American Journal of Engineering and Applied Sciences

Original Research Paper

Integration of Cyber-Physical Systems, Digital Twins and 3D Printing in Advanced Manufacturing: A Synergistic Approach

Antreas Kantaros and Theodore Ganetsos

Department of Industrial Design and Production Engineering, University of West Attica, Athens, Greece

Article history
Received: 29-12-2023
Revised: 02-01-2024
Accepted: 03-01-2024

Corresponding Author:
Antreas Kantaros
Department of Industrial Design and Production Engineering, University of West Attica, Athens, Greece
Email: akantaros@uniwa.gr

Abstract: The dynamic field of advanced manufacturing has seen a significant transformation with the convergence of Cyber-Physical Systems (CPS), Digital Twins (DT) and 3D Printing technologies. A comprehensive analysis of the integration of these cutting-edge technologies is presented, highlighting their synergistic potential and the impact on the ecosystem of industry 4.0. The intricate interplay between CPS, which amalgamates computing elements with physical processes, DT, which offers a virtual representation of physical assets and 3D printing, which enables on-demand fabrication of complex structures is examined. Thus, the crucial role of this integrated approach in enhancing production efficiency, product customization and overall system resilience is inderscored. The discussion revolves around the seamless data exchange facilitated by CPS, enabling real-time monitoring, control and optimization, coupled with the predictive insights derived from the virtual representation of DT. Moreover, the transformative impact of 3D printing is elucidated, in achieving unprecedented design flexibility, rapid prototyping and cost-effective small-batch production. Furthermore, this study examines the challenges and opportunities associated with the convergence of these technologies, emphasizing the critical need for robust cybersecurity measures, standardized communication protocols and scalable infrastructural support. This manuscript contributes to the ongoing discourse on the future of advanced manufacturing, underscoring the transformative potential of a synergistic approach in driving innovation and competitiveness in the global industrial landscape.

Keywords: Advanced Manufacturing, Cyber-Physical Systems (CPS), Digital Twins (DT), 3D Printing, Industry 4.0, Production Efficiency, Product Customization, System Resilience, Real-Time Monitoring

Introduction

The modern era of manufacturing is witnessing a profound revolution catalyzed by the convergence of Cyber-Physical Systems (CPS), Digital Twins (DT) and 3D Printing technologies. This amalgamation has paved the way for a paradigm shift in the traditional manufacturing landscape, enabling unprecedented levels of efficiency, customization and adaptability. CPS, encompassing interconnected computing and physical components, serves as the backbone for real-time data acquisition, analysis and control within manufacturing processes (Lee, 2015). Simultaneously, the concept of DT, providing a virtual replica of physical assets, has gained traction as a powerful tool for predictive analysis, performance optimization and simulation-based testing (Tao and Qi, 2019; Tsaramirsis *et al*., 2022).

Complementing these advancements, 3D Printing, or additive manufacturing, has garnered attention for its ability to realize intricate designs, rapid prototyping and cost-effective small-scale production (Kantaros and Piromalis, 2021a). The combination of these technologies in the manufacturing realm has led to the emergence of a novel approach that synergistically harnesses their individual strengths, promising enhanced productivity,

DOI: 10.3844/ajeassp.2024.1.22

reduced time-to-market ansd increased product innovation (Shahrubudin *et al*., 2019). This transformative amalgamation falls within the purview of industry 4.0, the current phase of the industrial revolution that emphasizes the fusion of digital technologies with traditional industrial processes, fundamentally altering the way products are manufactured, delivered and maintained (Ghobakhloo, 2020).

Industry 4.0 represents a significant departure from conventional manufacturing methodologies, integrating CPSs, Internet of Things (IoT) and cloud computing to create a smart, interconnected ecosystem of production. The seamless exchange of information between machines, products and human operators characterizes this fourth industrial wave, facilitating the emergence of highly flexible, autonomous and data-driven production systems. In this context, the integration of CPS, DT and 3D printing serves as a compelling embodiment of the industry 4.0 principles, illustrating the trans-formative potential of a cohesive technological framework in redefining the manufactur-ing landscape for the digital age. This study seeks to elucidate the intricate interplay be-tween these key technologies and their collective impact on advanced manufacturing processes, emphasizing the critical role of synergy in achieving unprecedented levels of efficiency and innovation.

The integration of CPSs, DTs and 3D printing within the framework of industry 4.0 heralds a new era of manufacturing marked by heightened connectivity, intelligent automation and data-driven decision-making (Dalenogare *et al*., 2018). The intricate web of interconnected paradigms, such as industrial IoT and smart manufacturing, signifies a larger, interwoven technological landscape where Cyber-Physical Systems (CPS), Digital Twins (DT) and 3D printing converge. Together, these frameworks not only shape but also interdependently propel the evolution of advanced manufacturing, offering a comprehensive and integrated approach to optimize processes, enhance productivity and drive innovation across industries. CPS, acting as the nerve center of this interconnected manufacturing environment, enables the seamless coordination and synchronization of various production processes, leading to improved resource utilization, predictive maintenance and optimized energy consumption. By facilitating real-time data monitoring and control, CPS empowers manufacturers to swiftly respond to dynamic market demands, minimize downtime and ensure the seamless integration of physical and digital realms (Jazdi, 2014).

What is more, in the domain of advanced manufacturing, the integration of Internet of Things (IoT), digital thread, Artificial Intelligence (AI) and Virtual/Augmented/Mixed Reality (VR/AR/MR) technologies has heralded a transformative epoch characterized by interconnectivity, cognitive automation and immersive experiences. The IoT, a linchpin of industry 4.0, establishes a framework of interconnected devices and systems, enabling seamless, real-time data exchange and fostering a networked ecosystem wherein ma-chines, products and human agents converge synergistically. Concurrently, the concept of digital thread intertwines with the IoT, epitomizing the digital continuum across a product's lifecycle, ensuring a cohesive flow of data throughout design, production and maintenance stages, thereby optimizing decision-making processes and enhancing traceability and transparency. AI, underpinned by sophisticated machine learning algo-rithms and predictive analytics, distills actionable insights from the vast reservoir of data amassed through the IoT and digital thread, revolutionizing paradigms in process opti-mization, predictive maintenance and adaptive manufacturing strategies. Furthermore, the amalgamation of VR/AR/MR technologies furnishes immersive simulations, endowing engineers and operators with augmented visualization capabilities, interactive training modules and real-time assistance, fostering innovative approaches and efficiency gains in design validation, training regimens and maintenance workflows. Figure 1, shows a relevant process workflow of a digital twin in additive manufacturing technologies.

Moreover, the deployment of DTs in tandem with CPS engenders a virtual replica of the physical manufacturing environment, offering an immersive platform for simu-lating and analyzing real-world scenarios. This virtual representation facilitates the visu-alization of complex manufacturing processes, thereby enabling the anticipation of potential bottlenecks, performance optimizations and the development of robust predictive maintenance strategies (Jiang *et al*., 2021). DTs, thus, play a pivotal role in enhancing operational transparency, fostering informed decision-making and fostering a proactive ap-proach to addressing potential production challenges before they materialize in the physical realm (Kantaros *et al*., 2021a).

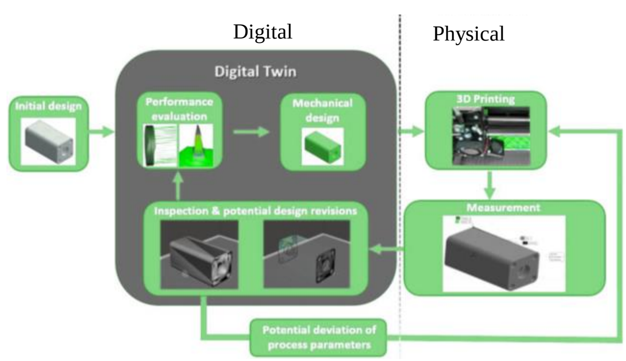

Fig. 1: Process workflow of a digital twin in additive manufacturing technologies

DOI: 10.3844/ajeassp.2024.1.22

In parallel, the integration of 3D printing technology within the industry 4. 0 framework ushers in a new era of design flexibility, rapid prototyping and customized production (Kantaros *et al*., 2022). The ability to fabricate intricate geometries and functional prototypes on-demand empowers manufacturers to streamline the product development lifecycle, reduce production lead times and facilitate cost-effective small-batch manufacturing. This transformative capability of 3D printing not only catalyzes innovation but also facilitates the creation of highly tailored products, catering to the evolving demands of a dynamic market landscape (Kantaros *et al*., 2023a).

Collectively, the synergistic integration of CPS, DTs and 3D Printing within the paradigm of industry 4. 0 embodies the transformative potential of advanced manufac-turing (Tao *et al*., 2019). This integration fosters a holistic approach to production, characterized by increased operational efficiency, product customization and the facilitation of sustainable manufacturing practices (Nagar *et al*., 2020).

The subsequent sections of this manuscript will delve deeper into the intricate dynamics and transformative implications of integrating Cyber Physical Systems (CPS), Digital Twins (DT) and 3D printing within the framework of industry 4.0. The following section will thoroughly explore the individual contributions and synergies of CPS, elucidating its pivotal role in orchestrating real-time data acquisition, analysis and control. Subsequently, the discussion will pivot to digital twins, illustrating their significance in providing virtual representations for predictive analysis, performance optimization and simulation-based testing. Moreover, the integration of 3D printing will be dissected to highlight its revolutionary capabilities in design flexibility, rapid prototyping and customized production within the industry 4.0 paradigm. Additionally, the challenges and opportunities associated with these integrations will be rigorously examined, emphasizing the critical need for standardized protocols and robust security measures. Finally, the manuscript will culminate in a comprehensive synthesis of key findings, underscoring the transformative potential of this integrated approach while outlining future research directions and practical applications in the domain of advanced manufacturing.

Cyber-Physical Systems

CPSs represent the integration of computational and physical elements where digital algorithms and physical components collaborate to create an interconnected ecosystem (Ryalat *et al*., 2023). In the context of modern manufacturing, CPS serves as a cornerstone for the realization of industry 4.0 principles, facilitating the seamless convergence of data analytics, machine learning and automation with physical manufacturing processes. By embedding sensors, actuators and control systems within the production environment, CPS enables real-time data acquisition, processing and feedback mechanisms, thereby fostering a highly responsive and adaptive manufacturing ecosystem (Hamzah *et al*., 2023).

The role of CPS in modern manufacturing is multi-faceted and crucial (García *et al*., 2024). Firstly, it facilitates the acquisition of comprehensive data sets pertaining to various facets of the production process, ranging from equipment performance and energy consumption to quality control metrics and supply chain logistics. This data-driven approach em-powers manufacturers to gain deep insights into production inefficiencies, anticipate maintenance requirements and optimize resource allocation, thereby enhancing overall operational efficiency and cost-effectiveness (Liu *et al*., 2017).

Secondly, CPS enables the implementation of predictive maintenance strategies, allowing manufacturers to preemptively identify and address potential equipment malfunctions or downtimes before they disrupt the production cycle (Meesublak and Klinsukont, 2020). By leveraging real-time data analytics and machine learning algorithms, CPS empowers manufactur-ers to detect anomalies, forecast maintenance needs and schedule repairs during planned downtime, thereby minimizing production interruptions and extending the lifespan of critical manufacturing assets (Lee *et al*., 2015).

Moreover, CPS fosters the development of interconnected and autonomous pro-duction systems, enabling streamlined communication and coordination between var-ious manufacturing components (Ding *et al*., 2019). This interconnectedness facilitates the orchestra-tion of complex production workflows, adaptive manufacturing processes and the seamless integration of disparate manufacturing stages, culminating in a highly agile and responsive production environment capable of accommodating dynamic market demands and rapid product iterations.

The components of CPSs encompass a sophisticated amalgamation of hardware, software and communication interfaces, designed to seamlessly integrate the physical and digital realms of manufacturing (Lee, 2008). These components typically include sensors for data acquisition, actuators for physical control, embedded computing systems for data processing and communication networks for real-time data transmission. Additionally, CPS architectures often incorporate advanced control algorithms, machine learning models and human-machine interfaces, facilitating efficient decision-making, system coordination and interactive user engagement within the manufacturing environment (Tan *et al*., 2008). Figure 2, depicts the prominent components of a CPS incorporated in the industry 4. 0 context.

DOI: 10.3844/ajeassp.2024.1.22

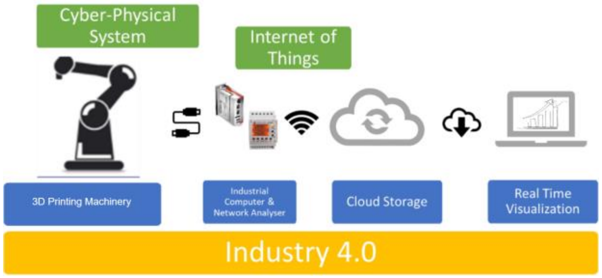

Fig. 2: Components of a CPS incorporated in the industry 4.0 context

One of the key characteristics defining CPS is its inherent capability to enable bi-directional communication between the physical components and the digital infra-structure (Akanmu and Anumba, 2015). This bidirectional data flow enables the continuous monitoring and control of physical processes through real-time data acquisition and feedback mechanisms. CPS leverages this real-time data to facilitate dynamic adjustments and optimizations within the manufacturing processes, thereby ensuring precise control, enhanced operational efficiency and the ability to promptly respond to changing production requirements or environmental conditions (Jia *et al*., 2015).

