Challenges and Opportunities in Integrating Generative AI with Digital Twins for Manufacturing Optimization

Mehdi Raoofi*, David Massetti*, Tiziano Miroglio*, Flavio Tonelli*

** University of Genoa, Dipartimento di Ingegneria Meccanica, Energetica, Gestionale e dei Trasporti, Via All'Opera Pia 15, 16145 – Genoa – Italy, (mehdi.raoofi@edu.unige.it, david.massetti@edu.unige.it, tiziano.miroglio@edu.unige.it, flavio.tonelli@unige.it)*

Abstract: The integration of Generative Artificial Intelligence (GAI) with Digital Twins (DTs) represents a frontier in manufacturing optimization, offering unique opportunities for efficiency, accuracy, and innovation, leading to a more sustainable resource management. Utilizing GAI and DT for energy, resource, and waste management fosters sustainability in manufacturing. These technologies enhance efficiency, promote eco-friendly practices, and bolster business reputation. This review paper delves into the dynamic synergy between GAI and DT, a combination poised to redefine predictive maintenance, process optimization, and the entire product lifecycle management within the manufacturing industry. Despite the promising potential, the fusion of these technologies encounters distinct challenges, including data privacy concerns, interoperability issues, and the need for scalable, real-time processing frameworks. Our comprehensive analysis aims to face these complexities by systematically examining the current landscape of GAI applications within DT, highlighting novel methodologies and technological advancements that enhance simulation accuracy and operational efficiency. By studying new and innovative approaches, this review aims at overcoming existing hurdles, maximizing the potential of DTs in manufacturing. The culmination of our findings not only underlines the importance of GAI in advancing digital twin technologies but also sets the stage for future research directions, emphasizing the development of more robust, efficient, and secure integrations. This comprehensive roadmap aims to guide researchers and practitioners in leveraging the benefits of GAI and DT for manufacturing excellence.

Keywords: Generative Artificial Intelligence, Digital Twins, Sustainability, Manufacturing Optimization, Product Lifecycle Management

1.Introduction

In today's competitive markets, digitalization in manufacturing is essential for productivity and innovation, especially with Industry 4.0 technologies (Grieves, 2016a). Generative Artificial Intelligence (GAI) offers advanced algorithms for predictive modeling and decision-making, leveraging technologies such as IoT sensors, data analytics, machine learning, and simulation tools. Integrating Digital Twins (DT) and GAI enables the creation of virtual representations and predictive capabilities in manufacturing processes. Despite their potential, several challenges hinder the effective implementation of GAI and DT integration. These include data interoperability and scalability, organizational resistance, the opacity and lack of explainability in GAI models, and issues with model accuracy, data quality, and standardization. Addressing these obstacles is crucial for maximizing the benefits of DT and GAI integration in manufacturing. The primary objective of this research is to tackle these difficulties by consolidating relevant case studies into three application areas: design, manufacturing, and operations, with decision-making as a common element. A systematic literature review process has been conducted analyzing scientific texts, including papers, articles, books and others. The research strategy aimed to provide a complete overview on the GAI and DT integration in manufacturing. The keywords and key phrases used were: '(generative) artificial intelligence', 'digital twin', 'machine learning', 'neural networks', '(big) data analytics', 'predictive maintenance', 'sustainability'. The relevance of the papers was firstly evaluated by reading the abstract and the introduction, choosing the most related to this research. Then, papers were selected based on their relevance and strong relation to the research topic, focusing on contributions related to DT and GAI integration. The paper analyzes the selected documents to examine integration levels, specific areas of focus, and technologies used. It explores emerging approaches to overcome identified challenges, including standardized frameworks, enhanced data analytics techniques, and collaborative industry initiatives (Das et al., 2023). This research aims to guide future directions, refine DT and GAI integration, and contribute to sustainable industrial practices through advanced technologies (Bert Baeck, 2023).

