal

4.1 Design stage

In engineering PLM, DT frameworks and technologies enhance the design stage in a responsive, dynamic and comprehensive manner. This section analyzes DT capabilities for product improvement.

DT-based design and production integration. DT approaches were used to integrate product design with production. (J. Guo et al. 2018) used a modular approach to assist designers in constructing a flexible DT with the purpose of design evaluation in the context of factory design. To assess product effectiveness, process and servicing decisions, (Schleich et al. 2017) proposed a comprehensive reference model hinged on the Skin Model Shapes concept while (Tao et al. 2018) presented a DT-driven product design method with a bicycle design case study to assist in iterative redesign of existing products. (Schluse et al. 2018) combined DT with model-based systems engineering and simulation technology in the form of Experimental DT, introducing an agile environment process encompassing the entire life cycle. (Dias-Ferreira et al. 2018) introduced a bio-inspired design framework for dynamic production environments, in which DT can be used to visualize the effectiveness of various interaction patterns.

Description of DT tools. Constructing DT for product design requires communication and computation tools. These technology building blocks reduce the design cost of new products and enable interoperability. (Damjanovic-Behrendt and Behrendt 2019) adopted the open source approach for the design of a DT demonstrator and while (Alam and El Saddik 2017) identified basic and hybrid computation-interaction modes with a DT architecture reference model in a telematics-based prototype driving assistance application.

Service innovation. Service innovation is demonstrated by (P. Zheng, Lin, et al. 2018) with a personalized smart wearable design via Smart PSS and DT to achieve user satisfaction with minimal environmental impact. Driven by smart connected devices, users can take part in the co-development of future products via cloud computing (P. Zheng, Xu, et al. 2018).

Analysis and validation through DT. To deal with geometric reconstruction problems, (Biancolini and Cella 2018) presented a mesh morphing workflow based on radial basis functions for model validation via DT.

4.2 Manufacturing stage

DT wields large influence in the Manufacturing stage with a wide range of novel and innovative studies aiming to make production process efficient, reliable and adaptable.

Production digitalization. To react better to shifting consumer trends, DT is used to digitalize process models. (Yuqian Lu and Xu 2019) introduced a cloud-based manufacturing system architecture to achieve on-demand production, thus achieving better business flexibility. Modeling techniques were studied for DT construction as (C. Liu et al. 2018) created a machine tool cyber twin, achieving better connectivity and flexibility. (Bao et al. 2018) proposed a DT modeling and operating construction approach in an aircraft structural parts machining cell case study while (Tan et al. 2019) proposed a DT construction framework which models IoT data into a simulation. For DT application in shop-floors, (Ding et al. 2019) used DT technologies to enhance interconnection and interoperability between cyber and physical shop-floors whereas (Haijun Zhang et al. 2018) presented a novel production system architecture that also supported job scheduling in an aircraft engine manufacturing case study.

Modeling strategies. To enhance output, DT modeling methodologies are built to suit diverse conditions. (Luo et al. 2018) proposed a multi-domain unified modeling method as a cyber-physical mapping strategy also used for fault prediction and diagnosis. (Y. Zheng et al. 2018) introduced parametric virtual modeling and construction flow of DT application subsystems to fulfilled the case of a welding production line. In an aircraft assembly context, (F. Guo et al. 2018) improved competitiveness with digital coordination model, utilizing DT to accomplish better flexible assembly accuracy and efficiency. (Sharif Ullah 2019) created a semantic modeling methodology to compute virtual abstractions for material removal processes.

Production optimization. Optimization of production aspects such as manufacturing speed and machine control were studied. In the dyeing and finishing industry, (Park et al. 2019) proposed a service-oriented platform to enhance performance measures and achieve cost reduction through optimization algorithms. (Moreno et al. 2017) showcased a DT for a sheet metal punching machine to optimize NC machining programs while, (Zhao et al. 2019) demonstrated a joint optimization DT model for coordinating micro punching processes to boost punching speed. Using geometric assurance DT, (Tabar et al. 2019) reduced computation speed for weld points. (J. Liu et al. 2019) described a DT-based machining process evaluation method for a marine diesel engine manufacturing process. (L. L. Liu et al. 2018) researched on a DT hot rolling production scheduling model and provide decision-aiding support. (Coronado et al. 2018) presented manufacturing execution system as a core DT technology for production control and optimization, allowing easy implementation and lowering costs. (Söderberg et al. 2018) applied real-time geometrical quality control for welded components through DT to enhance production quality for a range of welding processes.