Furthermore, CPS exhibits a high degree of adaptability and resilience, allowing manufacturing systems to dynamically reconfigure themselves in response to changing operational constraints or unforeseen disruptions (Bellman *et al*., 2020). The integration of self-monitoring capabilities within CPS enables the system to detect anomalies, mitigate potential risks and autonomously implement alternate production strategies to ensure continuous operations and minimal production downtimes. This adaptability is instrumental in enhancing the overall system robustness, fault-tolerance and sustainability, thus reinforcing the manufacturing ecosystem's ability to withstand unforeseen challenges and uncertainties (Zeadally *et al*., 2019).

Additionally, CPS fosters a holistic approach to data security and privacy, incor-porating robust encryption protocols, authentication mechanisms and access control frameworks to safeguard sensitive manufacturing data from unauthorized access or cyber threats (Song *et al*., 2017). By prioritizing data integrity and confidentiality, CPS ensures the protection of critical production information, intellectual property and sensitive oper-ational insights, thereby instilling trust and reliability within the interconnected man-ufacturing infrastructure (Fink *et al*., 2017).

The versatile nature of CPSs has led to their widespread adoption across diverse manufacturing domains, fostering innovation, efficiency and agility within the production ecosystem (Napoleone *et al*., 2020). One prominent application of CPS in manufacturing is its integration within smart factories, where CPS serves as the back-bone of interconnected production systems, orchestrating seamless communication and coordination between various manufacturing stages. In this context, CPS facilitates the real-time monitoring of equipment performance, production metrics and quality con-trol parameters, enabling manufacturers to optimize production workflows, minimize defects and enhance product consistency (Chen *et al*., 2020a).

Furthermore, CPS finds extensive application in the domain of predictive maintenance, where it aids in the proactive identification of equipment failures or performance degradation (Lee *et al*., 2017). By leveraging data analytics, machine learning algo-rithms and real-time sensor data, CPS enables manufacturers to detect early signs of equipment malfunction, schedule timely maintenance activities and prevent costly production downtimes. This proactive maintenance approach not only extends the lifespan of critical manufacturing assets but also minimizes unplanned disruptions, thereby enhancing overall production efficiency and equipment reliability (Kee *et al*., 2022).

Additionally, CPS plays a pivotal role in enabling the implementation of agile and flexible manufacturing processes, particularly in the context of adaptive production lines and rapid product customization (Zhang *et al*., 2016). By integrating CPS within the production environment, manufacturers can swiftly reconfigure production setups, recalibrate production parameters and accommodate rapid changes in product specifications or design requirements. This inherent flexibility allows manufacturers to cater to evolving market demands, reduce time-to-market for new product launches and capitalize on emerging market opportunities, thereby enhancing their competitive edge in the industry (Tran *et al*., 2019; Makri *et al*., 2022).

Moreover, CPS applications extend to supply chain management, where they fa-cilitate the optimization of logistics operations, inventory management and demand forecasting (Rehman and Gruhn, 2018). By integrating CPS within the supply chain infrastructure, manufac-turers can achieve real-time visibility into inventory levels, monitor shipment statuses and streamline the distribution process, thereby minimizing supply chain inefficiencies, reducing overhead costs and ensuring timely delivery of products to end consumers (Tonelli *et al*., 2021).

Through these diverse applications, CPS has emerged as a transformative tech-nology in modern manufacturing, redefining production paradigms and fostering a data-driven, interconnected and adaptive manufacturing ecosystem. In the subsequent sections, specific use cases and industrial implementations of CPS will be presented, elucidating their impact on enhancing manufacturing efficiency, product quality and overall operational resilience.

DOI: 10.3844/ajeassp.2024.1.22

Digital Twins

In parallel with the advancement of CPSs, the concept of DTs has garnered significant attention as a transformative tool within the industry 4.0 landscape (Stavropoulos, 2022). DTs refer to virtual replicas of physical assets, processes, or systems that are created, monitored and maintained through real-time data integration and advanced simulation techniques (Leng *et al*., 2021). These virtual representations enable manufacturers to gain a comprehensive and detailed understanding of the behavior, performance and lifecycle dynamics of physical assets, thereby facilitating in-formed decision-making, performance optimizations and predictive analysis in a risk-free virtual environment (Pires *et al*., 2019).

The importance of DTs within the industry 4.0 landscape is multifaceted. Firstly, DT fosters the creation of a digital thread that connects the various stages of product development, manufacturing and post-production services (Piromalis and Kantaros, 2022). By generating a synchronized data ecosystem encompassing the entire product lifecycle, DT enables manufacturers to trace the evolution of products, identify potential design flaws and streamline the product development process, thereby expediting time-to-market and enhancing overall product quality (Kantaros and Piromalis, 2022).

Moreover, DTs serve as a powerful tool for predictive analysis and per-formance optimization, enabling manufacturers to anticipate potential operational in-efficiencies, identify optimization opportunities and proactively address production challenges before they impact the physical manufacturing environment (Brockhoff *et al*., 2021). By lever-aging real-time data streams and advanced analytics, DT empowers manufacturers to simulate diverse operational scenarios, conduct what if analyses and refine production strategies, thereby enhancing production efficiency, minimizing resource wastage and ensuring consistent product quality throughout the manufacturing lifecycle (Kapteyn *et al*., 2021).

Additionally, DTs facilitate the implementation of remote monitoring and maintenance strategies, allowing manufacturers to remotely assess the perfor-mance of physical assets, diagnose potential issues and implement corrective measures without disrupting the ongoing production processes (Mihai *et al*., 2022). This remote monitoring capability not only minimizes the need for on-site inspections but also reduces maintenance costs, extends equipment lifespan and enhances the overall reliability of critical manufacturing infrastructure (Singh *et al*., 2021).

Through these pivotal roles, DTs have emerged as a cornerstone of the industry 4.0 landscape, fostering a seamless integration between the physical and digital realms of manufacturing and enabling manufacturers to achieve unprecedented levels of operational transparency, performance optimization and product innovation.

The concept of virtual representation forms the core of DTs, wherein physical assets, processes, or systems are meticulously recreated in a virtual environment, capturing their intricate geometries, functional attributes and operational characteristics (El Saddik, 2018). This virtual representation serves as a digital counterpart that closely mimics the behavior and performance of its physical counterpart, enabling manufac-turers to conduct comprehensive simulations, conduct performance analyses and ex-plore various design modifications without the need for physical prototyping. By creating a highly accurate and dynamic digital replica, manufacturers can gain invaluable insights into the underlying intricacies of their production systems, fostering informed decision-making and accelerating the pace of innovation within the manufacturing ecosystem (Schluse and Rossmann, 2016).

In tandem with this virtual representation, DTs facilitate real-time monitoring capabilities that enable manufacturers to gather and analyze data from physical assets instantaneously (Wang *et al*., 2021). By integrating sensor data, Internet of Things (IoT) devices and advanced data analytics, DT enables manufacturers to capture real-time insights into production metrics, environmental conditions and equipment performance, thereby fostering a proactive approach to production management and quality control (Constantinescu *et al*., 2020). This real-time monitoring capability empowers manufacturers to detect anomalies, deviations, or potential inefficiencies as they occur, allowing for swift corrective actions, proactive maintenance interventions and the optimization of production workflows to ensure optimal performance and product quality (Latif *et al*., 2023).

Furthermore, the combination of virtual representation and real-time monitoring within DTs enables manufacturers to bridge the gap between the physical and digital realms, facilitating a seamless exchange of data and insights that drive contin-uous improvements and innovation within the manufacturing processes (Gao *et al*., 2022). This integration fosters a holistic approach to production management, where real-time data insights obtained from the physical environment inform the refinement of the virtual model, while simulated scenarios and predictive analyses guide the optimization of physical operations, ultimately resulting in enhanced production efficiency, product quality and overall manufacturing resilience (Segovia and Garcia-Alfaro, 2022). Figure 3 depicts the DTs pillar technologies.

DOI: 10.3844/ajeassp.2024.1.22

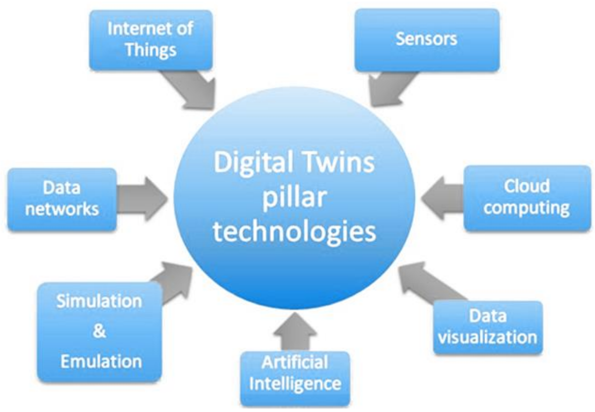

Fig. 3: Digital twin pillar technologies

Several prominent case studies have showcased the transformative impact of DTs in enhancing manufacturing efficiency, product quality and operational resilience across various industrial sectors. One notable example pertains to the aero-space industry, where the implementation of DTs has revolutionized the air-craft design and maintenance processes (Li *et al*., 2021). Major aircraft manufacturers have lever-aged DT to create virtual replicas of complex aircraft components, enabling them to simulate various flight conditions, analyze structural integrity and optimize mainte-nance schedules (Hänel *et al*., 2020). This proactive approach to aircraft maintenance has significantly reduced downtime, extended the lifespan of critical components and enhanced overall flight safety, thereby underscoring the pivotal role of DT in fostering operational relia-bility and cost-effective maintenance strategies within the aerospace industry (Petrescu and Petrescu, 2022).

In the automotive sector, DTs have facilitated the optimization of manufacturing processes and product design workflows (Piromalis and Kantaros, 2022). Leading automotive companies have utilized DT to create virtual models of production lines, enabling them to simulate production scenarios, identify potential bottlenecks and streamline assembly operations. This simulation driven approach has not only improved production throughput but has also facilitated the seamless integration of robotics and automation within the manufacturing environment, leading to enhanced production precision, re-duced error rates and accelerated time-to-market for new vehicle models (Smeets *et al*., 2023).

Moreover, the application of DTs in the pharmaceutical industry has enabled manufacturers to expedite the drug development process and enhance the efficacy of clinical trials (Chen *et al*., 2020b). By creating virtual representations of drug molecules and conducting in-silico simulations, pharmaceutical companies can assess the pharmaco-kinetic properties, predict potential side effects and optimize the formulation parameters before proceeding to costly and time-consuming clinical trials. This virtual testing approach has not only accelerated the drug discovery process but has also reduced the overall development costs and minimized the risks associated with late-stage trial failures, thereby fostering a more efficient and cost-effective approach to pharmaceutical research and development (Zobel-Roos *et al*., 2021).

Through these diverse case studies, the transformative potential of DTs in revolutionizing manufacturing practices has become increasingly evident. The ability of DT to facilitate predictive analysis, streamline design workflows and optimize operational processes underscores its significance as a pivotal enabler of innovation and efficiency within the contemporary manufacturing landscape. In the subsequent sections, we will delve into the key takeaways from these case studies, emphasizing the critical role of DTs in driving operational excellence, product innovation and sustainable growth within the manufacturing industry.

3D Printing in Advanced Manufacturing

In parallel with the advancements in CPSs and DTs, 3D printing technology has emerged as a disruptive force within the manufacturing landscape, revolutionizing the traditional paradigms of product design, prototyping and small-scale production (Kantaros *et al*., 2023b). Also known as additive manufacturing, 3D printing refers to the process of fabricating three-dimensional objects layer by layer from digital models, using a diverse range of materials, including polymers, metals, ceramics and composites (Kantaros *et al*., 2023c). This transformative technology has witnessed a remarkable evolution, expanding its application scope from rapid prototyping and concept modeling to the production of complex functional components for diverse industrial sectors (Kantaros and Karalekas, 2013).

The early stages of 3D printing technology primarily focused on rapid prototyping applications, enabling designers and engineers to swiftly translate digital concepts into tangible prototypes, thereby expediting the product development lifecycle and reducing the time-to-market for new innovations (Bak, 2003). As the technology matured, 3D printing capabilities extended beyond prototyping, facilitating the production of intricate and customized components that were previously unattainable through conventional manufacturing methods (Bak, 2003). This evolution paved the way for the widespread adoption of 3D printing in diverse sectors, including aerospace, healthcare, automotive and consumer goods, among others (Kantaros *et al*., 2023a-f; Ganetsos *et al*., 2023).

