2023 IEEE Smart Information Systems and Technologies (SIST)
4-6 May, 2023, Astana, Kazakhstan

Digital Twin for Additive Manufacturing: Challenges and Future Research Direction

Nursultan Jyeniskhan
Mechanical & Aerospace Engineering Department
Nazarbayev Univeristy
Astana, Kazakhstan
nursultan.jyeniskhan@nu.edu.kz

Karina Shaimergenova
Mechanical & Aerospace Engineering Department
Nazarbayev Univeristy
Astana, Kazakhstan
karina.shaimergenova@nu.edu.kz

Md. Hazrat Ali
Mechanical & Aerospace Engineering Department
Nazarbayev Univeristy
Astana, Kazakhstan
md.ali@nu.edu.kz

Essam Shehab*
Mechanical & Aerospace Engineering Department
Nazarbayev Univeristy
Astana, Kazakhstan
*essam.shehab@nu.edu.kz

2023 IEEE International Conference on Smart Information Systems and Technologies (SIST) | 979-8-3503-3504-0/23/$31.00 ©2023 IEEE | DOI: 10.1109/SIST58284.2023.10223556

***Abstract*—Digital twin (DT) and additive manufacturing (AM), also known as 3D printers, are most important practices in industry 4.0. 3D printers are the best candidate for manufacturing geometrically challenging products due to the increase in customized product. However, there are limitations and issues regarding product quality and process optimizations. Owing to a digital twin technology's ability to provide maximum benefits to the manufacturing field, especially additive manufacturing, it is considered one of the suitable technologies to integrate with. In recent years, digital twin gets more attention from both academia and industry. However, there are implementation challenges of digital twin technology. Thus, identifying and understanding these challenges are significant. Many challenges are mapped out from research papers and work in academia in this paper through narrative literature review. Identified challenges have been classified into eight key categories to formulate the future research direction. It is important to investigate the identified challenges and provide possible solutions to elevate the functionality of the digital twin model and improve additive manufacturing productivity and efficiency, ultimately achieve smart manufacturing.**

Keywords—digital twin, additive manufacturing, challenges, communication, data, IoT, uncertainties

I. Introduction

An increasing number of customized products are challenging to be fabricated due to the limitations of conventional manufacturing methods [1]. Thus, the additive manufacturing method is suitable for manufacturing complex products because of its potential to produce geometrically challenging products for high-value markets with minimal material wastage [1], [2]. This manufacturing method is also known as 3D printing, which creates a product by printing layer-by-layer until it reaches to final shape or product [3], [4]. Due to the high numbers of printing parameters, oftentimes there is inconsistent quality in final products, even defects [2]. In addition to this, due to the wide variety of limitations and issues of additive manufacturing, the digital twin is considered as one of the most suitable solutions for enhanced smart additive manufacturing [2], [5].

The term digital twin was introduced to manufacturing in 2002 by Michael Grieves. Initially, there was no universal definition of a digital twin [6]. One common explanation for the digital definition is the mirror of the physical twin into virtual environment and the convergence of the physical and virtual models [7]. Engineering research regarding digital twins is still in the infancy stage, but there has been enormous growth in publications in recent years and research activities by world-class technological companies [7]. In addition to its potential benefits of this technology, it is also considered a potential solution for additive manufacturing challenges and issues according to some researchers [1], [2], [5].

The expected benefits from implementing digital twin in additive manufacturing are cost-effectively acquiring the best combination of printing parameters to decrease trial and error process costs, monitoring manufacturing process and machine health, predictive maintenance, minimizing possible errors and defects, avoiding the cost, time, and material wastage [1], [8]–[12]. However, there are challenges to the digital twin and its implementation reference model in additive layer manufacturing [5], [7], which will be discussed broader in the following sections of this paper.