Individualized production. Besides enhancing manufacturing processes, DT allows the shift towards individualized production. (Hao Zhang et al. 2017) presented a DT-based approach to provide decision-aiding support and analytics for rapid individualized designing of a hollow glass production line. (Söderberg et al. 2017) utilized DT in the shift towards individualized production by leveraging simulations to control and optimize manufacturing systems. (Q. Liu et al. 2018) introduced the rapid individualized designing of automated flow-shop system through DT to provide design validation. (Leng et al. 2018) presented a mass individualization paradigm using DT to conduct parallel controlling, providing proactive decision support.

DT-enabled situational adjustments. DT allows adjustments towards practical situations and simulations to deal with production process irregularities. (Sierla et al. 2018) introduced a DT concept for automated assembly planning and asset coordination in a manufacturing cell. (Yuqian Lu and Xu 2018) encouraged DT adoption with a test-driven resource virtualization framework to virtualize complicated factory setups.

Monitoring production process. Operation monitoring and virtualization require vast amount of data. (Angrish et al. 2017) described an architecture based on NoSQL to store and handle streaming data in a scalable and flexible database in order to control virtualized production assets. (Morgan and O'Donnell 2018) demonstrated a cyber-physical monitoring process of a CNC machine using a range of real-time sensor input that serves as a platform for future DT development.

4.3 Distribution stage

In logistics, DT uses real-time tracking and other solutions to facilitate operations. As industry players shift towards smart warehouses with industrial robots, DT is utilized to enhance warehouse safety and efficiency.

Robot-human collaboration. Industrial robots are high-risk entities from a safety standpoint and DT assists in understanding and managing these robots to reduce health risks and reassure employees. For instance, (Petkovi 2018) proposed a Theory of Mind-based algorithm to perceive human reactions to robot assistants operating in changing environments via virtual reality DT. (Nikolakis et al. 2019) implemented a DT approach to enhance planning and control using simulations to analyze productivity in logistics operations. (Bilberg and Malik 2019) presented a DT-driven assembly system to demonstrate robotic automation with human flexibility.

Warehouse management. DT can optimize warehouse management systems by providing decision-aiding support and comprehensive outcome analytics. (Bottani et al. 2017) constructed a DT for job-shop production system involving scheduling for automated guided vehicles to transit in a logistics environment. (Baruffaldi et al. 2019) illustrated a novel warehouse management decision-support tool by addressing factors such as clients' data, cost and returns on investment uncertainty.

Supply chain optimization. (Defraeye et al. 2019) slashed perishable losses with the aid of DT by improving the refrigeration process and logistics during distribution.

4.4 Usage stage

DT's capability in the usage stage involves predicting and designing next generation products, product upgrading and supporting the upkeep of manufacturing assets. By utilizing data and analytics from sensors embedded in smart products and tools, operations, reconfigurations and maintenance processes can be improved.

Knowledge reuse and evaluation. DT provides decision-making support for multi-dimensional processes, strategy improvisation and process forecasting via knowledge recycling and awareness. (J. Liu et al. 2018) proposed a DT process reusability evaluation approach to prototype diesel engine models. (Arafsha et al. 2019) introduced a modular framework for DT creation through action monitoring and data analytics.

Workflow improvement. DT enhances conventional engineering analytics with information integration for a digitalized product life cycle. (Iglesias et al. 2017) aimed to enhance engineering analysis workflows to enhance JET divertor operations with the DT approach. (Haag and Anderl 2018) demonstrated a concept in which a DT will be developed alongside the product and remain its virtual counterpart throughout the entire product life cycle. (Schneider et al. 2019) presented a virtual engineering method, integrating DT paradigm with lifecycle approach in a desalination plant case study.

Shop-floor enhancement. Shop-floors are commonly associated as hives of activity in which DT can serve to improve the assembly layout, manage asset flow and integrate data to enhance production. (Tao and Zhang 2017) constructed a shop-floor DT and discussed key components towards a trend of new paradigm directed towards smart and connected shop-floors. (Zhuang et al. 2018) proposed a smart production management and control approach of product assembly shop-floors with a satellite assembly case study.

Digitalization of plant management. Digitizing plant infrastructure provides a comprehensive overview of the various inefficiencies plaguing the system whereby DT analytics and solutions can ensure operational reliability. (Electric 2016) used DT to monitor and optimize power plant performance and showcased the capability to balance and optimize trade-offs between uncertain factors. (He et al. 2018) demonstrated a cross-technology communication application to provide monitoring and decision-making support for an ultra-high voltage converter station case study.