In recent years, the advancements in 3D printing technology have led to significant improvements in printing speed, precision and material diversity, enabling manufacturers to produce highly complex structures, functional prototypes and end-use parts with enhanced mechanical properties and surface finishes (Peng *et al*., 2022). Furthermore, the integration of multi-material and multi-color printing capabilities has expanded the design possibilities, allowing for the creation of composite structures, gradient materials and visually appealing product aesthetics that meet the increasingly diverse and sophisticated consumer demands (Yuan *et al*., 2021).

The evolution of 3D printing technology has also led to the development of novel printing techniques, such as selective laser sintering, fused deposition modeling and stereolithography, each tailored to specific material requirements and application do-mains (Pagonis *et al*., 2023; Kantaros *et al*., 2013). These diverse printing techniques have facilitated the production of high-performance components, biocompatible medical devices and lightweight aero-space parts, underscoring the transformative potential of 3D printing in enabling design innovation, material optimization and manufacturing customization within the contemporary industrial landscape (Kantaros and Karalekas, 2014; Kantaros *et al*., 2016).

3D printing technology offers a myriad of advantages that have redefined manufacturing processes and product development strategies. One of the key advantages lies in its unparalleled design flexibility, enabling manufacturers to realize complex geometries, intricate lattice structures and customized product configurations that are otherwise impractical or economically unviable with traditional manufacturing methods (Kantaros, 2022a-b; Kantaros and Piromalis, 2021b). This design freedom fosters innovation, facilitates product differentiation and empowers designers to create highly intricate and lightweight components that offer superior performance characteristics and enhanced functionality (Kantaros and Ganetsos, 2023).

Additionally, the on demand and decentralized production capability of 3D printing technology offers significant supply chain benefits, enabling manufacturers to reduce inventory overheads, mitigate supply chain risks and meet localized market demands with minimal lead times (Ferdinand *et al*., 2016; Mueller *et al*., 2020). This decentralized production model fosters a more sustainable and cost-effective manufacturing approach, minimizing material wastage, transportation costs and the environmental footprint associated with traditional mass production methodologies (Kantaros *et al*., 2021b). Figure 4 depicts 3D printing machinery embedded in an industrial environment.

Fig. 4: 3D printing machinery embedded in industrial environment

However, 3D printing technology is not without limitations. One of the key challenges pertains to production scalability, as the speed and volume of 3D printing operations are comparatively lower than those of traditional manufacturing processes, making it less suitable for large-scale production runs (Kantaros and Diegel, 2018). Additionally, the material limitations as-sociated with certain 3D printing techniques may impose constraints on the mechanical properties, material durability and surface finishes of printed components, limiting their applicability in high-stress industrial applications (Stansbury and Idacavage, 2016).

Moreover, the initial capital investment and operating costs of 3D printing equipment can be relatively high, particularly for industrial-grade printers capable of handling complex materials and large-scale production volumes (Ravi *et al*., 2023). Additionally, the need for skilled technicians proficient in 3D printing operations and design optimization may present a significant barrier for small and medium-sized enterprises seeking to adopt this technology, thereby necessitating comprehensive training programs and expertise development initiatives to realize the full potential of 3D printing within the manu-facturing ecosystem (Li *et al*., 2017).

The versatile nature of 3D printing technology has catalyzed its adoption across a wide spectrum of industries, each leveraging its unique capabilities to drive innovation, streamline production and enhance product customization. In the aerospace sector, 3D printing has been instrumental in the production of lightweight, high-strength com-ponents, such as turbine blades, engine components and structural elements, thereby enabling significant reductions in aircraft weight, fuel consumption and maintenance costs (Joshi and Sheikh, 2015). Companies have also utilized 3D printing to produce complex geometries and optimized designs for spacecraft components, satellite parts and propulsion systems, thereby underscoring its pivotal role in enabling space exploration and satellite deployment initiatives (Martinez *et al*., 2022).

In the healthcare industry, 3D printing has revolutionized medical device manufacturing, enabling the production of patient-specific implants, prosthetics and surgical instruments tailored to individual anatomical requirements (Liaw and Guvendiren, 2017; Trenfield *et al*., 2019). Surgeons have lev-eraged 3D printed models to plan intricate surgical procedures, simulate complex operations and optimize treatment strategies for patients with intricate medical conditions. Additionally, the pharmaceutical sector has embraced 3D printing to develop personalized drug delivery systems, precise dosage forms and complex drug formulations, fostering a more patient-centric approach to medication administration and disease management (Imrie *et al*., 2023; Odendaal *et al*., 2023; Zhou *et al*., 2022).

The automotive industry has harnessed 3D printing technology to expedite the production of custom tooling, jigs and fixtures, facilitating the optimization of assembly line processes, reducing production lead times and enhancing overall manufacturing precision (Nichols, 2019; Savastano *et al*., 2016). Leading automotive manufacturers have also utilized 3D printing to fabricate lightweight components, intricate interior designs and aerodynamic proto-types, thereby enhancing vehicle performance, fuel efficiency and aesthetic appeal (de Mattos Nascimento *et al*., 2022). Furthermore, the consumer goods sector has capitalized on 3D printing to enable cus-tomized product designs, personalized accessories and bespoke consumer electronics, catering to the evolving preferences of discerning consumers and fostering brand differentiation in competitive market landscapes (Lecklider, 2017; Raina *et al*., 2021).

Moreover, the architecture and construction industry have embraced 3D printing technology to realize complex architectural structures, intricate building components and sustainable construction materials, facilitating the implementation of innovative and environmentally friendly building designs (Tay *et al*., 2017; Bazli *et al*., 2023). 3D printing has also found application in the creation of artistic sculptures, intricate jewelry designs and bespoke fashion accessories, enabling artists and designers to translate their creative visions into tangible, high-fidelity products with unparalleled design intricacy and aesthetic appeal (Pessoa *et al*., 2021; Wu *et al*., 2018).

Integration of Digital Twins and CPS

The synergistic integration of CPSs and DTs within the manufacturing ecosystem offers a transformative framework that fosters enhanced operational visibility, predictive insights and dynamic control over the production processes (Eckhart and Ekelhart, 2019). By combining the real-time data acquisition and control capabilities of CPS with the virtual simulation and predictive analysis functionalities of DTs, manufacturers can create a unified ecosystem that enables comprehensive monitoring, analysis and optimization of manufacturing operations in both the physical and digital domains (Josifovska *et al*., 2019).

CPS serves as the underlying infrastructure that facilitates the seamless integration of physical manufacturing assets with digital control systems, enabling the continuous acquisition of real-time data from various sensors and actuators embedded within the production environment (Flammini, 2021). This data is subsequently transmitted to the DTs, where it is used to create virtual replicas of the physical assets and processes, thereby facilitating the visualization of the entire manufacturing ecosystem in a digital environment. The virtual representations created by DTs enable manufactur-ers to conduct predictive simulations, analyze performance metrics and optimize production strategies, thereby fostering a proactive approach to production manage-ment and quality control (Yue *et al*., 2020).

Furthermore, the bidirectional data flow enabled by the integration of CPS and DTs ensures that insights derived from the virtual simulations are fed back into the physical manufacturing environment to inform real-time decision-making and process optimizations (Radanliev *et al*., 2022). By leveraging the predictive insights and recommendations gen-erated by DTs, manufacturers can fine-tune production parameters, recalibrate equipment settings and implement adaptive control strategies within the CPS infrastructure, thereby enhancing production efficiency, minimizing resource wastage and ensuring consistent product quality throughout the manufacturing lifecycle (Kan and Anumba, 2019).

Moreover, the seamless integration of CPS and DTs fosters a holistic approach to data-driven decision-making, enabling manufacturers to leverage real-time data in-sights and virtual simulations to identify production bottlenecks, optimize supply chain logistics and facilitate just in time manufacturing practices. This integration also facil-itates the implementation of agile production strategies, where dynamic changes in market demands or design specifications can be rapidly accommodated through real-time adjustments within the CPS infrastructure, guided by the predictive analysis and optimization recommendations provided by the DTs (Lee *et al*., 2020).

The seamless integration of CPSs and DTs within the manufacturing ecosystem is made possible by the pervasive deployment of advanced sensors, sophisticated data analytics tools and real-time feedback mechanisms, each playing a pivotal role in facilitating the dynamic exchange of information between the physical and digital realms of production (Berger *et al*., 2016). Sensors serve as the critical enablers of data acquisition within the CPS infrastructure, capturing real-time information on various production parameters, including temperature, pressure, humidity and ma-chine performance metrics. These sensors are strategically deployed across the manu-facturing environment to provide comprehensive visibility into the operational nuances and performance dynamics of critical production assets, thereby enabling the contin-uous monitoring and control of key manufacturing processes (Gurjanov *et al*., 2019). The data captured by these sensors are subsequently transmitted to the CPS framework, where they are processed, analyzed and used to generate actionable insights and control signals that optimize production efficiency and product quality (Song *et al*., 2019).

Data analytics, powered by advanced algorithms and machine learning models, serves as the backbone of the DTs, enabling manufacturers to derive meaningful in-sights from the vast streams of real-time data acquired from the CPS infrastructure (Lv *et al*., 2022). Data analytics tools facilitate the identification of production trends, anomaly detection and performance optimizations, allowing manufacturers to proactively ad-dress potential production challenges, anticipate maintenance requirements and streamline production workflows based on predictive analysis and simulation-driven insights provided by the DTs (Alam and El Saddik, 2017). The iterative refinement of these analytics models based on real-time data feedback fosters a continuous improvement cycle, driving manufacturing efficiency, product innovation and operational resilience within the contemporary production ecosystem.

Real-time feedback mechanisms, facilitated by the seamless integration of CPS and DTs, enable manufacturers to implement dynamic control strategies and adaptive production interventions based on the insights and recommendations generated by the virtual simulations and predictive analytics (Akanmu *et al*., 2021). Real-time feedback loops ensure that the recommendations and control signals generated by the DTs are promptly translated into actionable adjustments within the CPS infrastructure, thereby enabling manufacturers to fine-tune production parameters, optimize supply chain lo-gistics and mitigate potential operational risks in a timely and proactive manner (Shangguan *et al*., 2019). This agile feedback mechanism fosters a highly responsive and adaptive manufacturing ecosystem capable of swiftly addressing market demands, production fluctuations and unforeseen disruptions, thereby enhancing overall production efficiency and product quality (Negri *et al*., 2017).

Numerous case studies have demonstrated the successful integration of CPSs and DTs in enhancing manufacturing efficiency, product quality and operational resilience across diverse industrial sectors (Panetto *et al*., 2019). One compelling example arises from the heavy machinery manufacturing sector, where a leading industrial equipment manufacturer implemented a comprehensive CPS framework inte-grated with DTs to optimize production workflows and enhance equipment reliability. By embedding advanced sensors within critical manufacturing assets, the CPS infrastructure enabled real-time data acquisition, facilitating the continuous monitoring of equipment performance, energy consumption and predictive maintenance requirements (Rivera *et al*., 2021). The data captured by the sensors were subsequently fed into the DTs, allowing for virtual simulations and predictive analyses that informed proactive maintenance schedules, equipment recalibrations and production optimiza-tions, thereby reducing downtime, extending equipment lifespan and enhancing over-all operational efficiency (Suhail *et al*., 2022).

Similarly, in the automotive manufacturing sector, a prominent car manufacturer embraced the integration of CPS and DTs to streamline assembly line operations, optimize supply chain logistics and enhance product quality control. By deploying a network of sensors across the assembly line, the CPS framework facilitated the real-time monitoring of production metrics, component quality and process deviations, enabling manufacturers to identify potential bottlenecks, optimize inventory management and ensure consistent product specifications (Cooke, 2021). The data collected from the sensors were integrated into the DTs, enabling manufacturers to conduct virtual simulations of production workflows, validate design modifications and optimize production parameters, thereby enhancing production throughput, reducing defect rates and accelerating time-to-market for new vehicle models (Yasin *et al*., 2021).

Furthermore, in the pharmaceutical manufacturing sector, a leading drug development company leveraged the integration of CPS and DTs to accelerate the drug formulation process, enhance quality control and streamline regulatory compliance (Spyrou *et al*., 2023; IoT ONE, 2024). By deploying a network of sensors within the production environment, the CPS framework facilitated real-time data acquisition, enabling manufacturers to monitor critical process parameters, detect production deviations and ensure adherence to stringent quality standards. The data collected from the sensors were integrated into the DTs, enabling manufacturers to conduct virtual simulations of drug formulations, assess bioavailability profiles and optimize production parameters for batch consistency and regulatory compliance. This integration fostered a more streamlined and efficient drug development process, minimizing production costs, expediting regulatory approvals and ensuring the delivery of high-quality pharmaceutical products to end consumers (IoT ONE, 2024). Table 1, describes the synergy between digital twins and cyber-physical systems by driving manufacturing efficiency and quality control.