This research is funded[1] by Nazarbayev University and the main purpose of this research study is to identify the main challenges of digital twin implementation for the additive layer manufacturing field on a broader scale to leverage smart manufacturing not only in Kazakhstan, but in rest of the world. The identification of these challenges

[1] Nazarbayev University under the Faculty Development Competitive Research Grant Program (FDCRGP),

was through a narrative literature review technique. Identifying and understanding these obstacles would contribute to the digitalization of the additive manufacturing industry and are crucial for further research and recommendations to overcome currently existing challenges and approach one step closer to fully operable digital twins and intelligent additive manufacturing.

II. UNDERSTANDING DIGITAL TWIN

It is important to understand what digital twin and its primary functionality is before discussing its implementation challenges in additive manufacturing. Digital twin is a virtual model that perfectly mirrored from physical model and real-time integration among the models. The most important function of digital twin is the bidirectional communication between digital and physical models as shown in

Figure *1* [13], [14]. However, it is not always possible to achieve this without any middleware due to lack of in-built or embedded communication technology that compatible with digital model and other technologies.

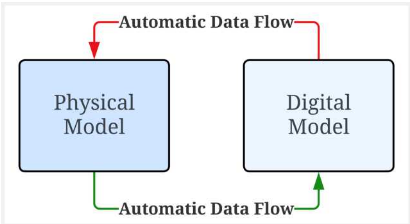

Figure 1. Digital Twin [13], [14]

Thus, middleware is essential and necessary for receiving data from physical model and send received data to digital model real-timely. Similarly, digital model send data to physical model through middleware real-times basis so the system can have bidirectional communication as shown in Figure 2 [15]. This architectural design is lacking in recent machines and technologies, which makes it challenging to acquire viable digital twin model.

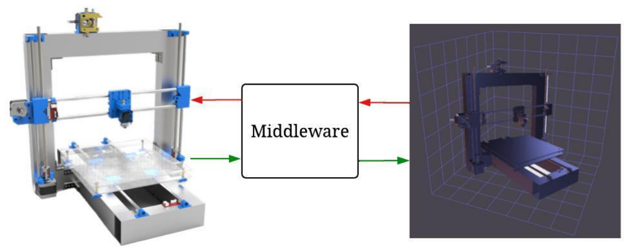

Figure 2. Communication Middleware for DT

One of the main reasons using digital twin in manufacturing is its ability to monitor manufacturing machines performance and receiving feedback regarding production line in real-time basis. This allows to manufacturer's predict the downtime issues earlier. The current development is in accordance with the fourth industrial revolution, which leverages device connection to make the notion of Digital Twin a reality for production operations [16]

III. ADDITIVE MANUFACTURING AND DIGITAL TWIN IN INDUSTRY 4.0

There are nine pillar technologies of the industrial fourth revolution as shown in

Figure *3*. As it can be seen from

Figure *3*, additive manufacturing is one of the nine pillar technologies of the industry 4.0 [17]. It is also important to address what are the pillar technologies of digital twin implementation to clearly see where digital twin technology take place in industry 4.0.

Figure *4* shows numerous technologies which are needed to implement digital twin in additive manufacturing such as Internet of Things (IoT), cloud computing, simulation and emulation, and artificial intelligence which are also important pillar technologies of industry 4.0 [5], [17]. Thus, the digital twin technology plays important role in the fourth industrialization period.

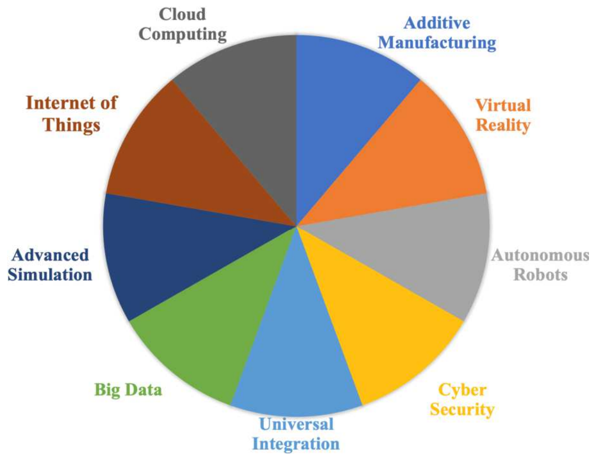

Figure 3. Pillar Technologies of Industry 4.0

It is important to note that, digital twin is in its development stages and contains various pillar technologies integrations which work in harmony. However, more system integration leads to more complexities and challenges. Thus, the challenges should be identified within the sub-systems, and then systems.

