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Integrating Digital Twins into Small to Medium Sized Manufacturers: A Roadmap for Engineering Internships*

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Industry 4.0 includes implementations of digital twins (DT) that facilitates smart manufacturing enhancements. Unfortunately, integrating DT into small and medium-sized manufacturers (SMM) continues to be a challenge. To address this problem, the landscape of DT literature was analyzed, and the results were used to create a phased DT integration plan for SMM involving engineering student interns. This paper presents the results of a systematic literature review (SLR) and a roadmap for DT adoption in SMM. Data was extracted from the included literature and qualitatively analyzed to determine themes related to the benefits, challenges, use cases, and best practices of DT. The benefits of implementing DT were efficiency/optimization, quality/customization, maintenance management, safety monitoring, and operator training. The challenges extracted to overcome in implementing DT were connectivity, data analytics, automation, and instrumentation. Relevant DT use cases among the literature were at the levels of machine, work cell, production line, and manufacturing factory. The best practices for DT applications were related to information exchange, digital representation, and reference architecture. Ultimately the literature analysis provided the background to create an integration framework for DT in SMM who struggle to take advantage of Industry 4.0 technology. Engineering educators can implement the provided roadmap to satisfy ABET student outcomes while promoting DT adoption in SMM by involving engineering student interns.

Keywords: digital twin; cyber physical system; smart manufacturing; intelligent manufacturing; engineering internships; engineering education

1. Introduction

The fourth industrial revolution began in the early 2000s. It followed major enhancements in technology from handcraft to machines, next from steam engines to electrification, and then from mass production to automation [1]. Integrating technologies such as artificial intelligence (AI), enabled cyber-physical systems (CPS) and digital twins (DT) to advance from smart manufacturing to intelligent manufacturing thus improving agility, quality, productivity, and sustainability.

Auburn University's Interdisciplinary Center for Advanced Manufacturing Systems in partnership with the Society of Manufacturing Engineers is conducting a five-year longitudinal study to analyze the adoption of smart manufacturing technology [2]. Original Equipment Manufactures representing large companies are implementing and using automation and the Internet of Things. However, Small and Medium-sized Manufacturers (SMM) as lower tier suppliers represent the largest proportion of United States' industrial base. SMM are lagging in innovation with barriers to awareness and evaluation of new technology systems. Critical business challenges are recognized to be operational efficiency and operations workforce. Furthermore, SMM place high value on use cases and peer experience as informational resources. Kunrath et al. [3] describe industry cases to provide engineering students with digital skills integrated into the curriculum. Academia can serve to identify available and to demonstrate applicable low-cost technology solution options for SMM with sponsored engineering internships.

The Pennsylvania State University Berks campus established a Digital Design and Manufacturing Center (DDMC) in 2019 with local industry leaders and higher education educators as its stakeholders. The DDMC was renamed the Manufacturing Innovation & Learning Laboratory (MILL) in 2024. The MILL's mission is to facilitate the process of transferring Industry 3.0 automation & 4.0 interconnectivity technologies to local manufacturing companies through collaborative initiatives. Progress requires multidimensional justification at

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small companies with limited resources for continuous improvement. Decision risk, financial return, ethical values, operational digitization, and data analytics are barriers that companies need to overcome to embrace a digital twin approach for products and processes to enhance their marketplace competitiveness. This study was motivated to elucidate the MILL's prevalent problem of "How can small manufacturing companies justify developing digital twins for their products and processes?"

The purpose of this paper is to provide an incremental strategy to integrate digital twins into SMM based on the best practices described in the literature. This effort provides opportunities for engineering student interns as well as provides a roadmap for future research areas to benefit SMM. This can ultimately maximize benefits and minimize challenges in adopting digital twin technology in SMM. The remainder of this paper will (1) present the results of a systematic literature review (SLR) using the method of Kitchenham & Charters [4] to identify research and to extract, evaluate, and synthesize use cases and best practices for SMM, and (2) present an overview of the incremental approach to integrate DT into SMM involving engineering student interns.

2. Background

The essential concepts related to the intricacies of this SLR are CPS, DT, and Internet of Things (IoT). CPS have core elements of sensors and actuators which are interconnected using IoT technologies. IoT refers to a network of interconnected devices that communicate and exchange information without human intervention. CPS can share data among machinery which improves many aspects of production. DT have virtual representations or models of physical objects that have sensors and actuators and can simulate the behavior, performance, and characteristics of a physical system – allowing analysis, optimization, and predictive maintenance. DT with core elements of models and data provide a model-based systems engineering approach to informed production using accurate predictions for rational decisions [5].

DT are an effective method to connect physical entities with virtual entities. From an initial application in the aerospace industry, DT have been applied in electric power generation, oil and gas, healthcare and medicine, maritime shipping, city management, agriculture, and construction [6]. However, manufacturing applications in aerospace and automotive are the most mature in driving operational improvements.

Advances in information technology are facilitating the integration of DT in manufacturing. DT contribute to improvements in product design, process optimization, and health management [5]. These engineering applications are expanding across manufacturers to improve product performance, production flexibility, and market competitiveness.

Smart manufacturing (SM) is associated with Industry 4.0 developments [7]. SM integrates design, production, and operations data for decision makers. Analysis of timely production metrics yields agility, quality, and productivity enhancements for manufacturers.

The IoT applied to a manufacturing factory is called the Industrial Internet of Things (IIoT). An IIoT improves production processes by networking sensors to control systems to optimally operate machinery. The major challenge for factory production is to operate the plant reliability at a profit [1]. Digital manufacturing relying on real-time data using a digital twin provides a state-of-the-art platform for effective production management. The physical equipment and its digital twin are networked to share data in both directions. Sensor data output from the physical equipment is input to the digital twin. The resulting simulation output from the digital twin can be input into the physical equipment's control system to provide a closed-loop control system. Historical and real-time physical data are combined with computational virtual data to be processed as big data analytics. This merger of data streams improves the control of the machinery and at the same time upgrades the process' analytical model leading to a more rational maintenance strategy and optimal decision making [8].

Smart manufacturing practices are achievable with the implementation of digital twins. Michael Grieves introduced the concept of digital twins in a 2003 Product Lifecycle Management course at the University of Michigan [8]. In 2012, the National Aeronautics and Space Administration defined digital twins for adoption within the aerospace and defense industry [9]. Large industrial companies predict 10% improved effectiveness in automated systems using digital twins [10]. However, small manufacturers (fewer than 500 employees as defined by the United States Small Business Administration) are especially challenged in having limited resources devoted to embracing new technology in achieving the benefits from innovation. Digital twin standards are being developed to facilitate modular approaches for cost effective implementation within the manufacturing industry.

Four previous literature reviews provided background for this SLR. Tao et al. [9] published a state-of-the art paper for DT in industry. The authors discussed the history of DT, the development of DT in industry, and the application of DT in industry, noting that machine health was the most popular implementation. Lattanzi et al. [10] published a review of practical industrial implementation for using digital twins in smart manufacturing. The authors discussed DT concepts and DT manufacturing applications identifying challenges such as communication protocols, model generation, and cost justification. Sharma et al. [11] published a review on DT current theory and practice. The authors discussed challenges preventing widespread implementation and open research questions regarding qualitative performance metrics. Bottjer et al. [12] published a review of unit level DT applications in manufacturing. The authors discussed the methods and technologies used for deploying unit level DT in manufacturing identifying research gaps such as generic reference models, services, content, and deployment. The SLR presented in this paper extends the previous reviews regarding benefits and challenges by focusing on use cases employing best practices. Practical applications developed from academic research can be extended to SMM through an incremental integration of DT utilizing engineering interns to improve operations and train machine operators in digital manufacturing technologies.