Synergy Between CPS, DTs and 3D Printing

The combination of CPSs and DTs has revolutionized the landscape of 3D printing, enabling manufacturers to optimize production workflows, enhance design precision and ensure consistent product quality through-out the additive manufacturing process (Nguyen *et al*., 2021). By integrating CPS within the 3D printing environment, manufacturers can leverage real-time monitoring capabilities to capture critical process parameters, including print speed, temperature variations, material flow rates and layer adhesion, ensuring precise control and quality assurance during the printing operation (Somers *et al*., 2023). Moreover, by integrating DTs within the 3D printing ecosystem, manufacturers can create virtual replicas of the additive manufacturing process, enabling the simulation of print geometries, material behavior and structural integrity within a risk-free virtual environment (Debroy *et al*., 2017). DTs facilitate predictive analysis and virtual simulations that enable manufacturers to identify potential print defects, optimize support structures and refine design configurations before initiating the physical printing process, thereby minimizing material wastage, reducing post-processing requirements and enhancing overall production efficiency (Mukherjee and DebRoy, 2019).

The synergy of CPS and DTs in the context of 3D printing enables man-ufacturers to establish dynamic feedback loops that foster continuous process improvements and iterative design optimizations (Cinar *et al*., 2020). The real-time data acquired by the CPS infrastructure are transmitted to the DTs, enabling manufacturers to conduct virtual simulations that inform real-time adjustments and process refinements within the additive manufacturing environment. This iterative refinement cycle fosters a more streamlined and efficient 3D printing process, minimizing print errors, optimizing material utilization and ensuring the production of high-fidelity components with superior mechanical properties and dimensional accuracy (Paripooranan *et al*., 2020).

Table 1: Synergistic integration of CPSs and DTs within the manufacturing ecosystem

Synergy aspect	Description
Enhanced operational visibility	CPS combined with DTs offers a unified ecosystem for comprehensive monitoring, analysis and optimization of manufacturing operations in both physical and digital realms. The integration enables visualization of the entire manufacturing ecosystem in a digital environment, fostering a proactive approach to production management and quality control
Real-time data acquisition	CPS infrastructure facilitates continuous real-time data acquisition from sensors and actuators embedded within the production environment. This data is transmitted to DTs to create virtual replicas, conduct predictive simulations, analyze performance metrics and optimize production strategies, ensuring proactive quality control and management
Bidirectional data flow	The integration ensures bidirectional data flow where insights from virtual simulations inform real-time decision-making and process optimizations within the physical manufacturing environment. Predictive insights guide adjustments in production parameters, equipment settings and adaptive control strategies, enhancing efficiency and product quality throughout the lifecycle
Holistic data-driven decision-making	Integration fosters a holistic approach to data-driven decision-making by leveraging real-time insights and virtual simulations. It identifies production bottlenecks, optimizes supply chain logistics, facilitates just-in-time manufacturing practices and accommodates dynamic changes in market demands or design specifications, ensuring adaptability and responsiveness
Pervasive sensor deployment	Advanced sensors within the CPS infrastructure capture real-time information on production parameters, enabling comprehensive visibility and control over critical assets. These sensors provide data for monitoring and controlling key manufacturing processes, enhancing operational efficiency and product quality throughout the production cycle
Data analytics and insights	DTs powered by advanced algorithms and machine learning models derive meaningful insights from real-time data acquired by CPS infrastructure. Data analytics tools identify production trends, detect anomalies, and optimize performance, enabling proactive addressing of potential production challenges and streamlining workflows based on predictive analyses
Dynamic control strategies	Real-time feedback mechanisms facilitated by CPS and DT integration empower dynamic control strategies and adaptive production interventions based on virtual simulations and predictive analytics. These feedback loops translate recommendations into actionable adjustments, enhancing overall production efficiency and product quality in a responsive manufacturing ecosystem
Industry case studies	Multiple case studies across industries demonstrate successful integration of CPS and DTs, optimizing workflows, enhancing equipment reliability, streamlining assembly line operations, optimizing supply chain logistics and accelerating drug formulation processes while ensuring quality control and regulatory compliance within diverse industrial sectors

Furthermore, the integration of CPS and DTs in 3D printing facilitates the implementation of adaptive control strategies that enable manufacturers to adjust print parameters, modify material compositions and calibrate production settings based on the insights and recommendations provided by the virtual simulations (Sieber *et al*., 2020). This adaptive control mechanism ensures the production of intricate and complex geometries, intricate lattice structures and customized product designs with enhanced surface finishes and mechanical integrity, thereby fostering design innovation, product customization and manufacturing agility within the additive manufacturing landscape (Zhang *et al*., 2020).

The integration of real-time monitoring and control capabilities facilitated by DTs in the context of 3D printing offers a range of transformative benefits that enhance production precision, process optimization and product quality assuance (Huang *et al*., 2021). By harnessing the power of real-time monitoring, manufacturers can capture critical process data, including temperature fluctuations, material flow rates and print layer adherence, allowing for comprehensive visibility into the intricate dynamics of the additive manufacturing process. This real-time data acquisition enables manufacturers to promptly detect potential production deviations, preemptively address print anomalies and ensure consistent print quality throughout the entire printing operation (Hyre *et al*., 2022).

Moreover, the implementation of real-time control mechanisms enabled by DTs empowers manufacturers to dynamically adjust print parameters, optimize material compositions and refine production settings based on the insights and rec-ommendations derived from the virtual simulations (Kalantari *et al*., 2022). By leveraging the predictive analytics and simulation-driven insights provided by the DTs, manufacturers can implement adaptive control strategies that ensure the precise control of print geometries, material properties and production specifications, thereby minimizing print errors, reducing post-processing requirements and enhancing the overall dimensional accuracy and surface finishes of the printed components.

Furthermore, real-time monitoring and control using DTs foster a proactive approach to quality assurance and defect mitigation within the 3D printing process (Pantelidakis *et al*., 2022). By continuously monitoring the production metrics and conducting virtual simulations, manufacturers can identify potential print defects, optimize support structures and validate design configurations before initiating the physical printing process. This proactive approach to quality assurance minimizes material wastage, reduces the likelihood of print failures and ensures the production of high-fidelity components with superior mechanical properties, dimensional accuracy and surface finishes, thereby fostering a more streamlined and efficient 3D printing process.

The integration of real-time monitoring and control capabilities using DTs in the realm of 3D printing underscores its transformative potential in enabling manufacturers to achieve unparalleled levels of production precision, process optimi-zation and product quality assurance. The synergy of real-time monitoring, DTs and 3D printing has enabled the realization of innovative manufacturing scenarios that have redefined product design, production precision and customization capabilities across various industrial sectors.

One compelling example arises in the field of biomedical engineering, where the integration of real-time monitoring and control using DTs has facilitated the production of patient-specific medical implants and prosthetics with intricate geometries and tailored material compositions (Erol *et al*., 2020). By continuously monitoring the pro-duction parameters and leveraging virtual simulations, manufacturers can ensure the precise customization of medical devices, optimizing their structural integrity, bio-compatibility and functional performance to meet the specific anatomical requirements of individual patients, thereby fostering a more patient-centric and personalized approach to medical device manufacturing (Isichei *et al*., 2023).

Also, in the aerospace sector, the synergy of real-time monitoring, DTs and 3D printing has empowered manufacturers to produce lightweight, high-strength components with intricate lattice structures and complex geometries that offer superior mechanical properties and enhanced fuel efficiency (Liu *et al*., 2021). By harnessing the insights and recommendations provided by the DTs, manufacturers can optimize the design configurations, material compositions and production parameters of critical aircraft components, thereby reducing the overall weight of aircraft structures, improving flight dynamics and ensuring compliance with stringent aerospace safety standards, thus fostering innovation and sustainability within the aerospace manufacturing sector (Mourtzis *et al*., 2021).

Moreover, in the consumer electronics industry, the integration of real-time mon-itoring, DTs and 3D printing has facilitated the rapid prototyping and customization of high-performance electronic devices with complex internal architectures and aesthetically appealing designs (Židek *et al*., 2020). By leveraging the predictive analytics and simulation-driven insights provided by the DTs, manufacturers can swiftly iterate through design concepts, validate product functionalities and customize product aesthetics based on evolving consumer preferences. This iterative prototyping approach fosters the rapid introduction of cutting-edge consumer electronics, reducing time-to-market, enhancing product differentiation and catering to the diverse and dynamic demands of the consumer electronics market (Lo *et al*., 2021).

Table 2: Synergy aspects of CPSs, Dts and 3D printing

Synergy Aspect	Description
Optimization of workflows	The combination of CPSs and DTs revolutionizes 3D printing, optimizing production workflows, enhancing design precision and ensuring consistent product quality throughout the additive manufacturing process
Real-time monitoring capabilities	Integration of CPS allows real-time monitoring of critical process parameters (e.g., print speed, temperature variations, material flow rates, layer adhesion) for precise control and quality assurance during printing
Virtual replicas and simulations	DT integration creates virtual replicas enabling simulations of print geometries, material behavior and structural integrity, minimizing material wastage and refining design configurations before physical printing, enhancing production efficiency
Continuous process improvements	Synergy of CPS and DTs establishes dynamic feedback loops for continuous process improvements. Real-time data from CPS inform virtual simulations in DTs, fostering a streamlined and efficient 3D printing process, minimizing errors and optimizing material utilization
Adaptive control strategies	Implementing adaptive control mechanisms empowered by DTs enables dynamic adjustments of print parameters, material compositions and production settings based on virtual simulations, ensuring precise control of geometries and specifications, enhancing dimensional accuracy and surface finishes of printed components
Proactive quality assurance	Real-time monitoring using DTs allows proactive identification of potential print defects, optimization of support structures and validation of design configurations before physical printing, minimizing material wastage, reducing print failures and ensuring high-fidelity components with superior properties and surface finishes
Industry applications	Integration of real-time monitoring, DTs and 3D printing across industries showcases transformative potential: Biomedical Engineering: Enables production of patient-specific medical implants with tailored compositions and structural integrity. Aerospace Sector: Empowers production of lightweight, high-strength components improving flight dynamics and compliance with safety standards. Consumer Electronics: Facilitates rapid prototyping and customization of high-performance devices

Through these novel manufacturing scenarios, the combined use of real-time monitoring, DTs and 3D printing has showcased its transformative potential in fostering unparalleled design innovation, precise product customization and dynamic manufacturing adaptability within diverse industrial contexts. These innovative applications demonstrate the capacity of this integrated approach to revolutionize traditional manufacturing processes, ushering in a new era of agile production, tailored product development and streamlined operational efficiencies. Table 2, depicts the synergy aspects of the aforementioned technologies.

Discussion

Despite the promising prospects offered by the integrated approach of real-time monitoring, DTs and 3D printing in manufacturing, several challenges and potential barriers hinder its seamless implementation across industrial settings (Lynch *et al*., 2023). One significant challenge pertains to the initial capital investment required to establish the robust infrastructure necessary for real-time monitoring and DTs integration. The acquisition of advanced sensing technologies, data analytics systems and high-performance computing capabilities can impose substantial upfront costs, especially for small and medium-sized enterprises with limited financial resources, potentially impeding their ability to adopt this integrated framework (Badenko *et al*., 2021; Nath *et al*., 2021).

The intricacies surrounding data management, integration and interoperability present formidable obstacles in implementing a cohesive and streamlined approach (Caldarelli *et al*., 2023; O'Connell *et al*., 2023). Within the dynamic landscape of industry 4.0, characterized by the convergence of diverse systems and technologies, the need to harmonize data streams becomes paramount. Established standard protocols such as ethernet, TCP/IP, Modbus and OPC serve as essential frameworks, facilitating the seamless exchange of information and enabling effective communication between heterogeneous systems (Folgado *et al*., 2023). These protocols, widely recognized and utilized in industry 4.0 environments, play a pivotal role in ensuring compatibility and smooth interoperability between various components and devices (Ladegourdie and Kua, 2022).

Furthermore, the application of open-source technology in both hardware and software solutions emerges as a pivotal strategy in overcoming financial constraints and addressing interoperability challenges (Damjanovic-Behrendt and Behrendt, 2019). Open-source technologies offer accessible and cost-effective alternatives, significantly reducing expenditures associated with proprietary systems. More than cost savings, embracing open-source solutions fosters a collaborative ecosystem, encouraging the development and adoption of standardized frameworks and protocols. This collaborative environment not only encourages innovation but also facilitates the sharing of knowledge and resources, mitigating the scarcity of technical expertise and resources that might impede the seamless integration of advanced manufacturing technologies within the industry 4.0 framework (Autiosalo *et al*., 2021). By leveraging open-source technology, organizations gain access to a vast pool of community-driven solutions, ultimately bolstering adaptability, scalability and the robustness of integrated systems in the rapidly evolving landscape of advanced manufacturing.

Additionally, the need for skilled professionals proficient in CPS, data analytics and 3D printing technologies poses a potential human resource challenge, particularly in regions where there is a shortage of specialized talent or limited access to comprehensive training programs (Cichon and Roßmann, 2018). Implementing this integrated approach necessitates a workforce equipped with interdisciplinary skills, including data analysis, software de-velopment and manufacturing expertise, which may require substantial investment in employee training and professional development initiatives.