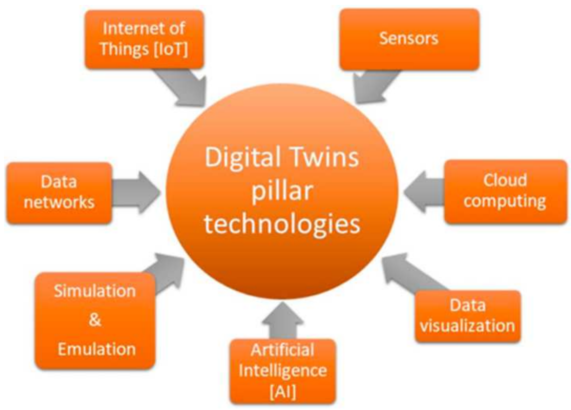

Figure 4. Digital Twin Pillar Technologies

IV. Identified Challenges

Through narrative literature review, after carefully reviewing identified research papers, there are eight key categories of digital twin implementation challenges were identified, as shown in Figure 5. All the identified challenges are explained in detail in this section.

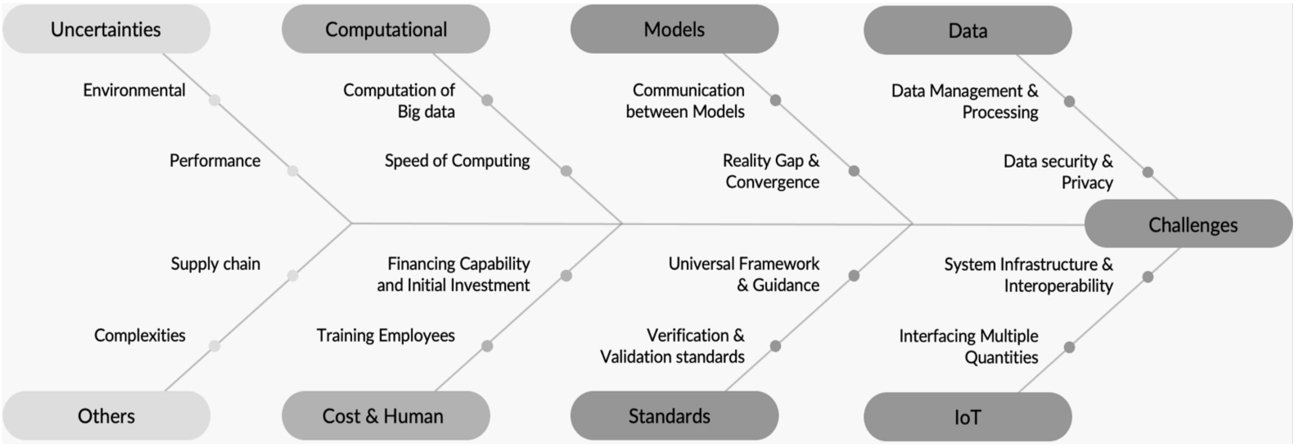

Figure 5. Digital Twin Implementation Challenges in Additive Manufacturing

A. *Data-Related Chalenges*

In Table I illustrates data-related challenges. The fundamental need for functional digital twin implementation for additive manufacturing is big data [5], [16]. However, receiving, storing, processing, managing, and transferring these data between models are challenging. Feeding the system with real-time data, at the same time, processing and managing real-time data are also among data-related challenges due to different data formats from various sensors and low-quality data [14], [18]–[21]. Security and privacy of these data also concerning aspects of data-related challenges. Thus, IT infrastructure plays a significant role in managing these issues. It is costly to construct such a system, so cloud service is a preferable option that comes with privacy and security concerns [14], [22]. Two-way communication between physical and virtual models is essential to digital twin implementation. Due to the deficiency of closed-loop data feedback is still a challenging topic to solve the bidirectional communication challenge between additive manufacturing machines and mirrored twins in the digital environment [1], [22].