3. Research Methods

The SLR protocol followed in this research illustrated in Fig. 1 and described in this section was confirmed by comparing Sauer and Seuring's [13] six-step guide. Stage 1 – Planning the review correlates with Step 1: Defining the research question, Step 2: Determining the required characteristics of primary studies, and Step 3: Retrieving a sample of potentially relevant literature. Stage 2 – Conducting the review correlates with Step 4: Selecting the pertinent literature and Step 5: Synthesizing the literature. Stage 3 – Reporting the review correlates with Step 6: Reporting the results. The SLR's purpose is to discover research gaps within the existing published literature and to justify developing and implementing DT solutions.

Table 1. SLR Process Stages (adapted from [4])

Stage 1 – Planning the Review. • Define research questions. • Develop search strategy. • Establish search criteria. • Select inclusion and exclusion criteria.
Stage 2 – Conducting the Review. • Identify study and selection. • Study quality assessment. • Extract data and synthesize.
Stage 3 – Reporting the Review • Specify publication sources. • Recognize research locations. • Note key technologies. • Discuss implementation approach. • Define terminology.

3.1 Planning the Review

A qualitative analysis was applied to review relevant evidence of digital twins used in smart manufacturing. Research questions guided the planning of the analysis. Various search strings screened databases for publications. Several databases were examined for robustness of returned articles. Inclusion and exclusion criteria were defined to justify the selection of the included papers in this SLR.

3.1.1 Review Objectives and Research Questions

This study began by investigating the response to the question of how small manufacturers can justify developing digital twins for their products and processes. The question's structure was intended to consider three aspects of adoption: impacted companies, implemented technologies, and realized outcomes. With establishing the implementation of digital twins as the objective, four research questions were formulated:

- RQ1. What are the benefits of implementing digital twins?
- RQ2. What are the challenges to overcome in implementing digital twins?
- RQ3. Which digital twin use cases are relevant to manufacturing companies?
- RQ4. What are the best practices for implementing digital twins in smart manufacturing applications?

The following sections present the data collection process to answer the above research questions.

3.1.2 Search Strategy

The SLR protocol defined the search strategy to find the search string anywhere in the selected research database's articles. The search terms used to investigate the research questions were "digital twin" and "smart manufacturing". A search string using both terms together with a selected synonym developed. Table 2 shows the results of these combined strings.

The terms "augmented reality" and "advanced manufacturing" were subsequently discontinued as being too broad for the research questions. After determining applicable search strings, appropriate research databases were examined.

3.1.3 Search Criteria

Three online databases queried relevant publications. Upon determining the search string, two additional databases of research articles complemented Google Scholar's initial assessment. Web of

Table 2. Google Scholar Search String Results

String	Results
"digital twin" AND "smart manufacturing"	8,540
("digital twin" OR "cyber physical system") AND "smart manufacturing"	12,600
("digital twin" OR "augmented reality") AND "smart manufacturing"	13,300
"digital twin" AND ("smart manufacturing" OR "advanced manufacturing")	11,200
"digital twin" AND ("smart manufacturing" OR "intelligent manufacturing")	11,200

Science by Clarivate indexed IEEE and ACM papers. Compendex by Elsevier included ASME along with IEEE and ACM papers. A comparison of these three databases with an expanded search string of [("digital twin" OR "cyber physical system" OR "augmented reality") AND ("smart manufacturing" OR "advanced manufacturing" OR "intelligent manufacturing")] for publication years January 2017 through September 2022 yielded 532 results at Web of Science, 1356 results at Compendex, and 2394 results at Google Scholar.

Compendex, a comprehensive engineering-focused database, was selected to index this study's engineering publications as being neither too narrow nor too broad. Web of Science indexed all journal publications of global citations. Google Scholar was deemed to be too broad with its search for scholarly research.

3.1.4 Inclusion and Exclusion Criteria

The research database selected for this study was Compendex. Compendex is a comprehensive engineering-focused database with over 4000 scholarly journals that indexed this study's engineering publications for relevance. Compendex by Elsevier (https://www.elsevier.com/solutions/engineering-village/databases) was accessed through the Penn State Library portal.

Table 3. Inclusion and Exclusion Search Results

Criterion	Results
("digital twin" OR "cyber physical") AND "smart manufacturing" OR "intelligent manufacturing"	1271
Limit to years 2017–2022	1203
Exclude Open Source	763
Limit to journal articles	347
Limit to English language	298

Returns filtered by both year and type significantly reduced the quantity of papers. The search string was narrowed to [("digital twin" OR "cyber physical") AND ("smart manufacturing" OR "intelligent manufacturing")]. Wang et al. [7] identified an exponential increase in publications starting in 2016, so this search was limited to the recent six-year period. Only eight articles were returned prior to 2017, and they were excluded. Open Access results were excluded. The criteria of excluding conference articles and only including journal articles in the English language further limited the results. Table 3 shows the number of returns for implementation of each criterion.

The search block ((((((("digital twin" OR "cyber physical") WN ALL) AND ((''smart manufacturing" OR "intelligent manufacturing") WN ALL))) NOT ({all} WN ACT)) AND ({ja} WN DT)) AND ({english} WN LA)) produced 298 citations. Fig. 1 shows the number of annual publications.

3.2 Conducting the Review

An experienced researcher validated the protocol using a trial survey of three papers.

3.2.1 Study Search and Selection

Compendex identified primary studies using the selected search block. Publications from 2017 through 2022 provided direct evidence concerning

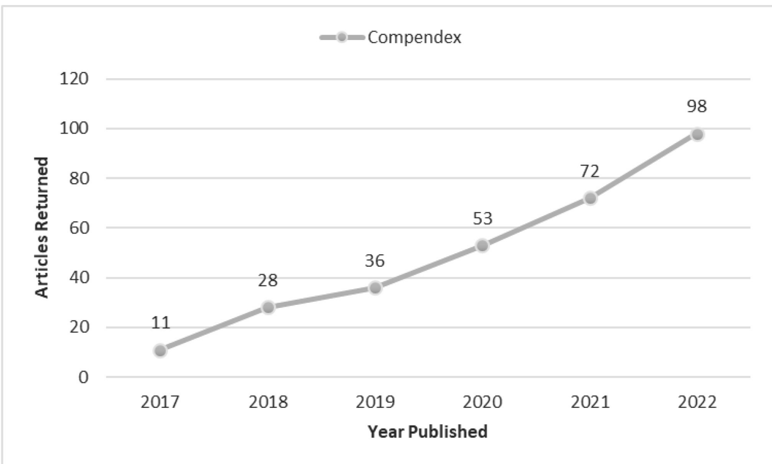

Fig. 1. Articles Returned versus Year Published.

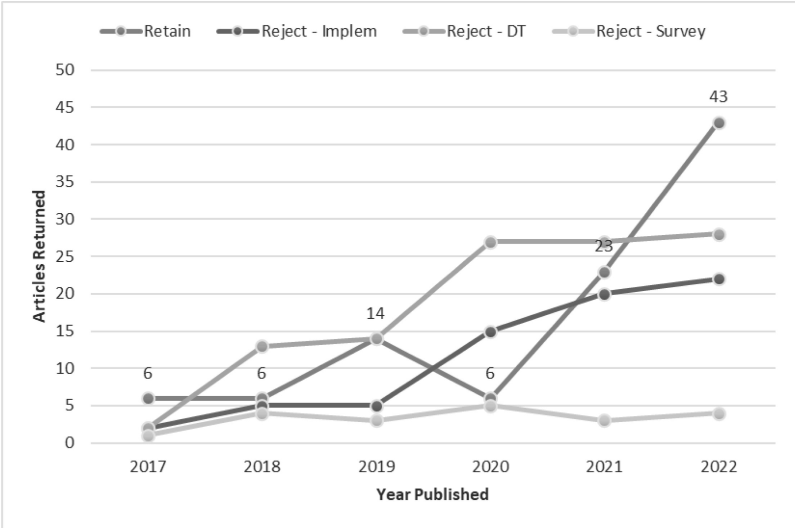

Fig. 2. Articles Returned by Category versus Year Published.

the research questions. The search block included the keywords "digital twin" or "cyber physical" to address the technology aspect and "smart manufacturing" or "intelligent manufacturing" to address the application aspect. Only peer-reviewed journal papers in the English language were included and open-source papers were excluded. The 298 resulting papers illustrated in Fig. 1 were downloaded into an Excel spreadsheet for further processing.