Moreover, ensuring regulatory compliance, particularly in sectors such as healthcare and aerospace, where stringent quality standards and safety regulations govern man-ufacturing practices, presents another potential barrier (Muhlheim *et al*., 2022a-b). Incorporating real-time monitoring and DTs within the manufacturing process demands adherence to industry-specific regulatory requirements, certifications and quality as-surance protocols, which may require comprehensive audits, compliance assessments and ongoing regulatory updates to ensure the seamless integration of these technologies without compromising product safety or regulatory compliance (Fakhraian *et al*., 2023).

Amid these challenges, ongoing research and development initiatives are actively addressing key limitations and driving forward the evolution of this integrated approach within the manufacturing domain. Advanced research endeavors are focusing on the development of cost-effective sensor technologies, scalable data analytics frameworks and user-friendly DTs platforms that streamline the implementation process and make it more accessible to a broader spectrum of manufacturing enterprises (Dingli and Haddod, 2019). By reducing the entry barriers associated with capital investment and technical expertise, these advancements are poised to democratize the adoption of this integrated framework and catalyze its widespread integration across diverse industrial sectors.

In addition, future trends in this field envision the convergence of artificial intel-ligence, machine learning and edge computing technologies with the integrated framework of real-time monitoring, DTs and 3D printing, ushering in a new era of intelligent manufacturing systems capable of autonomous decision-making, self-optimization and adaptive production control (Mostafa *et al*., 2021). The integration of AI-driven predictive analytics and machine learning algorithms is expected to enhance the capabilities of DTs in generating real-time insights, forecasting production trends and identifying potential process optimizations, thereby fostering a more proactive, data-driven and autonomous manufacturing ecosystem (Alexopoulos *et al*., 2020).

Furthermore, the advent of edge computing technologies is set to decentralize data processing and analysis, enabling real-time insights and decision-making capabilities at the production site itself (Muhlheim *et al*., 2022). By reducing latency, enhancing data security and enabling real-time control functionalities, edge computing facilitates the seamless integration of real-time monitoring systems with DTs, thereby fostering a highly responsive, agile and resilient manufacturing infrastructure capable of adapting to dynamic market demands and production fluctuations (Uhlmann *et al*., 2017).

Additionally, future research endeavors aim to address the regulatory complexities associated with the implementation of this integrated framework by fostering collaborative partnerships between industry stakeholders, regulatory authorities and research institutions (Lv *et al*., 2023). The development of comprehensive regulatory frameworks, standardized compliance protocols and industry-specific guidelines is expected to streamline the regulatory approval process and ensure the seamless integration of real-time monitoring, DTs and 3D printing technologies within the manufacturing field, fostering innovation, compliance and sustainability within the industry (Botín-Sanabria *et al*., 2022).

Also, investment in comprehensive training programs and skill development initiatives can empower the workforce with the necessary expertise in CPS, data analytics and 3D printing technologies, fostering a skilled workforce equipped to handle the complexities and intricacies of this integrated framework (Kamble *et al*., 2022). Training programs tailored to the specific needs of manufacturing enterprises, hands-on workshops and educational partnerships with academic institutions can bridge the skills gap and cultivate a talent pool proficient in the implementation, management and optimization of this integrated approach, thereby fostering a culture of continuous learning and professional development within the manufacturing workforce. Thus, the establishment of industry-specific consortia and standardization bodies can drive the development of unified protocols, interoperable systems and regulatory frameworks that streamline the implementation process and ensure compliance with industry-specific quality standards and safety regulations. By fostering collaboration among industry stakeholders, regulatory authorities and standardization bodies, these initiatives can promote the development of comprehensive guidelines, certification processes and quality assurance protocols that foster the seamless integration of this integrated framework within the manufacturing landscape, thereby fostering a culture of regulatory compliance, transparency and accountability within the industry (Peppler *et al*., 2020).

Furthermore, the adoption of a phased implementation approach, starting with pilot projects and small-scale deployments, can enable manufacturers to assess the feasibility, scalability and operational efficacy of this integrated framework within their specific production environments. By conducting comprehensive feasibility studies, performance evaluations and cost-benefit analyses, manufacturers can identify potential deployment challenges, optimize resource allocation and develop tailored implementation strategies that align with their unique operational requirements, thereby fostering a gradual and sustainable integration of this integrated framework within their manufacturing ecosystem.

Conclusion

In conclusion, this article underscores the transformative potential of integrating CPSs, DTs and 3D printing within the manufacturing sector. It highlights the pivotal role of real-time monitoring and control in enhancing production precision, product quality and operational efficiency within diverse industrial sectors. Despite the challenges and potential barriers associated with implementation, ongoing research and future trends emphasize the promising trajectory of this integrated approach, envisioning the convergence of advanced technologies and intelligent manufacturing systems that drive forward sustainable growth, technlogical advancement and enhanced competitiveness within the modern industrial ecosystem. Strategic approaches aimed at overcoming obstacles and fostering collaborative partnerships, workforce development and regulatory compliance are pivotal in advancing the seamless adoption and integration of this transformative framework, paving the way for a future characterized by agile production, tailored product development and streamlined operational efficiencies within the contemporary manu-facturing landscape.

The transformative potential of combining CPSs, DTs and 3D printing in advanced manufacturing is undeniable. This integration heralds a paradigm shift in traditional production cases, fostering unparalleled design innovation, manufacturing agility and operational resilience within the contemporary industrial sector. By harnessing real-time monitoring and control capabilities, manufacturers can ensure precise process optimization, product customization and quality assurance throughout the additive manufacturing process, thereby redefining the boundaries of product design, development and production efficiency. The predictive insights and dynamic control facilitated by DTs enable manufacturers to anticipate production challenges, streamline supply chain logistics and implement adaptive production strategies, fostering a proactive and responsive manufacturing ecosystem capable of swiftly adapting to dynamic market demands and production fluctuations. This integrated framework empowers manufacturers to achieve unprecedented levels of production precision, design flexibility and product excellence, leading to a new era of sustainable growth, technological advancement and enhanced competitiveness within the dynamic and evolving field of advanced manufacturing.

Acknowledgment

Thank you to the publisher for their support in the publication of this research article. We are grateful for the resources and platform provided by the publisher, which have enabled us to share our findings with a wider audience. We appreciate the efforts of the editorial team in reviewing and editing our work, and we are thankful for the opportunity to contribute to the field of research through this publication.

Funding Information

The authors have not received any financial support or funding to report.

Author’s Contributions

Antreas Kantaros: Written and edited.
Theodore Ganetsos: Conceptualization and edited.

Ethics

This article is original and contains unpublished material. The corresponding author confirms that all of the other authors have read and approved the manuscript and no ethical issues involved.

Conflicts of Interest

The authors declare no conflict of interest.

References

Akanmu, A. A., Anumba, C. J., & Ogunseiju, O. O. (2021). Towards next generation cyber-physical systems and digital twins for construction. *Journal of Information Technology in Construction*, *26*. https://doi.org/10.36680/j.itcon.2021.027

Akanmu, A., & Anumba, C. J. (2015). Cyber-physical systems integration of building information models and the physical construction. *Engineering, Construction and Architectural Management*, *22*(5), 516-535. https://doi.org/10.1108/ecam-07-2014-0097

Alam, K. M., & El Saddik, A. (2017). C2PS: A digital twin architecture reference model for the cloud-based cyber-physical systems. *IEEE access*, *5*, 2050-2062. https://doi.org/10.1109/access.2017.2657006

Alexopoulos, K., Nikolakis, N., & Chryssolouris, G. (2020). Digital twin-driven supervised machine learning for the development of artificial intelligence applications in manufacturing. *International Journal of Computer Integrated Manufacturing*, *33*(5), 429-439. https://doi.org/10.1080/0951192x.2020.1747642

Autiosalo, J., Siegel, J., & Tammi, K. (2021). Twinbase: Open-source server software for the digital twin web. *IEEE Access*, *9*, 140779-140798. https://doi.org/10.1109/access.2021.3119487

Badenko, V. L., Bolshakov, N. S., Tishchenko, E. B., Fedotov, A. A., Celani, A. C., & Yadykin, V. K. (2021). Integration of digital twin and BIM technologies within factories of the future. *Magazine of Civil Engineering*, (1 (101)), 10114. https://doi.org/10.34910/MCE.101.14

Bak, D. (2003). Rapid prototyping or rapid production? 3D printing processes move industry towards the latter. *Assembly Automation*, *23*(4), 340-345. https://doi.org/10.1108/01445150310501190

Bazli, M., Ashrafi, H., Rajabipour, A., & Kutay, C. (2023). 3D printing for remote housing: Benefits and challenges. *Automation in Construction*, *148*, 104772. https://doi.org/10.1016/j.autcon.2023.104772

Bellman, K., Landauer, C., Dutt, N., Esterle, L., Herkersdorf, A., Jantsch, A., ... & Tammemäe, K. (2020). Self-aware cyber-physical systems. *ACM Transactions on Cyber-Physical Systems*, *4*(4), 1-26. https://doi.org/10.1145/3375716

Berger, C., Hees, A., Braunreuther, S., & Reinhart, G. (2016). Characterization of cyber-physical sensor systems. *Procedia Cirp*, *41*, 638-643. https://doi.org/10.1016/j.procir.2015.12.019

Botín-Sanabria, D. M., Mihaita, A. S., Peimbert-García, R. E., Ramírez-Moreno, M. A., Ramírez-Mendoza, R. A., & Lozoya-Santos, J. D. J. (2022). Digital twin technology challenges and applications: A comprehensive review. *Remote Sensing*, *14*(6), 1335. https://doi.org/10.3390/rs14061335

Brockhoff, T., Heithoff, M., Koren, I., Michael, J., Pfeiffer, J., Rumpe, B., ... & Wortmann, A. (2021, October). Process prediction with digital twins. In *2021 ACM/IEEE International Conference on Model Driven Engineering Languages and Systems Companion (MODELS-C)* (pp. 182-187). IEEE. https://doi.org/10.1109/MODELS-C53483.2021.00032

Caldarelli, G., Arcaute, E., Barthelemy, M., Batty, M., Gershenson, C., Helbing, D., ... & Fernández-Villacañas, J. L. (2023). The role of complexity for digital twins of cities. *Nature Computational Science*, 1-8. https://doi.org/10.1038/s43588-023-00431-4

Chen, G., Wang, P., Feng, B., Li, Y., & Liu, D. (2020a). The framework design of smart factory in discrete manufacturing industry based on cyber-physical system. *International Journal of Computer Integrated Manufacturing*, *33*(1), 79-101. https://doi.org/10.1080/0951192x.2019.1699254

Chen, Y., Yang, O., Sampat, C., Bhalode, P., Ramachandran, R., & Ierapetritou, M. (2020b). Digital twins in pharmaceutical and biopharmaceutical manufacturing: A literature review. *Processes*, *8*(9), 1088. https://doi.org/10.3390/pr8091088

Cichon, T., & Roßmann, J. (2018, November). Digital twins: assisting and supporting cooperation in human-robot teams. In *2018 15th International Conference on Control, Automation, Robotics and Vision (ICARCV)* (pp. 486-491). IEEE. https://doi.org/10.1109/ICARCV.2018.8580634

Cinar, Z. M., Nuhu, A. A., Zeeshan, Q., & Korhan, O. (2020). Digital twins for industry 4.0: A review. In *Industrial Engineering in the Digital Disruption Era: Selected papers from the Global Joint Conference on Industrial Engineering and Its Application Areas, GJCIE 2019, September 2-3, 2019, Gazimagusa, North Cyprus, Turkey* (pp. 193-203). Springer International Publishing. ISBN-10: 9783030424152.

Constantinescu, C., Giosan, S., Matei, R., & Wohlfeld, D. (2020). A holistic methodology for development of Real-Time Digital Twins. *Procedia CIRP*, *88*, 163-166. https://doi.org/10.1016/j.procir.2020.05.029

Cooke, P. (2021). Image and reality: 'Digital twins' in smart factory automotive process innovation-critical issues. *Regional Studies*, *55*(10-11), 1630-1641. https://doi.org/10.1080/00343404.2021.1959544

Dalenogare, L. S., Benitez, G. B., Ayala, N. F., & Frank, A. G. (2018). The expected contribution of Industry 4.0 technologies for industrial performance. *International Journal of Production Economics*, *204*, 383-394. https://doi.org/10.1016/j.ijpe.2018.08.019

Damjanovic-Behrendt, V., & Behrendt, W. (2019). An open source approach to the design and implementation of Digital Twins for Smart Manufacturing. *International Journal of Computer Integrated Manufacturing*, *32*(4-5), 366-384. https://doi.org/10.1080/0951192x.2019.1599436

de Mattos Nascimento, D. L., Mury Nepomuceno, R., Caiado, R. G. G., Maqueira, J. M., Moyano-Fuentes, J., & Garza-Reyes, J. A. (2022). A sustainable circular 3D printing model for recycling metal scrap in the automotive industry. *Journal of Manufacturing Technology Management*, *33*(5), 876-892. https://doi.org/10.1108/jmtm-10-2021-0391

Debroy, T., Zhang, W., Turner, J., & Babu, S. S. (2017). Building digital twins of 3D printing machines. *Scripta Materialia*, *135*, 119-124. https://doi.org/10.1016/j.scriptamat.2016.12.005

Ding, K., Chan, F. T., Zhang, X., Zhou, G., & Zhang, F. (2019). Defining a digital twin-based cyber-physical production system for autonomous manufacturing in smart shop floors. *International Journal of Production Research*, *57*(20), 6315-6334. https://doi.org/10.1080/00207543.2019.1566661

Dingli, A., & Haddod, F. (2019). Interacting with intelligent digital twins. In *Design, User Experience and Usability. User Experience in Advanced Technological Environments: 8th International Conference, DUXU 2019, Held as Part of the 21st HCI International Conference, HCII 2019, Orlando, FL, USA, July 26-31, 2019, Proceedings, Part II 21* (pp. 3-15). Springer International Publishing. ISBN-10:9783030235406.