Increasing energy and resource efficiency. Reducing consumption is a key concern and DT is able to develop smart analytics models to enhance operational efficiency. (Kannan and Arunachalam 2019) developed a predictive model for redress life identification and computation with a DT grinding wheel case study. To improve fuel efficiency, (Coraddu et al. 2019) proposed a DT method to measure the influence of fouling on ships. (MacDonald et al. 2017) leveraged simulation from sensor data to predict failures and diagnose inefficiencies in an operating pump demonstration while (Ferguson et al. 2017) used a Siemens PLM software to simulate digital performance of water pumps, employing DT technologies to improve existing and next-generation products.

DT-driven PHM. As real-time monitoring and simulations pave way for predictive maintenance, (Y. Xu et al. 2019) presented a DT fault diagnosis method using deep transfer learning in development and maintenance for a car body-side production case study. (Tao, Zhang, Liu, et al. 2018b) demonstrated a PHM method with an equipment DT, making use of system interaction and data fusion in a wind turbine case study. (H. K. Wang et al. 2015) combined high-performance fatigue mechanics with filtering theories for aircraft diagnostics and prognostics while (Tao, Zhang, Liu, et al. 2018a) conducted a review, focusing on DT-driven PHM techniques and applications as an enabling technology for smart manufacturing. (Xia and Xi 2019) explored PHM methodologies for cyber-physical systems involving monitoring, data representation and computations, setting the stage for future DT applications.

4.5 End-of-Life stage

Termed reverse logistics by (Govindan and Soleimani 2017), this stage aims to reduce harmful repercussions on human and environment by emphasizing on disposal, remaining lifetime prediction, smart recycling and material recovery. (Yangguang Lu et al. 2019) proposed a DT approach for engine remanufacturing suited for small scale operations while (X. V. Wang and Wang 2019) developed DT product models to facilitate the recycling of electronic equipment. Using DT, (Popa et al. 2018) presented a novel approach to design a glass panel recycling flow and establish a process installation architecture which achieved a higher glass recovery rate.

Figure 7 shows a summary of DT benefits for each life cycle stage. With DT technology bolstering life cycles of products (J. Lee et al. 2016), control systems and resources can be put in place to intervene at the right moment on the right assets. The next section shows how DT is able to influence business aspects to increase profitability.

Design Stage	Manufacturing Stage	Distribution Stage	Usage Stage	End of Life Stage
Design & production integration Guo et al. (2019) Schleich et al. (2017) Tao et al. (2018) Schluse et al. (2018) **Description of DT tools** Damjanovic and Wernher (2018) Alam and Saddik (2017) **Service Innovation** Zheng et al. (2018) **Analysis & validation** Biancolini et al. (2019)	**Production digitalization** Lu and Xu (2019) Liu et al. (2018) Bao et al. (2018) Tan et al. (2019) Ding et al. (2018) Zhang et al. (2018) **Modelling strategies** Luo et al. (2019) Zheng et al. (2019) Guo et al. (2018) Ullah (2019) **Production optimization** Park et al (2019) Moreno et al. (2017) Zhao (2019) Tabar et al. (2019) Liu et al. (2019) Li-Lan Liu et al. (2019) Coronado et al. (2018) Soderberg et al. (2018) Xu (2017) **Individualized production** Zhang et al. (2017) Soderberg et al. (2017) Liu et al. (2018) Leng et al. (2019) **Situational adjustments** Sierla et al. (2018) Lu and Xu (2018) **Monitoring production process** Angrish et al. (2017)	**Robot-human collaboration** Petkovic et al. (2019) Nikolakis et al. (2019) Bilberg and Malik (2019) **Warehouse management** Bottani et al. (2017) Baruffaldi et al. (2019) **Supply chain optimization** Defraeye et al. (2019)	**Knowledge reuse & evaluation** Liu et al. (2019) Arafsha et al. (2019) **Workflow improvement** Iglesias (2017) Haag and Anderi (2018) Ferdinand et al. (2019) **Shop-floor enhancement** Tao and Zhang (2017) Zhuang et al. (2018) **Plant management digitalization** General Electric (2016) He et al. (2018) **Energy & resource efficiency** Kannan et al. (2019) Coraddu et al. (2019) MacDonald C. et al. (2017) Ferguson et al. (2017) **Prognostics health management** Xu et al. (2019) Tao et al. (2018) Wang et al. (2015) Tao at el. (2019)	Lu et al. (2019) Wang and Wang (2019) Popa (2018)

Figure 7. Summary of PLM advantages by DT

5. Business innovation perspectives

A growing number of industries are looking to improve profitability from cyber-physical technologies. (Baden-Fuller and Morgan 2010) defined BMs as the value developed and delivered to clients. (Adrodegari et al. 2017) explained about value monetization using BMs, describing it as a management method that bolsters critical decision-making. This section highlights the benefits received from DT adoption. Figure 8 adopts a combined set of BMs proposed by (Wirtz et al. 2016). In reality, such rigid configuration is not always achievable and therefore, only considered as interrelated.