TABLE I. Data – Related Chalenges

Challenge	Reference
Bidirectional data flow	[1]
IT infrastructure	[14]
Big Data	[5], [16]
Data transfer	[20]
Data management	[21]
Closed-loop data feedback deficient	[1], [22]
Data privacy	[14], [22]
Data security	[14], [22], [23]
Real-time data processing & Management	[19], [22]
Data sharing	[22]
Data acquisition and storage	[23], [24]
Lack of material properties data	[25]
Data quality	[23], [26]

B. *Models-Related and Standardization Challenges*

In Table II, challenges regarding virtual and physical models are stated. As mentioned before, communication among models is significant to implement a fully functional digital twin. The main challenges are the communication among models as one of the most important functionalities of a digital twin technology [14]. It is important to note that bigger communication latency result in a bigger reality gap issue which is difference between reality and digital twin [7], [20], [27]. More virtual and physical models converge, more digital twin model gets close to real-time monitoring with minimal data exchange latency [28].

TABLE II. Models – Related Challenges

Challenges	Reference
Communication between models	[14]
Interoperability	[18]
Reality gap	[20]
Communication latency	[7], [27]
Convergence between models	[27], [28]

In Table III, digital twin implementation standardization challenges are listed. The lack of universally following guidance and digital twin framework create challenges a widely accepted digital twin implement and model [21], [22]. Moreover, standardized DT characteristics and standardization principles are among standard-related challenges of the digital twin implementation in additive manufacturing [5], [22], [23]. In addition, as result of standardization and lack of real-world experimental data create difficulties regarding verification and validation of the digital twin [21], [25].

TABLE III. Standardization Challenges

Challenges	Reference
Universal guidance	[21]

Verification & Validation standards	[21]
Universal standardized DT characteristics	[22]
Compatible structure for comprehensive use	[22]
Widely accepted DT framework	[22]
Standardization principles	[23]
Experimental data for validation	[25]

C. Internet of Things (IoT) - Related Challenges

In Table IV, challenges regarding Internet of things (IoT) are listed. IoT is one of the most important pillar technologies of digital twin implementation. However, challenges regarding IoTs are the insufficiency of in-built sensors in additive manufacturing machines for extra data, additional sensors required to gather data from physical instances which is not practical [5], [29]. A number of sensors gather variety of data type and requires different system level to maintain it, which brings challenges of connectivity, IoT and Cloud integration, merging of different technologies and their interoperability, and interfacing multiple quantities [1], [14], [24]. All those challenges can be partially solved by an appropriate IoT and IT infrastructure which can bring cost-related challenges.

TABLE IV. IoT-REALTED CHALLENGES

Challenges	Reference
IoT & Cloud platform integration	[1], [19]
System interoperability	[5]
IoT Infrastructure & Connectivity	[14]
Interfacing multiple quantities	[24]
Non-intrusive sensor position	[29]

D. Computational Power and Cost-related Challenges

Big data and complex infrastructure require high computational power, time, and speed for the digital twin model to operate in optimum conditions [1], [20], [25]. Moreover, training machine learning and AI model needs high computational power and speed to process and analyze data to predict future behaviors of manufacturing processes and products to avoid the time, cost, and material wastage [25], [30]. The computational challenges of digital twin implementation in additive layer manufacturing are shown in Table VI.