Eckhart, M., & Ekelhart, A. (2019). Digital twins for cyber-physical systems security: State of the art and outlook. *Security and Quality in Cyber-Physical Systems Engineering: With Forewords by Robert M. Lee and Tom Gilb*, 383-412. ISBN-10: 9783030253110.

El Saddik, A. (2018). Digital twins: The convergence of multimedia technologies. *IEEE Multimedia*, *25*(2), 87-92. https://doi.org/10.1109/mmul.2018.023121167

Erol, T., Mendi, A. F., & Doğan, D. (2020, October). The digital twin revolution in healthcare. In *2020 4th International Symposium on Multidisciplinary Studies and Innovative Technologies (ISMSIT)* (pp. 1-7). IEEE. https://doi.org/10.1109/ISMSIT50672.2020.9255249

Fakhraian, E., Semanjski, I., Semanjski, S., & Aghezzaf, E. H. (2023). Towards Safe and Efficient Unmanned Aircraft System Operations: Literature Review of Digital Twins' Applications and European Union Regulatory Compliance. *Drones*, *7*(7), 478. https://doi.org/10.3390/drones7070478

Ferdinand, J. P., Petschow, U., & Dickel, S. (Eds.). (2016). *The decentralized and networked future of value creation: 3D printing and its implications for society, industry and sustainable development*. Springer. ISBN-10: 9783319316864.

Fink, G. A., Edgar, T. W., Rice, T. R., MacDonald, D. G., & Crawford, C. E. (2017). Security and privacy in cyber-physical systems. In *Cyber-Physical Systems* (pp. 129-141). Academic Press. ISBN-10: 9780128038017.

Flammini, F. (2021). Digital twins as run-time predictive models for the resilience of cyber-physical systems: A conceptual framework. *Philosophical Transactions of the Royal Society A*, *379*(2207), 20200369. https://doi.org/10.1098/rsta.2020.0369

Folgado, F. J., González, I., & Calderón, A. J. (2023). Data acquisition and monitoring system framed in Industrial Internet of Things for PEM hydrogen generators. *Internet of Things*, *22*, 100795. https://doi.org/10.1016/j.iot.2023.100795

Ganetsos, T., Kantaros, A., Gioldasis, N., & Brachos, K. (2023, June). Applications of 3D Printing and Illustration in Industry. In *2023 17th International Conference on Engineering of Modern Electric Systems (EMES)* (pp. 1-4). IEEE. https://doi.org/10.1109/EMES58375.2023.10171656

Gao, Z., Paul, A., & Wang, X. (2022). Guest editorial: Digital twinning: Integrating AI-ML and big data analytics for virtual representation. *IEEE Transactions on Industrial Informatics*, *18*(2), 1355-1358. https://doi.org/10.1109/tii.2021.3104815

García, S. N. M., Sánchez-Cabrera, A., Schiavone, E., & Skarmeta, A. (2024). Integrating the manufacturer usage description standard in the modelling of cyber-physical systems. *Computer Standards and Interfaces*, *87*, 103777. https://doi.org/10.1016/j.csi.2023.103777

Ghobakhloo, M. (2020). Industry 4.0, digitization and opportunities for sustainability. *Journal of Cleaner Production*, *252*, 119869. https://doi.org/10.1016/j.jclepro.2019.119869

Gurjanov, A. V., Zakoldaev, D. A., Shukalov, A. V., & Zharinov, I. O. (2019, March). Formation principles of digital twins of Cyber-Physical Systems in the smart factories of Industry 4.0. In *IOP conference series: Materials Science and Engineering* (Vol. *483*, p. 012070). IOP Publishing. https://doi.org/10.1088/1757-899x/483/1/012070

Hamzah, M., Islam, M. M., Hassan, S., Akhtar, M. N., Ferdous, M. J., Jasser, M. B., & Mohamed, A. W. (2023). Distributed Control of Cyber Physical System on Various Domains: A Critical Review. *Systems*, *11*(4), 208. https://doi.org/10.3390/systems11040208

Hänel, A., Schnellhardt, T., Wenkler, E., Nestler, A., Brosius, A., Corinth, C., ... & Ihlenfeldt, S. (2020). The development of a digital twin for machining processes for the application in aerospace industry. *Procedia CIRP*, *93*, 1399-1404. https://doi.org/10.1016/j.procir.2020.04.017

Huang, Z., Shen, Y., Li, J., Fey, M., & Brecher, C. (2021). A survey on AI-driven digital twins in industry 4.0: Smart manufacturing and advanced robotics. *Sensors*, *21*(19), 6340. https://doi.org/10.3390/s21196340

Hyre, A., Harris, G., Osho, J., Pantelidakis, M., Mykoniatis, K., & Liu, J. (2022). Digital twins: Representation, replication, reality and relational (4Rs). *Manufacturing Letters*, *31*, 20-23. https://doi.org/10.1016/j.mfglet.2021.12.004

Imrie, P., Diegel, O., & Jin, J. (2023). Direct-ink-write 3D printing of "living" polymer hydrogels via type I photoinitiated RAFT polymerization. *Polymer*, *276*, 125944. https://doi.org/10.1016/j.polymer.2023.125944

IoT ONE. (2024). Digital Twin in Pharmaceutical Manufacturing. *SIEMENS*. https://www.iotone.com/case-study/digital-twin-in-pharmaceutical-manufacturing/c1483

Isichei, J. C., Khorsandroo, S., & Desai, S. (2023). Cybersecurity and privacy in smart bioprinting. *Bioprinting*, e00321. https://doi.org/10.1016/j.bprint.2023.e00321

Jazdi, N. (2014, May). Cyber physical systems in the context of Industry 4.0. In *2014 IEEE International Conference on Automation, Quality and Testing, Robotics* (pp. 1-4). IEEE. https://doi.org/10.1109/AQTR.2014.6857843

Jia, D., Lu, K., Wang, J., Zhang, X., & Shen, X. (2015). A survey on platoon-based vehicular cyber-physical systems. *IEEE Communications Surveys and Tutorials*, *18*(1), 263-284. https://doi.org/10.1109/comst.2015.2410831

Jiang, Y., Yin, S., Li, K., Luo, H., & Kaynak, O. (2021). Industrial applications of digital twins. *Philosophical Transactions of the Royal Society A*, *379*(2207), 20200360. https://doi.org/10.1098/rsta.2020.0360

Joshi, S. C., & Sheikh, A. A. (2015). 3D printing in aerospace and its long-term sustainability. *Virtual and Physical Prototyping*, *10*(4), 175-185. https://doi.org/10.1080/17452759.2015.1111519

Josifovska, K., Yigitbas, E., & Engels, G. (2019, May). Reference framework for digital twins within cyber-physical systems. In *2019 IEEE/ACM 5th International Workshop on Software Engineering for Smart Cyber-Physical Systems (SEsCPS)* (pp. 25-31). IEEE. https://doi.org/10.1109/SEsCPS.2019.00012

Kalantari, S., Pourjabar, S., Xu, T. B., & Kan, J. (2022). Developing and user-testing a "Digital Twins" prototyping tool for architectural design. *Automation in Construction*, *135*, 104140. https://doi.org/:10.1016/j.autcon.2022.104140

Kamble, S. S., Gunasekaran, A., Parekh, H., Mani, V., Belhadi, A., & Sharma, R. (2022). Digital twin for sustainable manufacturing supply chains: Current trends, future perspectives and an implementation framework. *Technological Forecasting and Social Change*, *176*, 121448. https://doi.org/10.1016/j.techfore.2021.121448

Kan, C., & Anumba, C. J. (2019, June). Digital twins as the next phase of cyber-physical systems in construction. In *ASCE International Conference on Computing in Civil Engineering 2019* (pp. 256-264). Reston, VA: American Society of Civil Engineers. https://doi.org/10.1061/9780784482438.033

Kantaros, A. (2022a). 3D Printing in Regenerative Medicine: Technologies and Resources Utilized. *International Journal of Molecular Sciences*, *23*(23), 14621. https://doi.org/10.3390/ijms232314621

Kantaros, A. (2022b). Bio-Inspired Materials: Exhibited Characteristics and Integration Degree in Bio-Printing Operations. *American Journal of Engineering and Applied Sciences*, *15*(4), 255-263. https://doi.org/10.3844/ajeassp.2022.255.263

Kantaros, A., & Diegel, O. (2018). 3D printing technology in musical instrument research: Reviewing the potential. *Rapid Prototyping Journal*, *24*(9), 1511-1523. https://doi.org/10.1108/rpj-05-2017-0095

Kantaros, A., & Ganetsos, T. (2023). From Static to Dynamic: Smart Materials Pioneering Additive Manufacturing in Regenerative Medicine. *International Journal of Molecular Sciences*, *24*(21), 15748. https://doi.org/10.3390/ijms242115748

Kantaros, A., & Karalekas, D. (2013). Fiber Bragg grating based investigation of residual strains in ABS parts fabricated by fused deposition modeling process. *Materials and Design*, *50*, 44-50. https://doi.org/10.1016/j.matdes.2013.02.067

Kantaros, A., & Karalekas, D. (2014). FBG based in situ characterization of residual strains in FDM process. In *Residual Stress, Thermomechanics & Infrared Imaging, Hybrid Techniques and Inverse Problems, Volume 8: Proceedings of the 2013 Annual Conference on Experimental and Applied Mechanics* (pp. 333-337). Springer International Publishing. https://doi.org/10.1007/978-3-319-00876-9_41

Kantaros, A., & Piromalis, D. (2021a). Employing a low-cost desktop 3D printer: Challenges and how to overcome them by tuning key process parameters. *International Journal of Mechanics and Applications*, *10*(1), 11-19. https://doi.org/10.5923/j.mechanics.20211001.02

Kantaros, A., & Piromalis, D. (2021b). Fabricating lattice structures via 3D printing: The case of porous bio-engineered scaffolds. *Applied Mechanics*, *2*(2), 289-302. https://doi.org/10.3390/applmech2020018

Kantaros, A., & Piromalis, D. (2022). Setting up a Digital Twin Assisted Greenhouse Architecture. *American Journal of Engineering and Applied Sciences*. https://doi.org/10.3844/ajeassp.2022.230.238

Kantaros, A., Chatzidai, N., & Karalekas, D. (2016). 3D printing-assisted design of scaffold structures. *The International Journal of Advanced Manufacturing Technology*, *82*, 559-571. https://doi.org/10.1007/s00170-015-7386-6

Kantaros, A., Ganetsos, T., & Piromalis, D. (2023a). 3D and 4D Printing as Integrated Manufacturing Methods of Industry 4.0. *Kantaros, A., Ganetsos, T. & Piromalis, D. (2023). 3D and 4D Printing as Integrated Manufacturing Methods of Industry*, *4*, 12-22. https://doi.org/10.3844/ajeassp.2023.12.22

Kantaros, A., Ganetsos, T., & Petrescu, F. I. T. (2023b). Three-Dimensional Printing and 3D Scanning: Emerging Technologies Exhibiting High Potential in the Field of Cultural Heritage. *Applied Sciences*, *13*(8), 4777. https://doi.org/10.3390/app13084777

Kantaros, A., Ganetsos, T., & Piromalis, D. (2023c). 4D Printing: Technology Overview and Smart Materials Utilized. *Kantaros, A., Ganetsos, T. & Piromalis, D. (2023). 4D Printing: Technology Overview and Smart Materials Utilized. Journal of Mechatronics and Robotics*, *7*(1), 1-14. https://doi.org/10.3844/jmrsp.2023.1.14

Kantaros, A., Soulis, E., Petrescu, F. I. T., & Ganetsos, T. (2023d). Advanced Composite Materials Utilized in FDM/FFF 3D Printing Manufacturing Processes: The Case of Filled Filaments. *Materials*, *16*(18), 6210. https://doi.org/10.3390/ma16186210