3.2.2 Methodological Quality Assessment

Each paper's abstract was analyzed for relevance in answering the research questions. Three criteria were used for classification:

- What does a digital twin model represent? (product or process).
- What function does a digital twin perform? (design, manufacturer, or service).
- How does a company benefit by implementing a digital twin? (quality customization, efficiency optimization, or maintenance management).

The resulting 298 papers were qualitatively classified into four categories: idea studies (Reject – Survey), implementation relevant (Retain), marginally relevant (Reject – DT), and not relevant (Reject – Implem). There were 20 studies focusing on initial ideas (7% of the papers) labelled in Fig. 2 as Reject – Survey. There were 98 papers where the implementation of digital twin in manufacturing was relevant (33% of the papers) labelled in Fig. 2 as Retain. There were 69 research papers on digital twins that were marginally relevant as an ancillary element (23%) labelled in Fig. 2 as Reject – DT. Lacking digital twin implementation was judged not relevant in 111 papers or 37% labeled in Fig. 2 as Reject – Implem. Fig. 2 illustrates the sorting of papers into the four categories with annual count for the 98 retained papers identified for further study.

Publishing on the topic of Digital Twins in Smart Manufacturing had an increasing trend over the previous six years. The last two years, 2021 and 2022, produced 57% of the journal articles published in that period. Of the SLR retained journal articles, 67% were published in the last two years.

3.2.3 Data Extraction and Synthesis

Retained papers discussed a digital model representing a production (neither design nor service) process (neither material nor product). A prototype example of a digital twin exemplified the use case for 76% of the papers. Efficiency and optimization – minimize effort and maximize resource use – represented 44% of the papers. Quality and customization – improve attributes and adapt to change – represented 33% of the papers. Maintenance management – reduce equipment downtime – represented 15% of the papers. Safety monitoring – prevent harm – represented 8% of the papers. Fig. 3 shows a graphical representation of the 98 retained articles.

Several selected papers previously identified during the iterative search process were used in developing survey questions for quality assessment. The survey form of twenty-four questions available as a hyperlink[1] assessed the digital twin implementation in manufacturing papers. Multiple-choice and multiple-select questions along with their response selections were derived from the survey of ideas and search process papers. This survey's intent was to assess the selected papers from several viewpoints.

[1] https://docs.google.com/document/d/e/2PACX-1vQ3_EKS_czZkf_WxVaFU6f16mg_zs_nfjzHEA7IjG0qusX8pyhjF1JoSi3IH2f2AQ8c97OwayZI8KRV/pub

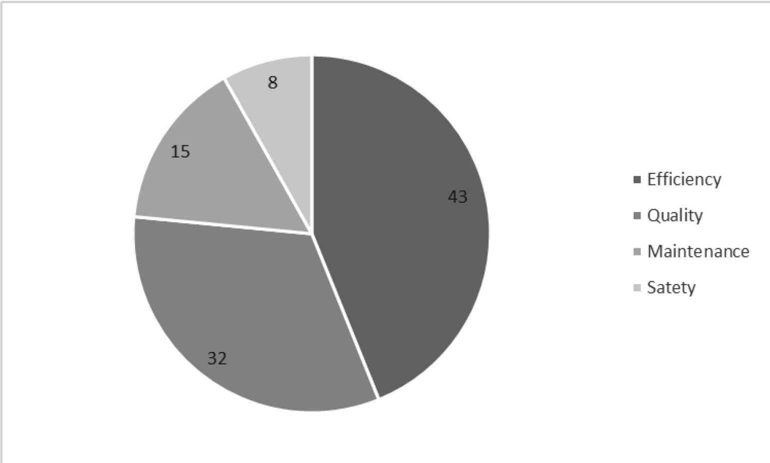

Fig. 3. Retained Articles by Implementation Rationale.

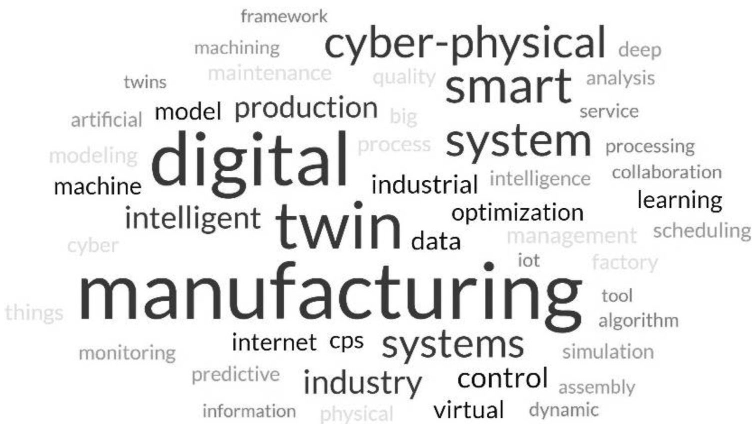

Fig. 4. Word Cloud of Retained Paper's Keywords

Interestingly, the scope of the digital twin implementation in the papers differed and could be categorized as follows: *lifecycle stage* [14], *model representation* [15], *physical production element* [16], *manufacturing process* [17], *digital twin layer* [18], *company benefit, challenges* [19], *value added* [20], *development framework* [20], *engineering standard* [21], and *key technologies* [22]. These authors' points of view were used to guide determining qualitative themes used to group the literature.

3.3 Overview of the Study

Keywords listed in the retained papers were extracted and analyzed in a Word Cloud to display term frequency as shown in Fig. 4. The primary emphasis on the terms digital, twin, and manufacturing validate the relevance of the retained papers to the research questions. The secondary emphasis on the terms cyber-physical, smart, and system further confirms that the literature aligns with the study's objectives. Tertiary emphasis on the terms industry, production, machine, control, model, data, and optimization indicates that the search contains papers with discussions of benefits, challenges, use cases, and best practices. The Word Cloud illustrates a strong connection between literature and research questions.

The publication sources were concentrated in several European journals. The research was dominated by lead authors from China. Most papers discussed key technologies required by digital twins. Many papers described the five layers associated with digital twin implementation. While definitions for digital twin and smart manufacturing are evolving, accepted broad definitions were cited.

3.3.1 Publication Sources

A twenty-four-question survey compiled quantitative and qualitative data from each paper. The analyzed literature citations are available as a hyperlink[1]. Of the top five journals, three were from the United Kingdon and two were from the

[1] https://docs.google.com/document/d/e/2PACX-1vSLICZRA5kIOjsaMgIeeOk9gcK_ECNXgVJ_6LQwql9oZolgfUbSeCMqYVTgXdql7MS-BeuIlqvc6q25/pub

Table 4. Retained Articles by Journal Frequency

Frequency	Ranking	Country	Journal
11	3.165	Netherlands	Journal of Manufacturing Systems
9	0.924	United Kingdom	International Journal of Advanced Manufacturing Technology
7	1.601	United Kingdom	Advanced Engineering Informatics
6	1.095	United Kingdom	International Journal of Computer Integrated Manufacturing
6	1.929	Netherlands	Journal of Intelligent Manufacturing

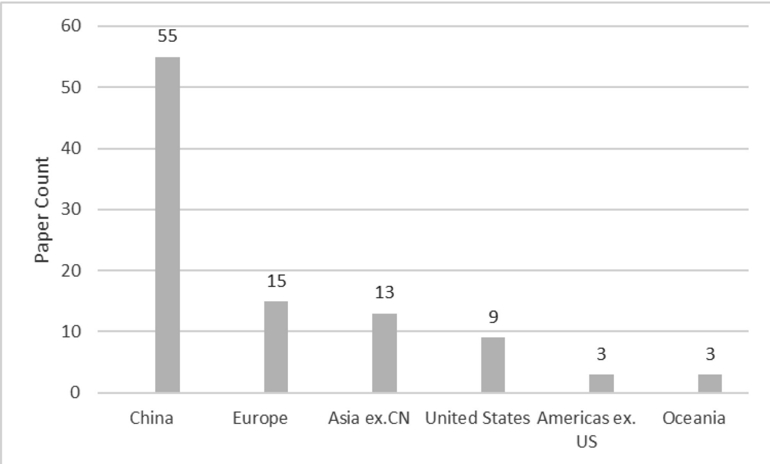

Fig. 5. Regions and Countries Represented by Retained Articles.