BMs affect different stakeholders when employed, which in this review, refer to the main beneficiaries upon successful implementation of DT. Identified stakeholder categories are shown in Table 14, representing DT stakeholders in manufacturing ecosystems. In this review, no articles were found to involve the network model and procurement model, since DT technologies do not aid external interactions to influence joint value creation and achieve cost-effective procurements. Although there is a growing trend of DT usage in construction, healthcare and other unconnected fields, DT remain predominantly applied in the manufacturing industry currently. Thus, this section strives to shed light on the versatility of DT and highlight its potential to value add to manufacturers and enterprises via BMs.

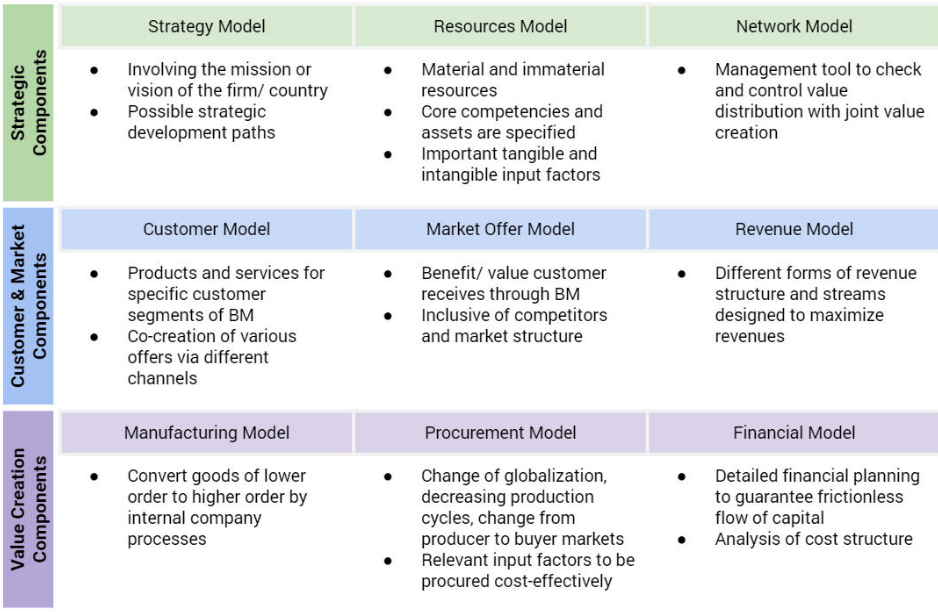

Figure 8. Components of the combined business model

Table 14. Definitions of the various stakeholders

Stakeholders	Description	Examples
System	Government agencies and systems	Land Transport Authorities
Planners	People creating/ implementing Digital Twin products	Designers, engineers, programmers, researchers
Users	End-product recipients	Customers, elderly, disabled, athletes
Enterprises	Companies/ Organizations that manufacture products	Siemens, Hewlett-Packard
Operators	Personnel in-charge of handing operations and production	Managers, shop-floor workers, executives
Maintenance	Personnel in-charge of maintaining the system	Troubleshooting team, support staff

5.1 Strategic components

Strategic components create value for the businesses via internal input factors and set the directions for optimal resource allocation in order to maximize profitability. The strategy model acts as a guide to influence development of BMs and comprises of policy making to capitalize on DT trends, thus maintaining the industries' relevance. Table 15 shows strategies undertaken by the various industries to incorporate DT into policymaking. Another part of strategic components is the resource model. DT optimizes resource allocation, enhance operational efficiency and increase product output. The same table shows DT's influence in the resource model with benefits including cost reduction, process monitoring and decision-making support for machine PHM. The industrial popularity of DT technologies proves that DT is versatile in many fields and the potential to value add to a large proportion of the stakeholder ecosystem.