TABLE V. COMPUTATIONAL CHALLENGES

Challenges	Reference
Computational time	[1]
Computational errors	[1]
Computational power	[20]
Speed of computing	[25]
Computation of Big Data	[25], [30]
AI model training computer power	[25], [30]

It is also a question of willingness to spend how much financial resources on this new technology, training employees according to needs for this new technology implementation. Moreover, there are concerns of performance and return on investment on digital twin implementation. These are the challenges concerning cost and human resource of an organization shown in Table V.

TABLE VI. COST – RELATED CHALLENGES

Challenges	Reference
Training	[5]
Financing capabilities	[5]
Cost	[19], [22], [23]

E. Uncertainties and Other Challenges

Other than the previously mentioned challenges, there are other challenges and uncertainties, listed in Table VII, of digital twin implementation in the additive manufacturing industry. Interestingly, all listed challenges regarding digital twin implementation, including uncertainties, are important and interconnected with each other. Thus, it is crucial to overcome these challenges to acquire a more functional, operable, standardized, and affordable digital twin.

TABLE VII. UNCERTAINTIES AND OTHER CHALLENGES

Challenges	Reference
Uncertainties	[13]
Complexities	[21]
Industry & Academia partnership	[25]
Organizational	[26]
Security	[26]
Environmental	[26]
Performance	[26]
Supply chain	[31]
System integration & infrastructure	[31]
Transition challenge	[32]

V. ANALYSIS OF THE SOURCES

There are 32 research studies are selected through narrative literature review and considered for analysis in this research work. ScienceDirect, IEEE Xplore, Google Scholar, and other database are used for identification of the sources as shown in Figure 6.

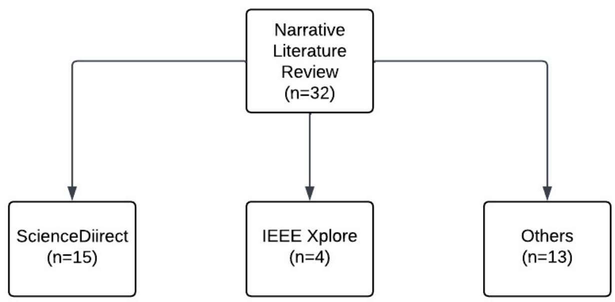

Figure 6. Database for Source Identification

Table VIII illustrates the name of the journal and proceedings of used research studies in this research. It can be seen from Table VIII, almost all of the identified papers are in good quality, reliable, and peer reviewed. One source is from the web that the summary of “Towards a True Digital Twin,” symposium in

Melbourne, Australia. The outcomes from the symposium by the industrial experts and academic researchers in the area of digital twin and additive manufacturing.

TABLE VIII. JOURNAL, PROCEEDING, AND OTHERS' DISTRIBUTION

Name	Amount
Additive Manufacturing	3
Comput Ind	3
Materials Today Proceedings	1
Manufacturing Letters	1
Procedia Manufacturing	1
Libraries at University of Nebraska-Lincoln	1
Applied System Innovation - MDPI	1
Advances in Science and technology	1
Robotics and Computer Integrated Manufacturing	1
Procedia CIRP	1
Scripta Materialia	1
KTH Royal Institute of technology	1
ECS Transactions	1
2017 Ninth International Conference on Ubiquitous and Future Networks (ICUFN)	1
IEEE Access	1
2021 6th South-East Europe Design Automation, Computer Engineering, Computer Networks and Social Media Conference (SEEDA-CECNSM)	1
2022 IEEE/ACM 10th International Workshop on Software Engineering for Systems-of-Systems and Software Ecosystems (SESoS)	1
Journal of Mechanical Engineering and Automation	1
Addit Manuf	1
Manuf Lett	1
International Journal of Scientific Research and Management	1
2022 IEEE International Conference on Industrial Engineering and Engineering Management (IEEM)	1
J Manuf Syst	1
Int J Comput Integr Manuf	1
IoTDI 2019 - Proceedings of the 2019 Internet of Things Design and Implementation	1
Applied Sciences - MDPI	1
Automation - MDPI	1

VI. DISCUSSION

In this research, the main key challenges of digital twin implementation for additive manufacturing are addressed to formulate further research directions. The most critical challenges from identified challenges were regarding data, IoT, universally applicable architecture and guidance to follow.