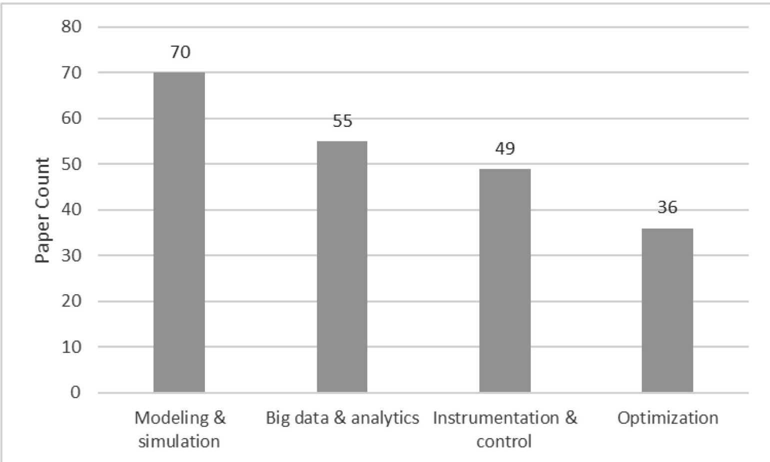

Fig. 6. Paper Frequency by Technologies Discussed.

Netherlands. The five Scientific Journal Rankings in 2021 ranged from a low of 0.924 to a high of 3.165. Table 4 lists the top five journal titles.

3.3.2 Research Locations

Countries and regions producing retained articles are illustrated in Fig. 5. Research conducted in Asia embodied 69% of the papers. China produced 56% of the relevant papers. Research conducted in the Americas embodied 12% of the papers. The United States produced 9% of the relevant papers. Research conducted in Europe embodied 15% of the papers.

3.3.3 Key Technologies

The research papers discussed four key technologies as shown in Fig. 6. Modeling and Simulation – computer representation that mimics the operation of a system – was represented the most often as 71% of the papers. Big data and analytics – decision-making information resulting from the systematic analysis of sensory statistics – was represented in 56% of the papers. Instrumentation and control – measurement sensors directing the operation of equipment – was represented in 50% of the papers. Optimization – making the most effective use of resources – was represented the least

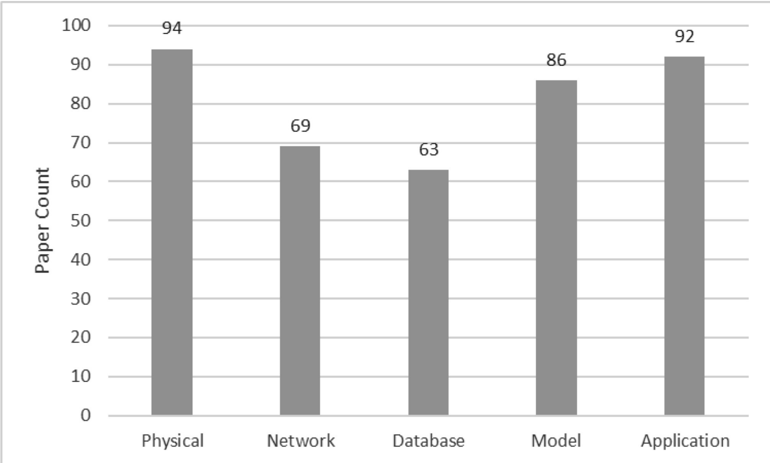

Fig. 7. Number of Papers Discussing Implementation Layers.

often as 37% of the papers. Modeling & simulation and big data & analytics were discussed more than instrumentation & control and optimization indicating a research opportunity in those under-reported areas.

3.3.4 Implementation Layers

Papers identified up to five layers in describing the implemented digital twin: physical, network, database, model, application. The survey asked which of the five layers were discussed in implementing digital twins. Most papers discussed *physical hardware* (actual production process), *manufacturing application* (control of production process), and *digital model* (simulation of production process producing outputs from inputs). Fewer papers included discussion of the *network connectivity* (connection of instrumentation to sense production process) and *database structure* (repository of sensory information). Hence, most papers included all layers (Fig. 7). A description of the physical layer existed in 96% of the papers. A description of the application layer existed in 94% of the papers. A description of the model existed in 88% of the papers. A description of the database existed in 64% of the papers. A description of the network existed in 70% of the papers.

4. Results

This section (and summarized in Table 5) presents the answers to each of the research questions with corresponding literature: *benefits* (labelled as efficiency, quality, maintenance, safety, or training), *challenges* (labelled as connectivity, data, automation, or instrumentation), *use cases* (labelled as machine, cell, line, or factory), and *best practices* (labelled as information, representation, or architecture).

4.1 RQ1: What are the Benefits of Implementing Digital Twins?

Qualitative company benefit themes that emerged were efficiency/optimization, quality/customization, maintenance management, safety monitoring, and operator training as shown in Fig. 8. Efficiency/optimization captured discussions of benefits measured by dollars, time, or quantity. Quality/customization captured discussions of benefits measured in specification metrics or process flexibility. Maintenance management captured discussions of benefits measured in machine health. Safety monitoring captured discussions of benefits measured in hazardous conditions. Operator training captured discussions of benefits measured in worker productivity. These five resulting themes were an extension of the literature analysis of Leng et al. [19].

Efficiency optimization benefits were grouped as improved production efficiency, reduced costs, shortened product lifecycle, optimized production process parameters, and collected operational data. Production efficiency was improved by decreasing defects, decreasing in-process inventory, and increasing inspection pass rate discussed by Ma et al. [71]. A digital twin driven production system was developed to simulate and optimize the production process for a heavy-duty vehicle gearbox. The authors reported improved metrics ranging from 14% to 89%. Reduced costs were realized by reducing energy consumption for heating and cooling discussed by Li et al. [59]. A digital twin based industrial information system was developed to monitor and control the heating and cooling equipment in a manufacturing facility. The authors reported reduced energy consumption from data driven decisions regarding operation and maintenance activities. Additional benefit cases are prevalent in the referenced literature.