Table 15. DT's influence on strategy components

BMs	Author	Industry	Stakeholders	Benefits
Strategy Model	(Zobel-Roos et al. 2019)	Biologics manufacturing	Enterprises	Impacts of DT and its shifts towards new BMs
	(Bruynseels et al. 2018)	Healthcare	System	Privacy and ethical issues as a result of DT
	(Cheng et al. 2018) (Tao and Zhang 2017)	Manufacturing	Enterprises	Transformation of digital factories into smart manufacturing and production
Resource	(Biancolini and Cella	Aerospace	Enterprises	DT approach to

Model	2018) (Bao et al. 2018) (F. Guo et al. 2018) (Flumerfelt 2017) (Haijun Zhang et al. 2018)		Operators	optimize production efficiency while lower cost and time for testing
	(Y. Xu et al. 2019)	Automotive	Enterprises Maintenance	Fault diagnosis in development and maintenance stages
	(J. Guo et al. 2018)	Consumer goods	Planners	Expand production efficiency through production re-designing
	(Love and Matthews 2019)	Construction	Enterprises	Increase productivity and cost improvements in facility management
	(He et al. 2018) (Tao, Zhang, Liu, et al. 2018b)	Energy & Power	Maintenance	Monitor and provide decision-aid for fault diagnosis, maintenance
	(Electric 2016)	Energy & Power	Operators	Optimize plant performance and business objectives
	(J. Liu et al. 2018) (Raman and Hassanaly 2019) (J. Wang et al. 2019)	Engine	Enterprises Planners	Lower production costs, reduce emissions via PHM optimization
	(Popa et al. 2018)	Glass recycling	Enterprises	Design processing architecture
	(Sharif Ullah 2019) (Kannan and Arunachalam 2019) (Moreno et al. 2017)	Industrial process	Enterprises Planners	DT construction and process simulation via semantic modeling for energy efficiency
	(Nikolakis et al. 2019) (Bottani et al. 2017)	Logistics	Enterprises Operators	Improve employees efficiency in warehouse and optimize production
	(Sierla et al. 2018) (Sun et al. 2020) (Zhuang et al. 2018)	Manufacturing (assembly)	Enterprises Operators	Automatic assembly planning and orchestrate production resources
	(Ding et al. 2019) (Tan et al. 2019) (W. Wang et al. 2020) (Dupláková et al. 2019)	Manufacturing	Enterprises Operators	Boosts productivity and flexibility with decision-aiding support via predictions and simulations
	(Coraddu et al. 2019)	Maritime	Enterprises	Reduce the significance of fouling on ships
	(Denos et al. 2018)	Materials (manufacturing)	Enterprises	DT simulations for non-destructive assessment of fiber orientation
	(Yuqian Lu and Xu 2018)	Mechanical seal systems	Enterprises Operators	Test-drive resource virtualization
	(Coronado et al. 2018)	OEM	Operators	MES shop-floor DT allows easy implementation and lowers costs for production run of titanium parts
	(MacDonald et al. 2017)	Pump	Maintenance	DT techniques to verify maintenance schedule
	(L. L. Liu et al. 2018)	Steel	Enterprises	Meet product quality and costs, aids resource and man-hour efficiency
	(Haag and Anderl 2018)	Test bench	Operators	Simulate continuous system health monitoring
	(Park et al. 2019)	Textile	Enterprises	Improve productivity and reduce energy costs via analytical techniques

				and IIoT data
	(Ferguson et al. 2017)	Water pump	Planners	Simulate product performance and accelerate product development process
	(Mishra et al. 2018)	Welding	Enterprises Operators	Lower maintenance, manpower and manufacturing costs and increase productivity
	(Schleich et al. 2017)	-	Enterprises	Evaluate consequences via virtual models using skin model shapes for virtual representation
	(Angrish et al. 2017)	3D printing	Planners	Enhance connectivity and data management

5.2 Customer and market components

This component focuses on consumer experiences and convenience through better-suited products and satisfaction while exploring alternatives to increase competitiveness through DT. The customer model focuses on attaining customer satisfaction through better quality products and services, while enlarging client bases via new market access and co-creation initiatives as shown in Table 16. Another aspect of the component is the market offer model. Known as value proposition, the market-offering model's objective is to increase product value by taking into account competitors and the entire market structure. Lastly, with existing forms of revenue streams (markup, licensing, subscription etc.), DT's role in designing revenue stream and structure is presented.