Kantaros, A., Soulis, E., & Alysandratou, E. (2023e). Digitization of ancient artefacts and fabrication of sustainable 3D-printed replicas for intended use by visitors with disabilities: The case of Piraeus archaeological museum. *Sustainability*, *15*(17), 12689. https://doi.org/10.3390/su151712689

Kantaros, A., Soulis, E., Ganetsos, T., & Petrescu, F. I. T. (2023f). Applying a Combination of Cutting-Edge Industry 4.0 Processes towards Fabricating a Customized Component. *Processes*, *11*(5), 1385. https://doi.org/10.3390/pr11051385

Kantaros, A., Giannatsis, J., & Karalekas, D. (2013, October). A novel strategy for the incorporation of optical sensors in Fused Deposition Modeling parts. In *Proc. Int. Conf. Adv. Manuf. Eng. Technol., Stockolm, Sweden* (pp. 163-170). https://www.diva-portal.org/smash/get/diva2:660817/FULLTEXT09.pdf#page=163

Kantaros, A., Piromalis, D., Tsaramirsis, G., Papageorgas, P., & Tamimi, H. (2021a). 3D printing and implementation of digital twins: Current trends and limitations. *Applied System Innovation*, *5*(1), 7. https://doi.org/10.3390/asi5010007

Kantaros, A., Laskaris, N., Piromalis, D., & Ganetsos, T. (2021b). Manufacturing zero-waste COVID-19 personal protection equipment: A case study of utilizing 3D printing while employing waste material recycling. *Circular Economy and Sustainability*, *1*, 851-869. https://doi.org/10.1007/s43615-021-00047-8

Kantaros, A., Diegel, O., Piromalis, D., Tsaramirsis, G., Khadidos, A. O., Khadidos, A. O., ... & Jan, S. (2022). 3D printing: Making an innovative technology widely accessible through makerspaces and outsourced services. *Materials Today: Proceedings*, *49*, 2712-2723. https://doi.org/10.1016/j.matpr.2021.09.074

Kapteyn, M. G., Pretorius, J. V., & Willcox, K. E. (2021). A probabilistic graphical model foundation for enabling predictive digital twins at scale. *Nature Computational Science*, *1*(5), 337-347. https://doi.org/10.1038/s43588-021-00069-0

Kee, K. K., Yew, S. L. B., Lim, Y. S., Ting, Y. P., & Rashidi, R. (2022). Universal cyber physical system, a prototype for predictive maintenance. *Bulletin of Electrical Engineering and Informatics*, *11*(1), 42-49. https://doi.org/10.11591/eei.v11i1.3216

Ladegourdie, M., & Kua, J. (2022). Performance Analysis of OPC UA for Industrial Interoperability towards Industry 4.0. *IoT*, *3*(4), 507-525. https://doi.org/10.3390/iot3040027

Latif, K., Sharafat, A., & Seo, J. (2023). Digital Twin-Driven Framework for TBM Performance Prediction, Visualization and Monitoring through Machine Learning. *Applied Sciences*, *13*(20), 11435. https://doi.org/10.3390/app132011435

Lecklider, T. (2017). High or low density matters. *EE-Evaluation Engineering*, *56*(1), 6-9.

Lee, E. A. (2008, May). Cyber physical systems: Design challenges. In *2008 11th IEEE International Symposium on Object and Component-Oriented Real-Time Distributed Computing (ISORC)* (pp. 363-369). IEEE. https://doi.org/10.1109/ISORC.2008.25

Lee, E. A. (2015). The past, present and future of cyber-physical systems: A focus on models. *Sensors*, *15*(3), 4837-4869. https://doi.org/10.3390/s150304837

Lee, J., Ardakani, H. D., Yang, S., & Bagheri, B. (2015). Industrial big data analytics and cyber-physical systems for future maintenance & service innovation. *Procedia Cirp*, *38*, 3-7. https://doi.org/10.1016/j.procir.2015.08.026

Lee, J., Azamfar, M., Singh, J., & Siahpour, S. (2020). Integration of digital twin and deep learning in cyber-physical systems: Towards smart manufacturing. *IET Collaborative Intelligent Manufacturing*, *2*(1), 34-36. https://doi.org/10.1049/iet-cim.2020.0009

Lee, J., Jin, C., & Bagheri, B. (2017). Cyber physical systems for predictive production systems. *Production Engineering*, *11*(2), 155-165. https://doi.org/10.1007/s11740-017-0729-4

Leng, J., Wang, D., Shen, W., Li, X., Liu, Q., & Chen, X. (2021). Digital twins-based smart manufacturing system design in Industry 4.0: A review. *Journal of Manufacturing Systems*, *60*, 119-137. https://doi.org/10.1016/j.jmsy.2021.05.011

Li, L., Aslam, S., Wileman, A., & Perinpanayagam, S. (2021). Digital twin in aerospace industry: A gentle introduction. *IEEE Access*, *10*, 9543-9562. https://doi.org/10.1109/access.2021.3136458

Li, Q., Kucukkoc, I., & Zhang, D. Z. (2017). Production planning in additive manufacturing and 3D printing. *Computers and Operations Research*, *83*, 157-172. https://doi.org/10.1016/j.cor.2017.01.013

Liaw, C. Y., & Guvendiren, M. (2017). Current and emerging applications of 3D printing in medicine. *Biofabrication*, *9*(2), 024102. https://doi.org/10.1088/1758-5090/aa7279

Liu, S., Bao, J., Lu, Y., Li, J., Lu, S., & Sun, X. (2021). Digital twin modeling method based on biomimicry for machining aerospace components. *Journal of Manufacturing Systems*, *58*, 180-195. https://doi.org/10.1016/j.jmsy.2020.04.014

Liu, Y., Peng, Y., Wang, B., Yao, S., & Liu, Z. (2017). Review on cyber-physical systems. *IEEE/CAA Journal of Automatica Sinica*, *4*(1), 27-40. https://doi.org/10.1109/jas.2017.7510349

Lo, C. K., Chen, C. H., & Zhong, R. Y. (2021). A review of digital twin in product design and development. *Advanced Engineering Informatics*, *48*, 101297. https://doi.org/10.1016/j.aei.2021.101297

Lv, Z., Chen, D., Feng, H., Singh, A. K., Wei, W., & Lv, H. (2022). Computational intelligence in security of digital twins big graphic data in cyber-physical systems of smart cities. *ACM Transactions on Management Information Systems (TMIS)*, *13*(4), 1-17. https://doi.org/10.1145/3522760

Lv, Z., Cheng, C., & Lv, H. (2023). Blockchain Based Decentralized Learning for Security in Digital Twins. *IEEE Internet of Things Journal*. https://doi.org/10.1109/jiot.2023.3295499

Lynch, K. M., Issa, R. R., & Anumba, C. J. (2023). Financial digital twin for public sector capital projects. *Journal of Computing in Civil Engineering*, *37*(3), 04023003. https://doi.org/10.1061/jccee5.cpeng-4961

Makri, C., Gürdür Broo, D., & Neely, A. (2022). Human-in-Loop Decision-Making and Autonomy: Lessons Learnt from the Aviation Industry Transferred to Cyber-Physical Systems. *Technologies*, *10*(6), 120. https://doi.org/10.3390/technologies10060120

Martinez, D. W., Espino, M. T., Cascolan, H. M., Crisostomo, J. L., & Dizon, J. R. C. (2022). A comprehensive review on the application of 3D printing in the aerospace industry. *Key Engineering Materials*, *913*, 27-34. https://doi.org/10.4028/p-94a9zb

Meesublak, K., & Klinsukont, T. (2020, August). A cyber-physical system approach for predictive maintenance. In *2020 IEEE International Conference on Smart Internet of Things (Smart IoT)* (pp. 337-341). IEEE. https://doi.org/10.1109/SmartIoT49966.2020.00061

Mihai, S., Yaqoob, M., Hung, D. V., Davis, W., Towakel, P., Raza, M., ... & Nguyen, H. X. (2022). Digital twins: A survey on enabling technologies, challenges, trends and future prospects. *IEEE Communications Surveys and Tutorials*. https://doi.org/10.1109/comst.2022.3208773

Mostafa, F., Tao, L., & Yu, W. (2021). An effective architecture of digital twin system to support human decision making and AI-driven autonomy. *Concurrency and Computation: Practice and Experience*, *33*(19), e6111. https://doi.org/10.1002/cpe.6111

Mourtzis, D., Togias, T., Angelopoulos, J., & Stavropoulos, P. (2021). A digital twin architecture for monitoring and optimization of fused deposition modeling processes. *Procedia CIRP*, *103*, 97-102. https://doi.org/10.1016/j.procir.2021.10.015

Mueller, T., Elkaseer, A., Charles, A., Fauth, J., Rabsch, D., Scholz, A., ... & Scholz, S. G. (2020). Eight weeks later-the unprecedented rise of 3D printing during the COVID-19 pandemic-a case study, lessons learned and implications on the future of global decentralized manufacturing. *Applied Sciences*, *10*(12), 4135. https://doi.org/10.3390/app10124135

Muhlheim, M. D., Ramuhalli, P., Huning, A., Guler Yigitoglu, A., Wood, R. T., & Saxena, A. (2022a). Status Report on Regulatory Criteria Applicable to the Use of Digital Twins.

Muhlheim, M., Ramuhalli, P., Huning, A., Guler Yigitoglu, A., Saxena, A., & Wood, R. T. (2022b). *Regulatory Requirements, Guidance and Review of Digital Twins*. Oak Ridge National Lab. (ORNL), Oak Ridge, TN (United States). https://www.osti.gov/servlets/purl/1901641

Mukherjee, T., & DebRoy, T. (2019). A digital twin for rapid qualification of 3D printed metallic components. *Applied Materials Today*, *14*, 59-65. https://doi.org/10.1016/j.apmt.2018.11.003

Nagar, S. V., Chandrashekar, A. C., & Suvarna, M. (2020). Optimized additive manufacturing technology using digital twins and cyber physical systems. In *Cyber-Physical Systems and Digital Twins: Proceedings of the 16th International Conference on Remote Engineering and Virtual Instrumentation 16* (pp. 65-73). Springer International Publishing. ISBN-10: 9783030231613.

Napoleone, A., Macchi, M., & Pozzetti, A. (2020). A review on the characteristics of cyber-physical systems for the future smart factories. *Journal of Manufacturing Systems*, *54*, 305-335. https://doi.org/:10.1016/j.jmsy.2020.01.007

Nath, S. V., Van Schalkwyk, P., & Isaacs, D. (2021). *Building industrial digital twins: Design, develop and deploy digital twin solutions for real-world industries using Azure digital twins*. Packt Publishing Ltd. ISBN-10: 9781839214516.

Negri, E., Fumagalli, L., & Macchi, M. (2017). A review of the roles of digital twin in CPS-based production systems. *Procedia Manufacturing*, *11*, 939-948. https://doi.org/10.1016/j.promfg.2017.07.198

Nguyen, T. N., Zeadally, S., & Vuduthala, A. B. (2021). Cyber-physical cloud manufacturing systems with digital twins. *IEEE Internet Computing*, *26*(3), 15-21. https://doi.org/10.1109/mic.2021.3058921

Nichols, M. R. (2019). How does the automotive industry benefit from 3D metal printing?. *Metal Powder Report*, *74*(5), 257-258. https://doi.org/10.1016/j.mprp.2019.07.002

O'Connell, E., O'Brien, W., Bhattacharya, M., Moore, D., & Penica, M. (2023, May). Digital Twins: Enabling Interoperability in Smart Manufacturing Networks. In *Telecom* (Vol. *4*, No. 2, pp. 265-278). https://doi.org/10.3390/telecom4020016

Odendaal, J. H., Le Guen, M. J., Diegel, O., Bhatia, N., Wilson, R., & Potgieter, J. (2023). On using steerable needles for the 3D printing of biomaterials. *Materials Today: Proceedings*. https://doi.org/10.1016/j.matpr.2023.03.821

Pagonis, K., Zacharia, P., Kantaros, A., Ganetsos, T., & Brachos, K. (2023, June). Design, Fabrication and Simulation of a 5-Dof Robotic Arm Using Machine Vision. In *2023 17th International Conference on Engineering of Modern Electric Systems (EMES)* (pp. 1-4). IEEE. https://doi.org/10.1109/EMES58375.2023.10171749

Panetto, H., Iung, B., Ivanov, D., Weichhart, G., & Wang, X. (2019). Challenges for the cyber-physical manufacturing enterprises of the future. *Annual Reviews in Control*, *47*, 200-213. https://doi.org/10.1016/j.arcontrol.2019.02.002

Pantelidakis, M., Mykoniatis, K., Liu, J., & Harris, G. (2022). A digital twin ecosystem for additive manufacturing using a real-time development platform. *The International Journal of Advanced Manufacturing Technology*, *120*(9-10), 6547-6563. https://doi.org/10.1007/s00170-022-09164-6

Paripooranan, C. S., Abishek, R., Vivek, D. C., & Karthik, S. (2020, December). An implementation of AR enabled digital twins for 3-D printing. In *2020 IEEE International Symposium on Smart Electronic Systems (iSES)(Formerly iNiS)* (pp. 155-160). IEEE. https://doi.org/10.1109/iSES50453.2020.00043

Peng, X., Yue, L., Liang, S., Montgomery, S., Lu, C., Cheng, C. M., ... & Qi, H. J. (2022). Multi-Color 3D Printing via Single-Vat Grayscale Digital Light Processing. *Advanced Functional Materials*, *32*(28), 2112329. https://doi.org/10.1002/adfm.202112329

Peppler, K., Huang, J., Richey, M. C., Ginda, M., Börner, K., Quinlan, H., & Hart, A. J. (2020). Key principles for workforce upskilling via online learning: A learning analytics study of a professional course in additive manufacturing. *arXiv preprint arXiv:2008.06610*. https://doi.org/10.48550/ARXIV.2008.06610

Pessoa, S., Guimarães, A. S., Lucas, S. S., & Simões, N. (2021). 3D printing in the construction industry-A systematic review of the thermal performance in buildings. *Renewable and Sustainable Energy Reviews*, *141*, 110794. https://doi.org/10.1016/j.rser.2021.110794

Petrescu, R. V. V., & Petrescu, F. I. T. (2022). The current stage in aerospace at the end of 2020. *Independent Journal of Management and Production*, *13*(1), 405-478. https://dialnet.unirioja.es/servlet/articulo?codigo=8639594

Pires, F., Cachada, A., Barbosa, J., Moreira, A. P., & Leitão, P. (2019, July). Digital twin in industry 4.0: Technologies, applications and challenges. In *2019 IEEE 17th International Conference on Industrial Informatics (INDIN)* (Vol. 1, pp. 721-726). IEEE.