Table 5. Retained Papers by Category

Literature	Benefit	Challenge	Use case	Framework
Aggarwal et al. (2022) [23]	efficiency	automation	factory	architecture
Angrish et al. (2017) [24]	efficiency	conn, auto	machine	architecture
Banda et al. (2022) [25]	maintenance	auto, inst	machine	representation
Bao et al. (2022) [26]	quality	auto, inst	line	representation
Brovkova et al. (2021) [27]	efficiency	conn, data, inst	line	representation
Cai et al. (2021) [28]	quality	conn, data	line	information
Chen & Chang (2021) [29]	efficiency	auto, inst	machine	information
Christou et al. (2022) [30]	qual, maint	conn, data	line	architecture
Deebak & Al-Turjman (2022) [31]	maintenance	data, inst	machine	representation
Ding et al. (2021) [32]	quality	data	line	architecture
Draganescu et al. (2021) [33]	quality	data, inst	machine	representation
Elhabashy et al. (2019) [34]	safety	connectivity	factory	architecture
Eugeni et al. (2022) [35]	efficiency	conn, data, inst	line	information
Fan et al. (2021) [36]	efficiency	conn, data, auto	machine	architecture
Fan et al. (2022) [37]	efficiency	connectivity	factory	architecture
Fattahi et al. (2021) [38]	quality	conn, data, inst	machine	information
Febriani et al. (2020) [39]	efficiency	conn, data	cell	architecture
Gao et al. (2021) [40]	maint, safe	data, inst	machine	representation
García et al. (2022) [41]	qual, train	-	line	information
Geng et al. (2022) [42]	training	conn, data	machine	information
Guo et al. (2021) [43]	efficiency	conn, inst	line	information
Hu et al. (2020) [44]	quality	conn, data	line	information
Huang et al. (2021) [45]	eff, qual	conn, data, auto	cell	information
Huang et al. (2020) [46]	quality	conn, data	line	information
Hung et al. (2022) [47]	eff, qual, maint	conn, data	line	architecture
Jiang et al. (2022) [48]	quality	data, auto	line	architecture
Jiang et al. (2021) [49]	eff, maint, safe	conn, inst	factory	representation
Jiao et al. (2022) [50]	qual, safe	automation	cell	representation
Kang et al. (2019) [51]	efficiency	conn, data	machine	information
Khan et al. (2022) [52]	eff, train	conn, data	line	architecture
Krishnamurthy & Cecil (2018) [53]	qual, train	connectivity	cell	information
Lattanzi et al. (2021) [10]	eff, maint	conn, data, auto	factory	representation
Lee et al. (2017) [54]	qual, maint	auto, inst	machine	representation
Li et al. (2019) [55]	maintenance	data, inst	machine	information
Li et al. (2022a) [56]	safety	conn, data, auto	cell	information
Li et al. (2020) [57]	efficiency	data, auto	factory	information
Li et al. (2022b) [58]	quality	auto, inst	line	representation
Li et al. (2022c) [59]	efficiency	conn, auto	factory	architecture
Li et al. (2022d) [60]	efficiency	data	line	architecture
Li et al. (2022e) [61]	quality	conn, auto	machine	representation
Lin et al. (2021a) [62]	quality	conn, auto	cell	information
Lin et al. (2021b) [63]	efficiency	conn, data	line	information
Liu et al. (2019a) [64]	eff, qual	conn, data	line	architecture
Liu et al. (2021) [65]	quality	conn, auto, inst	machine	information
Liu et al. (2022a) [66]	quality	auto, inst	machine	representation
Liu et al. (2019b) [67]	eff, qual	data, auto	line	representation
Liu et al. (2022b) [68]	eff, qual, maint	data, auto	machine	representation
Lu & Xu (2018) [69]	eff, qual	conn, auto	factory	information
Luo et al. (2019) [70]	maintenance	auto, inst	machine	representation
Ma et al. (2020) [71]	eff, qual	conn, auto	line	information
Ma et al. (2021) [72]	efficiency	automation	cell	architecture
Maia et al. (2022) [73]	safety	conn, auto, inst	line	information
Min et al. (2019) [74]	qual, train	data, auto, inst	factory	representation

Table 5. *Continued*

Literature	Benefit	Challenge	Use case	Framework
Mondal & Wong (2022) [75]	safety	automation	factory	information
Namjoshi & Rawat (2022) [76]	efficiency	conn, inst	factory	information
Naqvi et al. (2022) [77]	maintenance	data	cell	information
Nie et al. (2022) [78]	quality	data	factory	representation
Nie & Chen (2022) [79]	efficiency	connectivity	cell	information
Nuñez & Borsato (2017) [80]	maintenance	data, inst	machine	representation
Pacaux-Lemoine et al. (2022) [81]	safe, train	conn, auto	cell	information
Park et al. (2019) [82]	quality	connectivity	factory	information
Park et al. (2022) [83]	efficiency	conn, auto	line	architecture
Pei et al. (2021) [84]	quality	conn, data	line	information
Qamsane et al. (2022) [85]	maintenance	conn, data	line	architecture
Ramezankhani et al. (2021) [86]	efficiency	data	cell	representation
Rodrigues et al. (2022) [87]	efficiency	conn, auto, inst	line	architecture
Rossit et al. (2019) [88]	efficiency	data	line	architecture
Rubio et al. (2018) [89]	maintenance	conn, auto, inst	machine	architecture
Sharif Ullah (2019) [90]	eff, maint, safe	-	machine	representation
Stark et al. (2017) [91]	eff, qual	conn, inst	cell	architecture
Su et al. (2021) [92]	-	auto, inst	machine	representation
Tao et al. (2019) [93]	safe, train	conn, data, auto	factory	information
Tarallo et al. (2018) [94]	eff, qual, train	automation	machine	information
Wan et al. (2017) [95]	maintenance	data	machine	information
Wang et al. (2020) [96]	eff, qual, safe	auto, inst	cell	architecture
Wang et al. (2022a) [97]	quality	auto, inst	machine	representation
Wang et al. (2022b) [98]	eff, qual	conn, data, auto	line	information
Wang et al. (2019) [99]	maintenance	auto, inst	machine	representation
Wang et al. (2022c) [100]	efficiency	automation	cell	information
Wang et al. (2022d) [101]	safe, train	connectivity	line	information
Weckx et al. (2022) [102]	quality	data	machine	representation
Wenna et al. (2022) [103]	eff, safe	auto, inst	cell	representation
Woo et al. (2018) [104]	efficiency	conn, data	machine	architecture
Xia & Xi (2019) [105]	maintenance	data, inst	cell	representation
Xu et al. (2021) [106]	eff, qual	conn, data	line	information
Yang et al. (2022) [107]	efficiency	connectivity	line	information
Yaqot et al. (2022) [108]	efficiency	auto, inst	factory	representation
Yifan et al. (2022) [109]	efficiency	conn, inst	factory	architecture
Zeng & Luo (2022) [110]	Safety	conn, auto, inst	cell	representation
Zhang et al. (2019) [111]	efficiency	conn, data	line	representation
Zhang et al. (2022) [112]	efficiency	automation	line	representation
Zhao et al. (2022a) [113]	quality	automation	machine	representation
Zhao et al. (2022b) [114]	quality	auto, inst	machine	representation
Zheng & Sivabalan (2020) [115]	eff, maint, safe	conn, auto, inst	cell	architecture
Zheng et al. (2021) [116]	quality	conn, data, auto	machine	representation
Zhu et al. (2022) [117]	quality	automation	cell	information
Zhuang et al. (2018) [8]	efficiency	conn, data, auto	factory	architecture
Zhuang et al. (2021) [118]	efficiency	conn, data	cell	representation

As expected, economic improvements dominated the benefit achieved by implementing DT in manufacturing. Businesses must remain profitable as competition impacts their marketplace. While maintaining profitability, the next benefit of relevance was quality. Enhancing quality by reducing variability was a strong motivating factor for implementing process digitization. Once a profitable and high-quality product was successfully produced, continued competition required sustainability by managing maintenance downtime. Hence, the third benefit of maintenance management. In tight labor markets, recruiting and retaining machinery operators leads to the final grouping

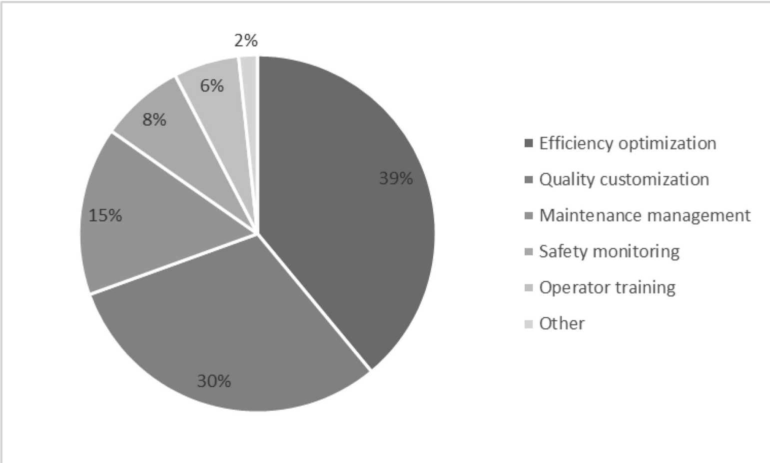

Fig. 8. Company Benefit by Theme Proportion.

of benefits. Monitoring safety and operator training can be enhanced through simulation provided by DT. A hierarchy of benefits resulted through the SLR indicating areas for additional research.