Table 16. DT's influence on customer and market components

BMs	Author	Industry	Stakeholders	Benefits
Customer Model	(Alam and El Saddik 2017)	Automotive	Enterprises	DT used in a driving assistance application
	(Tao et al. 2018)	Bicycle	Planners	DT to redesign bicycle for customer satisfaction
	(H. Kim et al. 2018)	Education	Users	Driver training service via DT to improve experience quality of users
	(Hao Zhang et al. 2017)	Glass production	Planners	Provide individualized designing of production lines
	(Laaki et al. 2019)	Healthcare	Operators Users	DT to facilitate remote surgery, thus enlarging customer base
	(Q. Liu et al. 2018) (Zhao et al. 2019)	Industrial process	Planners Users	DT methodology to allow rapid designing of individualized requirements
	(Leng et al. 2018)	Manufacturing (board-type product)	Enterprises	DT aids smart workshops with mass individualization paradigm
	(Söderberg et al. 2017)	Sheet metal welding assembly	Planners	Higher quality individualized production based on geometry assurance concept
	(Arafsha et al. 2019)	Wearable	Users	Enable seamless adaptability between wearable and networks via data management
	(Bolton et al. 2018)	-	Operators	DT conceptual framework creates customer experiences for b2b and b2c markets

Market Offer Model	(P. Zheng, Lin, et al. 2018)	Wearable Consumer goods	Users	DT-Smart PSS for customer satisfaction and generate e-services as a bundle
Revenue Model	(Leng et al. 2019)	3D Manufacturing	Designers Users	Social manufacturing utilizing blockchain allows economic gains
	(Yuqian Lu and Xu 2019)	OEM	Enterprises Users	Pay-as-you-go model allows users to pay based on the amount of service used

5.3 Value creation components

Value creation components emphasizes on creating customer value through better quality products, cost effective procurements and detailed financial planning to attain a frictionless capital flow. In addition, value creation for stakeholders insures the future availability of investment capital for operations. The manufacturing model aims to improve product quality via internal company processes with Table 17 showing DT providing positive value creation to existing products and services. The financial model in the same table shows how DT supports budgetary management through cost structure analysis and detailed financial outlines.

Table 17. DT's influence on value creation components

BMs	Author	Industry	Stakeholders	Benefits
Manufacturing Model	(Schluse et al. 2018)	Automotive	Enterprises	Experimental DT creates dependable systems with cheaper development process and better designs
	(Abramovici et al. 2016)	Automotive	Operators	Cross-enterprise semantic data management for smart devices and DT
	(Senthilnathan and Annapoorani 2018)	Electronics circuits	Planners	DT approach alleviates steady-state-error
	(Luo et al. 2018) (Guerra et al. 2019)	OEM	Enterprises Operators	Reduces sudden failure probability and improve stability of CNCMT
	(Y. Zheng et al. 2018) (Söderberg et al. 2018)	OEM Welding	Enterprises	Improves welding quality of product and ensures operation efficiency in the production line
Financial Model	(Baruffaldi et al. 2019)	Logistics	Enterprises	Simulate financial statistics and efficiency of warehouse management

By highlighting the application benefits of this technology from a management standpoint, this review offers guidance for future DT adopters to capitalize on the advantages and stand out from the competition. With the consumer market expecting highly personalized smart products to be offered as services, it is apparent that as Industry 4.0 revolutionizes the rules of business, conventional business and marketing strategies will become unproductive (Ghobakhloo 2018). Thus, in order to develop new strategies, the current levels of digital capabilities have to be evaluated so that enterprises can capitalize on the opportunities offered by DT.

6. Discussion and future directions

6.1 Discussion

When Michael Grieves first introduced DT in 2003, it was a concept for product monitoring throughout the lifecycle. From the articles reviewed in 2017, developments on DT were directed towards establishing a real-time 2-way communication before evolving into a dynamic virtual entity with model simulations in 2018. Today, digital cooperation is emphasized with decision-aiding support to optimize production performance and maximize profitability. DT security and privacy concerns are envisaged to be a key discussion point for future DT and the maturity of DT technologies demonstrates its potential to hold a strong presence in Industrial 4.0 and automation of manufacturing facilities.