Currently, not all challenges can be solved. Still, three ways to solve most of the challenges can be identified: using existing technologies and methods from related industries, human decision factors, and developing and creating new technologies and practices for solving challenges.

For example, the solution to the problem of data transfer and its protection can already be found in the data engineering industry. Machine learning (ML) will make it possible to turn DT into a real-time mode with defect tracking. A properly designed middleware architecture will allow seamless and bi-directional data communication. In other words, these components (middleware, ML) should be explicitly designed for the needs of DT in AM.

Other challenges, such as the price of the product and other financial difficulties, can only be solved by establishing an optimized 3D printing production process. This problem can only be solved with sufficient experience and knowledge in this area, which leads to the fact that the solution directly depends on human involvement and interest in the scientific and industrial environment.

The third group of challenges can be solved only with the application and development of new technologies. The integration of IoT & Cloud platforms needs significant improvement as the AM industry is not ready to integrate this technology fully.

For more efficient and accurate solutions to challenges, it is proposed to build a general map of the relationship of challenges not only for their causes but also for their solution. This will help to see the whole picture of the digitalization process and the allocation of resources to address them. Moreover, it can be helpful in digitalizing not only AM but also other industries.

VII. CONCLUSION

A digital twin is one of the suitable technologies to digitize the additive manufacturing field, eventually reducing cost, time, material waste, increasing production efficiency and productivity. However, digital twin implementation challenges are mapped out from recent works, papers, and categorized into eight categories. The most critical challenges were IoT, Big Data, and widely acceptable digital twin standards and guidelines. Other remaining challenges are least important; hence, most of them are interconnected. Solving and improving these challenges is important to increase the functionality and comprehensive adaptability of digital twins in additive manufacturing. Thus, as a recommendation for future works, these challenges can be considered opportunities for research and investigation. In addition, it is equally important to identify and map out the interconnections of challenges and identify the degree of connections among challenges.

ACKNOWLEDGMENT

The authors gratefully acknowledge funding support from Nazarbayev University under the Faculty Development Competitive Research Grant Program (FDCRGP), Grant No. 11022021FD2904.

REFERENCES

[1] R. K. Phanden, S. V. Aditya, A. Sheokand, K. K. Goyal, P. Gahlot, and A. Jacso, "A state-of-the-art review on implementation of digital twin in additive manufacturing to