4.2 RQ2: What are the Challenges to Overcome in Implementing Digital Twins?

Qualitative company challenge themes that emerged: connectivity, data analytics, automation, and instrumentation are shown in Fig. 9. Connectivity captured discussions of challenges related to data flow networks. Automation captured discussions of challenges related to automatic control of machinery. Analytics captured discussions of challenges related to analysis of data. Instrumentation captured discussions of challenges related to sensory measurement collection. These four resulting themes were an extension of the literature analysis of Leng et al. [19].

Data flow challenges included cybersecurity, modularity, synchronization, monitoring, and diagnosis. Namjoshi & Rawat [76] discussed securing industry data used in design, machining, inspection, and scheduling to realize smart factory's potential. A cyber-physical production system's data was secured for monitoring and control to enhance productivity. Cybersecurity measures protected manufacturing data to preserve competitiveness. Lattanzi et al. [10] discussed the difficulty in maintaining synchronization between the physical equipment and its virtual representation for practical implementation. Two-way communication protocols struggle to exchange incompatible data formats established from different standards. Fusing data from various production domains requires the integration of various technologies for consistent usefulness. Effective networks provide the means for data to flow efficiently through the digitally connected system.

Contrary to the benefits results, the challenges question identified issues to be addressed simultaneously. First and foremost was connectivity. The

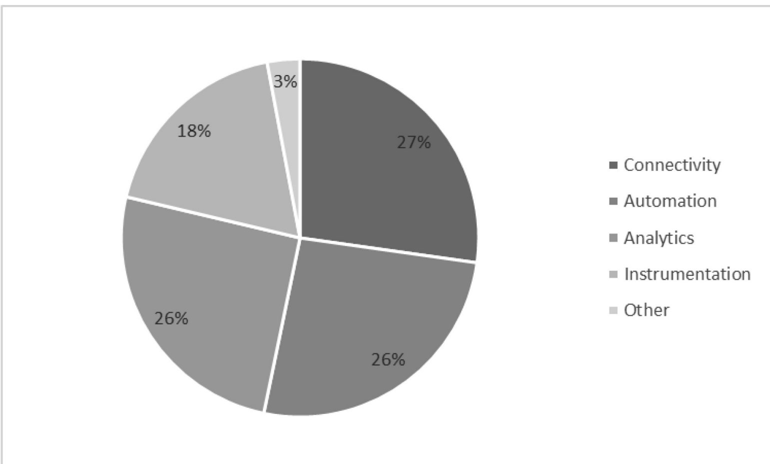

Fig. 9. Company Challenges by Theme Proportion.

need for manufacturers to interconnect machinery with a network is fundamental to implementing DT. The deployment of the Internet of Things will directly address this challenge as standards are published. Once the production data is centrally available then analytics can be used to identify trends and predict outcomes for various operational decisions. Many SMM began their business using manual processes that over time have been automated. Rapid Return on Investment (ROI) dictates that technologies must be implemented in small increments in rapid succession to build momentum for a change mindset. Legacy machinery lacks internal sensors that are standard in state-of-the art machinery requiring the installation of external sensors to collect data streams to monitor processes. The integration of these elements facilitated by a DT provides the benefits identified in the previous section.

4.3 RQ3: Which Digital Twin use Cases are relevant to Manufacturing Companies?

Qualitative use cases emerged from retained papers for digital twins relevant to SMM. Four categories delineated the shop-floor production element: machines, work cells, production lines, and factories. Manufacturing factories are composed of a hierarchy of elements at the shop-floor level. Individual machines combine into work cells. A few work cells coordinate into a production line. Several production lines constitute a manufacturing system. Production line – a sequence of equipment to assemble an object – represented 34% of the papers. Machine – apparatus to perform a specific function–represented 26% of the papers. Work cell–arrangement of machinery to perform a specific process – represented 23% of the papers. System – collection of manufacturing equipment within a factory – represented 11% of the papers. No production element represented 6% of the papers. The prevalent use cases are visualized on Fig. 10. These four resulting themes were an extension of the manufacturing systems from Groover [16].

Production line use cases at the system level are best illustrated with two use cases. Pei et al. [84] discussed a solar cell production line. Fabrication quality metrics were monitored and analyzed to control parameters correlated to detecting mechanisms that produced defects. Their application paradigm improved quality prediction accuracy to 97.8%. Zhang et al. [112] discussed a satellite assembly, integration, and test shop floor. Material flow and processes were modeled to represent the multiple stations required in the production sequence. Their DT framework was validated for a complex production line. Both papers demonstrate the previously discussed benefits and challenges of incorporating DT in manufacturing operations.

Use cases at the production line level are prevalent. Coordinating the processing and transportation of material through the fabrication process was optimized. Most use cases at the machine level address physics-based prediction of tool life important for high volume production scenarios. Use cases at the work cell level involved data sharing in a digital thread where one machine's output is another machine's input. Future research was focused on coordinating activity at the factory level through resource optimization. DT are the backbone to provide operational managers with current information on the status of their plant for data-driven decision making.

4.4 RQ4: What are the Best Practices for Implementing Digital Twins in Smart Manufacturing Applications?

Three themes characterized the development frame-

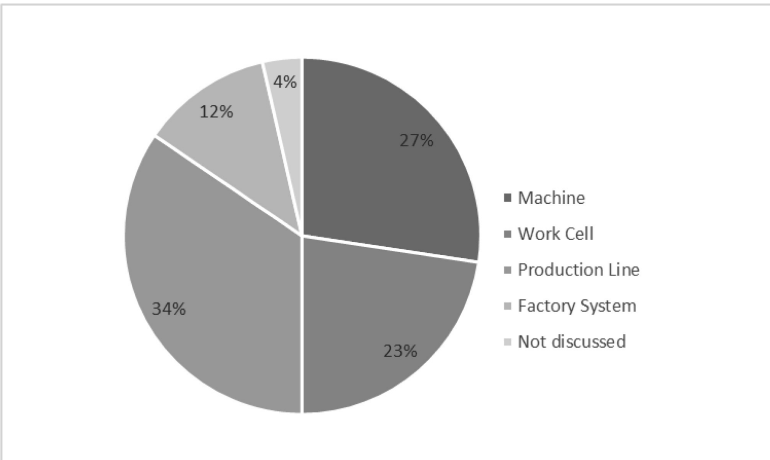

Fig. 10. Use Cases by Theme Proportion.

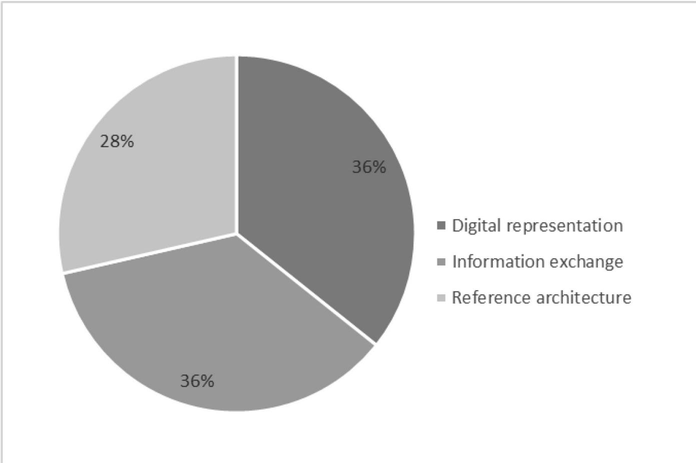

Fig. 11. Best Practices by Theme Proportion.

work for digital twins as shown in Fig. 11. Digital Representation and Information Exchange were equally discussed as the development framework for the digital twins (36% of papers). Reference Architecture was a lesser driver of development– 28% of papers. These three resulting themes were an extension of the case scenarios from Shao [20].