The technical aspect reveals DT tools used in smart manufacturing featuring overlapping DT methodologies and manufacturing procedures such as the NSGA-II algorithm and MES. These manufacturing perspectives reveal the various types of DT such as partial, clone and augmented DT to be created for different applications (Kucera et al. 2016), providing a road map for developers addressing specific issues. The engineering PLM aspect reflects a lack of focus on the end-of-life stage. Hence, further studies are required to transform the product lifecycle into a continuous cycle as part of smart manufacturing paradigm (Flumerfelt 2017). Remanufacturing DT hold a probable approach in reducing and reusing obsolete products due to environmental concerns. Technology-business integration displays different strategies and forecast for upper management to conduct sales effectively. With revenue models, quality products and co-creation, consumer satisfaction is achieved with paradigms such as mass individualization. In addition, product-service bundle offerings are gaining popularity, lowering principal costs and optimizing output by offering automated real-time situational recommendations. In combining and deploying relevant BMs, enterprises can enhance their unique industry forte with DT to stay competitive. For example, small businesses as highlighted by (Yuqian Lu and Xu 2019) and (Park et al. 2019) were able to adopt new revenue and resource models with the aid of DT, proving that DT-enabled BMs are viable. While DT is not only low cost solution to increase business competitiveness, they also benefit stakeholders ranging from customers to management while allowing employees to adopt a supervisory role.

Vast expansion in application potential ensures the continuous evolution of the DT concept. Hence, it is important to understand and identify the areas of research that authors are embarking on. From the eight key DT future directions, improvement on DT quality such as mappings and simulations before embarking on novel industry applications is crucial as only with refined DT features can further utilization such as incorporating virtual reality, quality decision support be more effective.

6.2 Future directions

As DT technology advances, researchers have highlighted the future directions to encourage mass adoption by enterprises. Table 18 identifies eight major aspects in which DT has room for further development. With increasing research done on combining DT with emerging technologies such as blockchain and virtual reality, applications in new fields such as infrastructure, education and healthcare are imminent. DT enables automation, accessibility and transparency while lowering principle costs such as resources and man-hours. While majority of the studies view application to other domains as potential future work, DT technical aspects are not well established enough to ensure success in other fields.

To better comprehend researchers' views regarding DT future perspectives, the significance of each perspectives is described in the following. A modular approach allows the construction of flexible DT, resulting in new application modes while reducing development time. Realizing modeling consistency and accuracy will improve the quality of DT, enhancing the benefits of DT applications. Incorporation of Big Data analytics into DT will provide more insights, resulting in better decision-making support while improvements in DT simulations allows better monitoring and transparency during processes. Virtual Reality integration unlocks further advancements into relevant fields such as education while extending DT to other domains allow better assimilation with the company's strategic objectives and production process. Efficient mapping of cyber-physical entities enable effective mechanisms to support situational adjustments and reduce uncertainty. Lastly, cloud and edge computing integration allows DT to process at a faster pace while processing vast amounts of heterogeneous and semantic data.

The 8 future perspectives are summed up into the 3 essential DT perspectives to improve the comprehensiveness of this section. Technical aspect. Most authors believe that improving modeling and simulation accuracy in a standardized manner is a key direction towards a higher quality DT. Engineering PLM aspect. The PLM paradigm allows a broader application of DT as enterprises push towards green manufacturing with DT optimizing quality production throughout a full loop cycle. Business aspect. DT with Big Data capabilities allows management to make informed decisions via its decision-aiding functionalities.

Table 18. Future perspectives for DT development

Category	Author	Future Perspectives	Description
Technical Aspect	(J. Guo et al. 2018) (Y. Zheng et al. 2018)	Modular based DT	Modular approaches aid flexible DT construction to suit different evaluation criteria in a time saving manner.
	(El Saddik 2018) (Koulamas and Kalogeras 2018) (Morse et al. 2018) (Haijun Zhang et al. 2018) (Liu et al. 2018) (Yuqian Lu et al. 2020) (Nikolakis et al. 2019) (R. Stark et al. 2017) (Raman and Hassanaly 2019) (Tao, Zhang, Liu, et al. 2018a) (Tao and Zhang 2017) (Damjanovic-Behrendt and Behrendt 2019) (Luo et al. 2018)	Modeling consistency and accuracy	Modeling consistency enables knowledge reuse and increases the interoperability of production systems. Meanwhile, increased model accuracy facilitates better DT functionalities to provide coherent decision-making outcomes.
	(Lee et al. 2018) (Schluse et al. 2018) (Helu et al. 2018) (Taylor 2019) (Tao, Cheng, and Qi 2018)	Improve DT simulation	Better real-time simulation allows operators to determine and fix complications in shop-floor systems.
	(Qi and Tao 2018) (Oyekan et al. 2018)	VR integration into DT	VR integration provides a low cost solution for better visualization and strategy development for collaborative systems.
	(Saddik 2018) (Guo et al. 2018) (Liu et al. 2019) (J. Liu et al. 2018) (Bolton et al. 2018) (Tao et al. 2018) (Tao and Qi 2019) (Tao and Zhang 2017) (Damjanovic-Behrendt and Behrendt 2019) (Zhang et al. 2019)	Efficient mapping system between physical and virtual data	Improving traditional data acquisition and processing approaches allows the implementation of communication interfaces, resulting in user confidence and system reliability.
	(Coronado et al. 2018) (Bao et al. 2018) (Kannan and Arunachalam 2019) (Fraga-Lamas and Fernández-Caramés 2019) (Tao et al. 2018) (Xu 2017)	Cloud/ Edge computing integration	Provides seamless integration for manufacturing systems