monitor and control parts quality," *Mater Today Proc*, pp. 88–93, 2022, doi: 10.1016/j.matpr.2021.12.217.
[2] L. Scime, A. Singh, and V. Paquit, "A scalable digital platform for the use of digital twins in additive manufacturing," *Manuf Lett*, vol. 31, pp. 28–32, 2022, doi: 10.1016/j.mfglet.2021.05.007.
[3] U. Delli and S. Chang, "Automated Process Monitoring in 3D Printing Using Supervised Machine Learning," *Procedia Manuf*, vol. 26, pp. 865–870, 2018, doi: 10.1016/j.promfg.2018.07.111.
[4] V. K. Kadam, S. Kumar, A. Bongale, and V. Kadam, "Real-Time Monitoring of FDM 3D Printer for Fault Detection Using Real-Time Monitoring of FDM 3D Printer for Fault Detection Using Machine Learning: A Bibliometric Study Machine Learning: A Bibliometric Study Real-Time Monitoring of FDM 3D Printer for Faul," no. May, 2021, [Online]. Available: https://digitalcommons.unl.edu/libphilprac
[5] A. Kantaros, D. Piromalis, G. Tsaramirsis, P. Papageorgas, and H. Tamimi, "3D Printing and Implementation of Digital Twins: Current Trends and Limitations," *Applied System Innovation*, vol. 5, no. 1, pp. 1–13, 2022, doi: 10.3390/asi5010007.
[6] E. Shehab *et al.*, "Developing a Digital Twin for Carbon Fiber Composites Recycling: Challenges and Future Research Direction," *Advances in Materials Science (ICAMS 2021)*, vol. 116, pp. 61–66, 2022, doi: 10.4028/p-h01m30.
[7] Y. Lu, C. Liu, K. I. K. Wang, H. Huang, and X. Xu, "Digital Twin-driven smart manufacturing: Connotation, reference model, applications and research issues," *Robot Comput Integr Manuf*, vol. 61, no. August 2019, p. 101837, 2020, doi: 10.1016/j.rcim.2019.101837.
[8] D. Mourtzis, T. Togias, J. Angelopoulos, and P. Stavropoulos, "A Digital Twin architecture for monitoring and optimization of Fused Deposition Modeling processes," *Procedia CIRP*, vol. 103, pp. 97–102, 2021, doi: 10.1016/j.procir.2021.10.015.
[9] T. Debroy, W. Zhang, J. Turner, and S. S. Babu, "Building digital twins of 3D printing machines".
[10] M. Moretti and N. Senin, "In-process monitoring of part warpage in fused filament fabrication through the analysis of the repulsive force acting on the extruder," *Addit Manuf*, vol. 49, no. November 2021, p. 102505, 2022, doi: 10.1016/j.addma.2021.102505.
[11] M. Moretti, A. Rossi, and N. Senin, "In-process simulation of the extrusion to support optimisation and real-time monitoring in fused filament fabrication," *Addit Manuf*, vol. 38, no. December 2020, p. 101817, 2021, doi: 10.1016/j.addma.2020.101817.
[12] M. Moretti, A. Rossi, and N. Senin, "In-process monitoring of part geometry in fused filament fabrication using computer vision and digital twins," *Addit Manuf*, vol. 37, no. July 2020, p. 101609, 2021, doi: 10.1016/j.addma.2020.101609.
[13] T. O. R. F. Shimamura and D. Timper, "A feasibility study of Digital Twin for additive manufacturing From the perspective of resource efficiency ," 2021.
[14] A. D. Khandare, V. S. Jadhav, S. P. Deshmukh, and K. K. Rane, "Digital Twins for Manufacturing Process and System: A State of the Art Review," *ECS Trans*, vol. 107, no. 1, pp. 15497–15508, 2022, doi: 10.1149/10701.15497ecst.
[15] S. Yun, J. H. Park, and W. T. Kim, "Data-centric middleware based digital twin platform for dependable cyber-physical systems," *International Conference on Ubiquitous and Future Networks, ICUFN*, pp. 922–926, 2017, doi: 10.1109/ICUFN.2017.7993933.
[16] A. Fuller, Z. Fan, C. Day, and C. Barlow, "Digital Twin: Enabling Technologies, Challenges and Open Research," *IEEE Access*, vol. 8, pp. 108952–108971, 2020, doi: 10.1109/ACCESS.2020.2998358.
[17] D. Holmes, M. Papathanasaki, L. Maglaras, M. A. Ferrag, S. Nepal, and H. Janicke, "Digital Twins and Cyber Security - solution or challenge?," *6th South-East Europe Design Automation, Computer Engineering, Computer Networks and Social Media Conference, SEEDA-CECNSM 2021*, 2021, doi: 10.1109/SEEDA-CECNSM53056.2021.9566277.