Two best practices papers are noteworthy within the development framework of information exchange shown in Fig. 12. Krishnamurthy & Cecil [53] discussed signals to be exchanged in distinct networks between user and core tasks. A framework for IoT based collaborations is presented for information flow in a cyber physical system. The authors' validation process employed the assembly process for electronic circuit boards. Kang et al. [51] discussed signals from data collection & device control to both user tasks & core tasks. Real-time data from a shop floor environment was used to simulate machinery processes to improve product throughput. The authors' application addressed automated assembly and automated inspection production steps.

Only nine papers or 9% discussed an engineering standard incorporated into their use case either completely or partially. Engineering standards can assist in implementing digital twins by specifying industrial procedures agreed upon. An opportunity exists for governing organizations to establish best practice standards to guide the deployment of digital twins in small and midsized enterprises who are mostly lacking sufficient resources to establish in-house state-of-the-art practices.

5. Discussion: Roadmap for DT Integration using Engineering Interns

Recognition from the research question on best practices that engineering standards were not widely used in deploying DT led to the development of an incremental integration framework discussed in Section 5.1. Section 5.2 examines theoretical versus practical learning in engineering education curriculum with an emphasis on problem-based learning beyond a capstone course. Engaging engineering interns at SMM provides the technical skills necessary to cost effectively adopt innovative technologies as outlined in Section 5.3.

5.1 An Incremental SMM DT Integration Framework

Digitization is the foundation to adopting advanced manufacturing technologies [119]. Manufacturers can use large data sets collected from production processes to reveal operational trends for monitoring product quality. Automating repetitive tasks with robotics improves efficiency and eliminates variation leading to higher quality products. Simulation using virtual representations of processes to validate improvements can enhance production effectiveness. System integration provides unified data in a central repository for analysis to yield informed decision making. The IoT increases communication interconnectivity to provide real-time visibility for optimized operational performance. DT are an enabling technology that facilitates innovation. Digitalization requires a significant resource investment to integrate DT into SMM's process. Incrementally developing DT reduces the risk and builds momentum for innovation. The research project establishes development phases, defines the required information for digital representation, and discusses the applicable industry engineering standard.

A gap uncovered in the SLR was the minimal number of publications that used an engineering standard to guide their study. Industry can operate on standardized procedures to maximize product

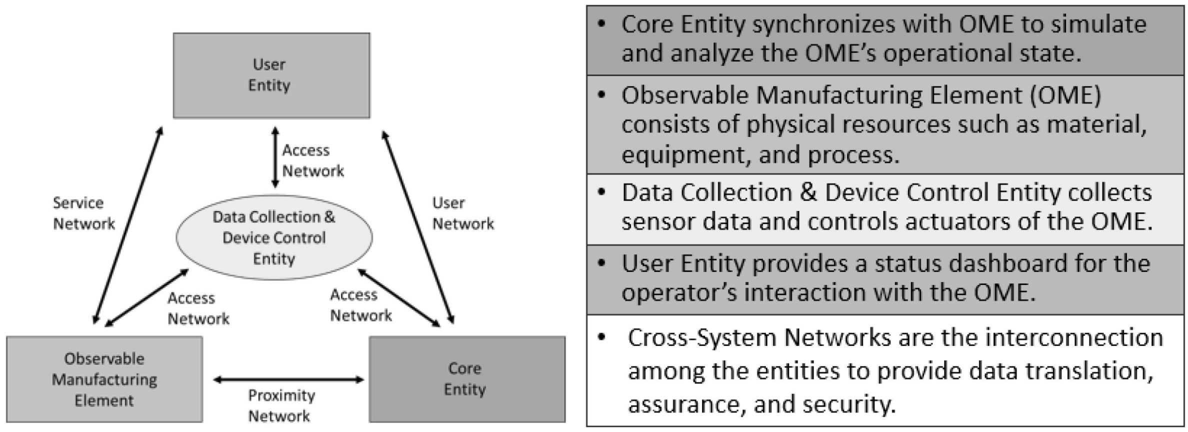

Fig. 12. Five-Element Framework for Digital Twin (adapted from [20, 111]).

quality while minimizing process cost as reflected in the International Standards Organization's ISO 23247 Digital Twin Framework for Manufacturing, Parts 1–4 published in 2021. Using a five-element framework for a DT shown in Fig. 12, a proof-of-concept process will be developed [120]. By establishing an integrated manufacturing use case applying best practices from industry standards, SMM can realize the substantial benefits of implementing DT in their processes.

The Observable Manufacturing Element (OME) consists of physical resources such as material, equipment, and process. Part 3 of the ISO standard specifies seven informational attributes for digital representation for each OME [121]. Each OME requires a mandatory unique identifier. Optional attributes include characteristics, schedule, status, location, report, and relationship. The material OME is the physical matter that is processed into a product. The equipment OME is the physical object that operates on the material. The process OME is the operations to perform the fabrication task.

The Core Entity synchronizes with the OME to simulate and analyze the OME's operational state. Zhang et al. [111] described basic components necessary for a DT coupled in function and structure to mirror the production process. This functional mirror captured manufacturing resources for unified management and on-demand use. The structural mirror presented a graphical user interface to view and set parameters enhancing decision making. A digital model will be used to simulate the kinematic behavior of a CNC Router for optimization and training.

The Data Collection and Device Control Entity collects sensor data and controls actuators of the OME. An instrumentation suite of sensors will collect measurements to correlate to control parameters. The operational data will be analyzed in time and frequency domains to assure compliance with part fabrication specifications.

The User Entity provides a status dashboard for the operator's interaction with the OME. LabVIEW will be used for input sensor measurements and output actuator signals. A dashboard will be constructed to display visual status of monitoring and controlling data flows to complete the DT.

The Cross-System Networks for service, user, proximity, and access are the interconnection among the entities to provide data translation, assurance, and security. The ISO standard Part 4 [122] describes the information exchange framework by defining four networks to connect each entity to share data. The User Network allows the user to manage the DT core entity. The Service Network connects the user to the OME. The Access Network facilitates communication interaction between the user, core, and database entities. The Proximity Network provides real-time data flow between the OME and core entity.

5.2 Practical Experience Gap in Engineering Education

Engineering education has historically emphasized theory over practice in its curriculum. ABET [123] requires engineering students from accredited programs to participate in a culminating engineering experience that incorporates appropriate standards with multiple constraints. Many engineering programs use a capstone design project to satisfy this curriculum criterion. However, institution policies require awarding academic credit for work, such as internships, in lieu of courses.

Wandahl et al. [124] pursued a problem-based learning approach by using an industry internship with the theme of innovation to enhance a graduate engineering program. Both companies and students found value in the experience leading to a recommendation to incorporate an optional or compulsory internship into engineering programs. Practical work experience during college benefited students in procuring their first job after graduation. Graduates that worked with professionals were better prepared to transition from academia to industry. Furthermore, partnerships with employers enhanced faculty's connection to the professional workforce.

Hynek et al. [125] identified the lack of practical problems used in academic courses to provide students' real applications of the subject matter. The authors noted that companies provide their new hires with relevant work experience after graduation, but this limits their practice to a small number of individuals. Incorporating industrial practices and significant problems in the curriculum prepares students for career success. Close cooperation with local engineering companies guided faculty to develop assignments enhancing students' preparation for entry level engineering positions.

Zeid et al. [126, 127] proposed a project-based, team-work curriculum to enable career transition to advanced manufacturing employment. Technical expertise focused on advanced manufacturing, animation, and technical illustration knowledge. Innovation traits focused on entrepreneurship, creativity, and collaboration abilities. Skills identified for success included critical thinking, problem solving, cross-disciplinary thinking, information literacy, global awareness, adaptability, initiative, accountability, and leadership. Their objective was to supply unfilled manufacturing positions with qualified job seekers through hands-on coursework and experiential learning from industry partnered internships.

ABET's [123] student outcomes direct an engineering program's educational objectives in preparing graduates to enter professional practice. Students must demonstrate the ability to analyze complex problems, draw conclusions from experimental data, communicate effectively, and collaborate in a team environment. Internships provide a learning opportunity to practice and master these engineering skills.