Piromalis, D., & Kantaros, A. (2022). Digital twins in the automotive industry: The road toward physical-digital convergence. *Applied System Innovation*, *5*(4), 65. https://doi.org/10.3390/asi5040065

Radanliev, P., De Roure, D., Nicolescu, R., Huth, M., & Santos, O. (2022). Digital twins: Artificial intelligence and the IoT cyber-physical systems in Industry 4.0. *International Journal of Intelligent Robotics and Applications*, *6*(1), 171-185. https://doi.org/10.1007/s41315-021-00180-5

Raina, A., Haq, M. I. U., Javaid, M., Rab, S., & Haleem, A. (2021). 4D printing for automotive industry applications. *Journal of The Institution of Engineers (India): Series D*, 1-9. https://doi.org/10.1007/s40033-021-00284-z

Ravi, P., Burch, M. B., Farahani, S., Chepelev, L. L., Yang, D., Ali, A., ... & Grawe, B. (2023). Utility and costs during the initial year of 3D printing in an academic hospital. *Journal of the American College of Radiology*, *20*(2), 193-204. https://doi.org/10.1016/j.jacr.2022.07.001

Rehman, S. U., & Gruhn, V. (2018). An effective security requirements engineering framework for cyber-physical systems. *Technologies*, *6*(3), 65. https://doi.org/10.3390/technologies6030065

Rivera, L. F., Jiménez, M., Tamura, G., Villegas, N. M., & Müller, H. A. (2021). Designing run-time evolution for dependable and resilient cyber-physical systems using digital twins. *Journal of Integrated Design and Process Science*, *25*(2), 48-79. https://doi.org/10.3233/jid210014

Ryalat, M., ElMoaqet, H., & AlFaouri, M. (2023). Design of a smart factory based on cyber-physical systems and internet of things towards industry 4.0. *Applied Sciences*, *13*(4), 2156. https://doi.org/10.3390/app13042156

Savastano, M., Amendola, C., D′ Ascenzo, F., & Massaroni, E. (2016). 3-D printing in the spare parts supply chain: An explorative study in the automotive industry. In *Digitally supported innovation: A Multi-Disciplinary View on Enterprise, Public Sector and User Innovation* (pp. 153-170). Springer International Publishing. https://doi.org/10.1007/978-3-319-40265-9_11

Schluse, M., & Rossmann, J. (2016, October). From simulation to experimentable digital twins: Simulation-based development and operation of complex technical systems. In *2016 IEEE International Symposium on Systems Engineering (ISSE)* (pp. 1-6). IEEE. https://doi.org/10.1109/SysEng.2016.7753162

Segovia, M., & Garcia-Alfaro, J. (2022). Design, modeling and implementation of digital twins *Sensors*, *22*(14), 5396. https://doi.org/10.3390/s22145396

Shahrubudin, N., Lee, T. C., & Ramlan, R. J. P. M. (2019). An overview on 3D printing technology: Technological, materials and applications. *Procedia Manufacturing*, *35*, 1286-1296. https://doi.org/10.1016/j.promfg.2019.06.08

Shangguan, D., Chen, L., & Ding, J. (2019, February). A hierarchical digital twin model framework for dynamic cyber-physical system design. In *Proceedings of the 5th International Conference on Mechatronics and Robotics Engineering* (pp. 123-129).

Sieber, I., Thelen, R., & Gengenbach, U. (2020). Enhancement of high-resolution 3D inkjet-printing of optical freeform surfaces using digital twins. *Micromachines*, *12*(1), 35. https://doi.org/10.3390/mi12010035

Singh, M., Fuenmayor, E., Hinchy, E. P., Qiao, Y., Murray, N., & Devine, D. (2021). Digital twin: Origin to future. *Applied System Innovation*, *4*(2), 36. https://doi.org/10.3390/asi4020036

Smeets, J., Öztürk, K., & Liebich, R. (2023). Digital twins for automotive development: Two wheelers application. *Advanced Engineering Informatics*, *56*, 101982. https://doi.org/10.1016/j.aei.2023.101982

Somers, R. J., Douthwaite, J. A., Wagg, D. J., Walkinshaw, N., & Hierons, R. M. (2023). Digital-twin-based testing for cyber–physical systems: A systematic literature review. *Information and Software Technology*, *156*, 107145. https://doi.org/10.1016/j.infsof.2022.107145

Song, E. Y., Burns, M., Pandey, A., & Roth, T. (2019, March). IEEE 1451 smart sensor digital twin federation for IoT/CPS research. In *2019 IEEE Sensors Applications Symposium (SAS)* (pp. 1-6). IEEE. https://doi.org/10.1109/SAS.2019.8706111

Song, H., Fink, G. A., & Jeschke, S. (Eds.). (2017). *Security and privacy in cyber-physical systems: Foundations, principles and applications*. John Wiley & Sons. ISBN-10: 9781119226048.

Spyrou, O., Hurst, W., & Verdouw, C. (2023). Virtual Reality-Based Digital Twins: A Case Study on Pharmaceutical Cannabis. *Big Data and Cognitive Computing*, *7*(2), 95. https://doi.org/10.3390/bdcc7020095

Stansbury, J. W., & Idacavage, M. J. (2016). 3D printing with polymers: Challenges among expanding options and opportunities. *Dental Materials*, *32*(1), 54-64. https://doi.org/10.1016/j.dental.2015.09.018

Stavropoulos, P. (2022). Digitization of Manufacturing Processes: From Sensing to Twining. *Technologies*, *10*(5), 98. https://doi.org/10.3390/technologies10050098

Suhail, S., Malik, S. U. R., Jurdak, R., Hussain, R., Matulevičius, R., & Svetinovic, D. (2022). Towards situational aware cyber-physical systems: A security-enhancing use case of blockchain-based digital twins. *Computers in Industry*, *141*, 103699. https://doi.org/10.1016/j.compind.2022.103699

Tan, Y., Goddard, S., & Perez, L. C. (2008). A prototype architecture for cyber-physical systems. *ACM Sigbed Review*, *5*(1), 1-2. https://doi.org/10.1145/1366283.1366309

Tao, F., & Qi, Q. (2019). Make more digital twins. *Nature*, *573*(7775), 490-491. https://doi.org/10.1038/d41586-019-02849-1

Tao, F., Qi, Q., Wang, L., & Nee, A. Y. C. (2019). Digital twins and cyber-physical systems toward smart manufacturing and industry 4.0: Correlation and comparison. *Engineering*, *5*(4), 653-661. https://doi.org/10.1016/j.eng.2019.01.014

Tay, Y. W. D., Panda, B., Paul, S. C., Noor Mohamed, N. A., Tan, M. J., & Leong, K. F. (2017). 3D printing trends in building and construction industry: A review. *Virtual and Physical Prototyping*, *12*(3), 261-276. https://doi.org/10.1080/17452759.2017.1326724

Tonelli, F., Demartini, M., Pacella, M., & Lala, R. (2021). Cyber-Physical Systems (CPS) in supply chain management: From foundations to practical implementation. *Procedia CIRP*, *99*, 598-603. https://doi.org/10.1016/j.procir.2021.03.080.

Tran, N. H., Park, H. S., Nguyen, Q. V., & Hoang, T. D. (2019). Development of a smart cyber-physical manufacturing system in the industry 4.0 context. *Applied Sciences*, *9*(16), 3325. https://doi.org/10.3390/app9163325

Trenfield, S. J., Awad, A., Madla, C. M., Hatton, G. B., Firth, J., Goyanes, A., ... & Basit, A. W. (2019). Shaping the future: Recent advances of 3D printing in drug delivery and healthcare. *Expert Opinion on Drug Delivery*, *16*(10), 1081-1094. https://doi.org/10.1080/17425247.2019.1660318

Tsaramirsis, G., Kantaros, A., Al-Darraji, I., Piromalis, D., Apostolopoulos, C., Pavlopoulou, A., ... & Khan, F. Q. (2022). A modern approach towards an industry 4.0 model: From driving technologies to management. *Journal of Sensors*, *2022*, 1-18. https://doi.org/10.1155/2022/5023011.

Uhlmann, E., Laghmouchi, A., Geisert, C., & Hohwieler, E. (2017). Decentralized data analytics for maintenance in industrie 4.0. *Procedia Manufacturing*, *11*, 1120-1126. https://doi.org/10.1016/j.promfg.2017.07.233

Wang, K. J., Lee, Y. H., & Angelica, S. (2021). Digital twin design for real-time monitoring-a case study of die cutting machine. *International Journal of Production Research*, *59*(21), 6471-6485. https://doi.org/10.1080/00207543.2020.1817999

Wu, P., Zhao, X., Baller, J. H., & Wang, X. (2018). Developing a conceptual framework to improve the implementation of 3D printing technology in the construction industry. *Architectural Science Review*, *61*(3), 133-142. https://doi.org/10.1080/00038628.2018.1450727

Yasin, A., Pang, T. Y., Cheng, C. T., & Miletic, M. (2021). A roadmap to integrate digital twins for small and medium-sized enterprises. *Applied Sciences*, *11*(20), 9479. https://doi.org/10.3390/app11209479

Yuan, J., Chen, G., Li, H., Prautzsch, H., & Xiao, K. (2021). Accurate and Computational: A review of color reproduction in Full-color 3D printing. *Materials and Design*, *209*, 109943. https://doi.org/10.1016/j.matdes.2021.109943

Yue, T., Arcaini, P., & Ali, S. (2020, October). Understanding digital twins for cyber-physical systems: A conceptual model. In *International Symposium on Leveraging Applications of Formal Methods* (pp. 54-71). Cham: Springer International Publishing. https://doi.org/10.1007/978-3-030-83723-5_5

Zeadally, S., Sanislav, T., & Mois, G. D. (2019). Self-adaptation techniques in cyber-physical systems (CPSs). *IEEE Access*, *7*, 171126-171139. https://doi.org/10.1109/access.2019.2956124

Zhang, L., Chen, X., Zhou, W., Cheng, T., Chen, L., Guo, Z., ... & Lu, L. (2020). Digital twins for additive manufacturing: A state-of-the-art review. *Applied Sciences*, *10*(23), 8350. https://doi.org/10.3390/app10238350

Zhang, Y., Qian, C., Lv, J., & Liu, Y. (2016). Agent and cyber-physical system based self-organizing and self-adaptive intelligent shopfloor. *IEEE Transactions on Industrial Informatics*, *13*(2), 737-747. https://doi.org/10.1109/tii.2016.2618892

Zhou, Y., Riding, P., Eccleston, K., Tan, A., Anton, E., Platt, I., ... & Diegel, O. (2022, December). Additive Manufacturing of Human Torso Phantom for Microwave Imaging. In *2022 IEEE Conference on Antenna Measurements and Applications (CAMA)* (pp. 1-3). IEEE. https://doi.org/10.1109/CAMA56352.2022.10002592

Židek, K., Piteľ, J., Adámek, M., Lazorík, P., & Hošovský, A. (2020). Digital twin of experimental smart manufacturing assembly system for industry 4.0 concept. *Sustainability*, *12*(9), 3658. https://doi.org/10.3390/su12093658

Zobel-Roos, S., Schmidt, A., Uhlenbrock, L., Ditz, R., Köster, D., & Strube, J. (2021). Digital twins in biomanufacturing. *Digital Twins: Tools and Concepts for Smart Biomanufacturing*, 181-262. https://doi.org/10.1007/10_2020_146