[18] J. Michael, J. Pfeiffer, B. Rumpe, and A. Wortmann, "Integration Challenges for Digital Twin Systems-of-Systems," Proceedings - 10th IEEE/ACM International Workshop on Software Engineering for Systems-of-Systems and Software Ecosystems, SESoS 2022, vol. 1, pp. 9–12, 2022, doi: 10.1145/3528229.3529384.
[19] C. A. Odada, J. B. Byiringiro, and F. M. Madaraka, "Development of Data-Driven Digital Twin for Real-Time Monitoring of FDM 3D Printer," *Journal of Mechanical Engineering and Automation*, vol. 2021, no. 2, pp. 25–35, 2021, doi: 10.5923/j.jmea.20211002.01.
[20] L. Yi, M. Glatt, S. Ehmsen, W. Duan, and J. C. Aurich, "Process monitoring of economic and environmental performance of a material extrusion printer using an augmented reality-based digital twin," *Addit Manuf*, vol. 48, 2021, doi: 10.1016/j.addma.2021.102388.
[21] A. Hyre, G. Harris, J. Osho, M. Pantelidakis, K. Mykoniatis, and J. Liu, "Digital twins: Representation, Replication, Reality, and Relational (4Rs)," *Manuf Lett*, vol. 31, pp. 20–23, 2022, doi: 10.1016/j.mfglet.2021.12.004.
[22] P. M. Bhattarai, P. Shrestha, and R. Chohan, "Digital Twin and Its Implementation in 3D Printing: A Research Review," *International Journal of Scientific Research and Management*, vol. 10, no. 07, pp. 49–68, 2022, doi: 10.18535/ijsrm/v10i07.ms01.
[23] C. Kober, M. Fette, and J. P. Wulfsberg, "Challenges of Digital Twin Application in Manufacturing," 2022 IEEE International Conference on Industrial Engineering and Engineering Management (IEEM), Kuala Lumpur, Malaysia, pp. 162–168. 2022, doi: 10.1109/IEEM55944.2022.9989654.
[24] A. Phua, C. H. J. Davies, and G. W. Delaney, "A digital twin hierarchy for metal additive manufacturing," *Comput Ind*, vol. 140, p. 103667, 2022, doi: 10.1016/j.compind.2022.103667.
[25] G. Dayalan and M. Tony, "Towards a true digital twin for the metal Additive Manufacturing process," 2019. https://www.metal-am.com/articles/towards-a-true-digital-twin-for-the-metal-additive-manufacturing-process/
[26] M. Perno, L. Hvam, and A. Haug, "Implementation of digital twins in the process industry: A systematic literature review of enablers and barriers," *Comput Ind*, vol. 134, p. 103558, 2022, doi: 10.1016/j.compind.2021.103558.
[27] J. Osho *et al.*, "Four Rs Framework for the development of a digital twin: The implementation of Representation with a FDM manufacturing machine," *J Manuf Syst*, vol. 63, no. April, pp. 370–380, 2022, doi: 10.1016/j.jmsy.2022.04.014.
[28] I. Onaji, D. Tiwari, P. Soulatiantork, B. Song, and A. Tiwari, "Digital twin in manufacturing: conceptual framework and case studies," *Int J Comput Integr Manuf*, vol. 35, no. 8, pp. 831–858, 2022, doi: 10.1080/0951192X.2022.2027014.
[29] S. R. Chhetri, S. Faezi, A. Canedo, and M. A. Al Faruque, "QUILT: Quality inference from living digital twins in IoT-enabled manufacturing systems," *IoTDI 2019 - Proceedings of the 2019 Internet of Things Design and Implementation*, pp. 237–248, 2019, doi: 10.1145/3302505.3310085.
[30] L. Zhang *et al.*, "Digital twins for additive manufacturing: A state-of-the-art review," *Applied Sciences (Switzerland)*, vol. 10, no. 23, pp. 1–10, 2020, doi: 10.3390/app10238350.
[31] C. Mandolla, A. M. Petruzzelli, G. Percoco, and A. Urbinati, "Building a digital twin for additive manufacturing through the exploitation of blockchain: A case analysis of the aircraft industry," *Comput Ind*, vol. 109, pp. 134–152, 2019, doi: 10.1016/j.compind.2019.04.011.
[32] M. A. Rahman *et al.*, "A Cloud-Based Cyber-Physical System with Industry 4.0: Remote and Digitized Additive Manufacturing," *Automation*, vol. 3, no. 3, pp. 400–425, 2022, doi: 10.3390/automation3030021.