PLM Aspect	(Madni et al. 2019) (Popa et al. 2018) (Iglesias et al. 2017) (Ewins 2016) (Neill 2016) (Lee et al. 2015) (Liu et al. 2018) (Laaki et al. 2019) (Ding et al. 2019) (Kannan and Arunachalam 2019) (Bruynseels et al. 2018) (Flumerfelt 2017) (Haag and Anderl 2018) (Zheng, Lin, et al. 2018)	DT expands to other domains 1. New markets (e.g. Construction) 2. Integration of smart connected equipment into DT 3. Product reliability, security and privacy throughout lifecycle	DT technology is adaptable and applying them to other industries such as healthcare and construction is very plausible. Forming the basis of many future technologies, DT can tackle privacy issues, product lifecycle process and product quality etc.
Business Aspect	(Zhuang et al. 2018) (Hao Zhang et al. 2017) (Cavalcante et al. 2019) (Moyne, James; Iskandar 2017) (Leng et al. 2018) (Wang et al. 2020)	Incorporation Big Data analytics into DT models for value generation	With Big Data analytics incorporated, DT exposure to a broader range of useful data increases, optimizing forecast effectiveness.

7. Conclusion

In recent times, awareness on DT technology as an enabling tool for bridging physical and cyber world has been growing exponentially. DT has been exploited for a wide range of applications, resulting in various interpretations and developments without a unified concept. To bridge this gap, this paper presents a systematic survey of existing DT research published in the last 5 years. Findings on the key benefits of DT are outlined below and categorized into three broad areas. It is hoped that this will provide insights on its future applications for a wider range of stakeholders and industries.

Technical aspect. DT creation and development requires extensive knowledge on different technologies to ensure seamless integration between heterogeneous components. To overcome this challenge, four essential categories of *communication*, *representation*, *computation* and *microservices* were identified, forming a technology stack to ensure a coherent and consistent DT implementation. Tools and models used by researchers to add value towards productivity and adaptability of DT systems are classified accordingly, to serve as a reference model for academics and industries in their exploration and applications of DT in the near future.

Engineering PLM aspect. As DT technology is primarily applied in the manufacturing industry, the analysis of engineering PLM aspects aims to reflect the effectiveness of DT towards the handling of products as it moves through typical lifespan stages. The PLM stages are subdivided into specific advantages that DT brings to facilitate innovation and growth towards smart manufacturing. As green, social, individual, intelligent, service-oriented and other manufacturing characteristics have become the development requirements and trends of the future manufacturing industry, this engineering perspective brings forth a vision of sustainable product development by utilizing DT technologies to extend the cradle to grave process into a full loop cycle. By promoting awareness on the benefits of DT to enhance the effectiveness of production operations via quantitative methods, comprehensive analysis and application case studies such as robot-human collaboration, knowledge reuse etc., it becomes clear that realizing DT interactions between human, machine, objects and environment in simulation models and manufacturing processes will gradually become vital for production systems.

Business aspect. DT brings forth a wide variety of benefits from a business perspective for both small and large enterprises. Three essential components, *strategic*, *customer and market*, and *value creation* were identified, encompassing BMs achieving value monetization when incorporated with DT. Industries and stakeholders are determined to provide a comprehensive analysis towards the benefits of DT, allowing upper management to envision a future, where DT plays an essential role in delivering value to consumers and maximizing profits.

Furthermore, this study analysed the trends and viewpoints of existing research and established eight objectives to improve current DT. In the near future, the standards for real-time two-way mapping between physical and virtual models are essential towards the development of an updated and transparent DT system, in order to achieve successful decision-making outcomes and increase users' trust. The authors hope that this research can be regarded as a guideline for more research and discussion on DT aspects towards smart manufacturing and Industry 4.0.

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