5.3 Involving Engineering Student Interns

Employing engineering students as interns is a low-cost approach to enhancing a company's technical capabilities as well as preparing future graduates to contribute to the manufacturing economy. Employers typically assign an intern to assist a senior company engineer in conducting that mentor's duties. Interns perform a variety of tasks that engage their analytical, empirical, collaborative, and communicative skills. Technical supervisors assess the internship experience across several dimensions: knowledge of engineering principles, ability to solve technical problems, performance of meaningful measurements, interpretation of experimental results, commitment to professional ethics, function effectively as a team member, documentation of results in written reports, and listen actively to comments.

Industry supervisors' evaluations from two academic years at Penn State Berks quantify the effectiveness of the internship experiences in their baccalaureate program. Fig. 13 illustrates success in

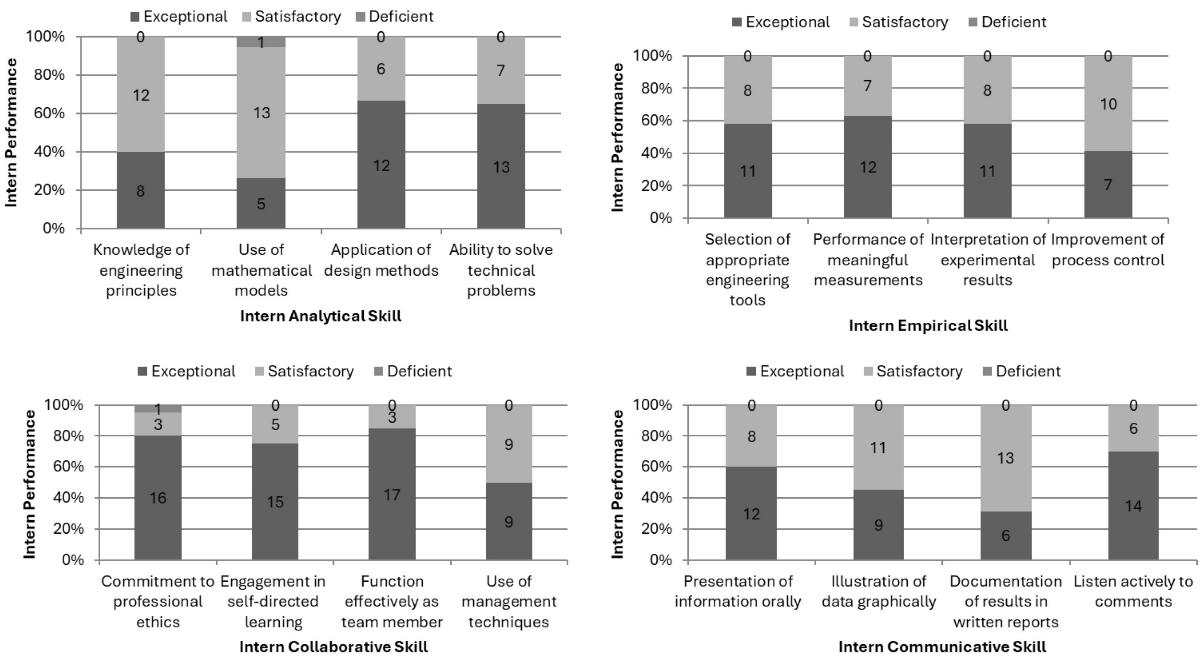

Fig. 13. Supervisor evaluations of interns across four outcomes.

demonstrating professional skills in the workplace. Interns performed exceptionally in analytical skills between 25% and 65% of their assignments. Interns performed exceptionally in empirical skills between 40% and 60% of their assignments. Interns performed exceptionally in collaborative skills between 50% and 80% of their assignments. Interns performed exceptionally in communicative skills between 30% and 70% of their assignments. The remainder of the ratings were satisfactory except for two exceptions of deficient regarding modeling and ethics.

Penn State Berks and Duryea Technologies formed a partnership supported by a State of Pennsylvania Manufacturing Fellows Initiative grant. This innovation project provided faculty supervision of eight undergraduate engineering students to develop and validate DT in collaboration with Duryea Technologies. The students applied SM technologies by immersion in an on-site manufacturing environment to increase their interest in a manufacturing career. An intern each semester was assigned to one of the elements in the DT framework illustrated in Fig.12. The Core Entity intern created a Fusion 360 kinematic digital model of Duryea's CNC mill and a detailed model of a production canister clamp ring. The Cross-system Networks intern established an Industrial Internet of Things using engineering standards to connect mill performance data to a server stored database. The Data Collection and Device Control Entity intern computed data analytics to correlate sensor measurements of power, temperature, vibration, and acoustic to spindle speed, feed rate, depth of cut, and radius of cut. The User Entity intern developed a dashboard to visualize a display of data trends in time using a statistical process control format with control limits. Integrating a DT in the production process maintained the part quality while reducing the fabrication time, thus improving productivity.

In executing the research project, the interns also achieved the previously identified internship outcomes. The four interns formed an integrated team demonstrating interpersonal collaboration. Progress meetings and weekly reports assured the principal investigator that communications were timely and effective. The design of digital models and monitoring displays invoked relevant analysis techniques. Collection and processing of measurement data validated testing protocols. The student interns worked on an enriching manufacturing project that assessed their mastery of learning outcomes expected from the undergraduate program.

The manufacturing company provided real-world applications for improving the manufacturing process of an existing part to demonstrate to students the value of manufacturing to Pennsylvania's economy. The small manufacturer gained insight into the benefits of Industry 4.0 productivity gains through technology transfer to improve their competitive position in the marketplace. The Manufacturing Innovation & Innovation Laboratory at Penn State Berks coordinates faculty expertise with regional manufacturers to enhance their operations with industry's best practices. The proof-of-concept implementation plan for digital twin technology validated under this project is applicable to other small manufacturers in the region to overcome barriers to adopting innovative technologies.

6. Conclusion and Future Work

This study identified several research gaps that significantly contribute to the barriers inhibiting SMM from deploying digital twins to engage in smart manufacturing. The first research gap showed that while efficiency and quality aspects dominate as the benefit rationale in the published literature, both *safety* and *training* were under-reported areas requiring additional research. The second research gap showed that *implementation challenges* for companies were roughly shared among connectivity, automation, data analytics, and instrumentation indicating a modular approach to integration is warranted. The third research gap showed that *use cases were limited for SMM.* Reported use cases were more prevalent for machine and production line implementations for larger operations than for work cell and manufacturing factory applications indicating the need for a systems integration approach for smaller operations. The fourth research gap was *lack of focus on holistic approaches* indicating that development frameworks were mostly divided between digital representation, information exchange, and reference architecture demonstrating a specific approach rather than a universal approach. There is great need for engineering standards to guide implementation evidenced by only nine papers using an accepted standard. The literature review provided ample examples of deploying DT by larger manufacturing companies.

The next research phase is to coordinate steps in deploying DT into SMM. Involving engineering student interns both to satisfy ABET student outcomes and to integrate digital technologies to enhance productivity was outlined. By establishing an integrated manufacturing use case using best practices from industry standards, SMM can realize the substantial benefits of implementing DT in their processes. The mission of the MILL can be fulfilled with a risk managed phased approach to implementation of DT at SSM. Barriers to innovation can be overcome while enhancing operator safety using training simulations with DT. The validated proof-of-concept will be taught to engineering students to deploy during industry internships.

Data Availability – Two datasets generated by the survey research are publicly available as Google Docs. The survey questions for the current study are at https://docs.google.com/document/d/e/2PACX-1vQ3_EKS_czZkf_WxVaFU6f16mg_zs_nfjzHEA7IjG0qusX8pyhjF1JoSi3IH2f2AQ8c97OwayZI8KRV/pub. The list of literature sources for the current study is at https://docs. google.com/document/d/e/2PACX-1vSLICZRA5-kIOjsaMgIeeOk9gcK_ECNXgVJ_6LQwql9oZolgfUbSeCM-qYVTgXdql7MS-BeuIlqvc6q25/pub.

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