2.DT and AI

The concept of DT emerged in 2002, introducing a novel approach to manage physical processes. A DT is a virtual model that acts as a counterpart to a physical object (Mateev, 2023; Rathore et al., 2021). This virtual replica allows for a deeper understanding and improved control of the real-world system it represents. Real-time DTs, acting as dynamic digital replicas of physical assets, augment monitoring, diagnostic, and forecasting functionalities (Abusohyon et al., 2021;R. Revetria et al., 2019). This synergistic interaction reduces downtime, extends asset lifespan, and contributes to the realization of Industry 4.0's vision, characterized by smarter, interconnected, and autonomous systems (Falekas & Karlis, 2021; Wenqiang Yang et al., 2022; Aivaliotis et al., 2019; Booyse et al., 2020; G. Wang et al., 2019). The fusion of DT with AI has strongly revolutionized this technology. AI algorithms can analyze the vast amount of data collected from the physical object through sensors (IoT). This data analysis allows AI to not only identify patterns but also predict future behaviour and optimize processes within the DT. The insights collected from the digital model can then be fed back to the physical system, leading to real-world improvements (Rathore et al., 2021). In Figure 1 this concept is presented, by representing the two elements of *Real World* and *Digital Twin*, with the AI integration, underlining the possibilities of communication between the two entities. AI's contribution lies in its ability to exploit the vast amount of data collected from the physical object through the IoT and Big Data technologies. AI algorithms leverage machine learning and pattern recognition techniques to analyze this data, not just for understanding current states, but also for predicting future behaviour. This predictive capability enables process optimization within the digital model. By simulating various scenarios and their potential outcomes, AI empowers informed decision-making in the real world. DT and AI stand at the head of technological innovation in manufacturing, offering opportunities for enhancing sustainability across the product life cycle. DT embodies a virtual counterpart of physical systems, facilitating real-time synchronization, optimization, and sustainability monitoring, while AI harnesses advanced algorithms for predictive modelling and decision-making within the framework of Industry 4.0, contributing to sustainable resource management and eco-friendly practices (Barricelli et al., 2019).

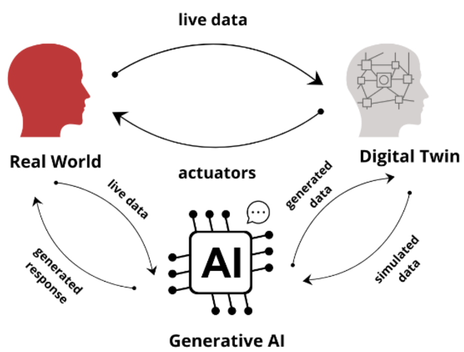

Figure 1. Representation of DT and GAI integration, Figure Created by Author

3.Generative AI Technologies for Digital Twins

GAI also referred to as Artificial Intelligence Generated Content (AIGC), representing an innovative subfield within AI (Mateev, 2023). Unlike traditional expert systems focused only on data analysis and action, GAI possesses the important ability to produce novel content. This capability is centred in the principle of modelling the probability distribution underlying a given dataset. By elaborating vast amounts of data, these models can generate new content that exhibits characteristics similar to the original data (Mateev, 2023). The generative process typically includes two crucial stages (Xu et al., 2023), (Liu et al., 2023):

- User Intent Extraction and Comprehension: During this stage, the model deciphers the user's desires or goals by analyzing the provided input.
- Desired Content Generation: Leveraging the extracted user intent, the model produces new content that aligns with the user's identified needs.

Recent advancements in generative AI are primarily driven by two key factors:

- Evolving Foundation Models: These models serve as the backbone for generative AI. Their continuous growth in size and complexity empowers the creation of more sophisticated content.
- Large-Scale Dataset Training: By training on significantly larger datasets, generative models acquire the ability to learn intricate patterns and relationships within the data. This refined learning process leads to the generation of more nuanced and realistic content.

Generative AI models can be broadly classified into two main categories (Xu et al., 2023; Yandrapalli, 2023):

- Unimodal Models: These models operate on data within a single modality. In simpler terms, they process and generate content in the same format (e.g., text input leads to text output).
- Multimodal Models: These models exhibit greater flexibility by accepting instructions across different modalities (text, image, etc.) and generating outputs in various formats.

The extraordinary capabilities of GAI have opened ways for its application in a diverse range of fields, which will be explored in detail in the next sections. One remarkable example of a GAI model is the Generative Pre-trained Transformer (GPT) series developed by OpenAI. These models belong to the Large Language Model (LLM) class and leverage neural networks and reinforcement learning for content generation. The most recent iteration, GPT-4, continues to push the boundaries of generative AI with its immense capabilities (Das et al., 2023b; Mateev, 2023; Xu et al., 2023; Yandrapalli, 2023).

4.Applications of Generative AI for Digital Twins in Manufacturing

While Generative Artificial Intelligence (GAI) and Digital Twins (DTs) offer significant possibilities, sustainable manufacturing remains fundamental. Transitioning to sustainable production systems necessitates a complete re-evaluation of value creation. Implementing sustainable strategies within company structures enhances operational performance and production efficiency (Demartini et al., 2017). Leveraging GAI within DTs holds potential for optimizing manufacturing processes, improving product quality, and reducing costs. This study explores the applications of GAI in DTs for manufacturing optimization by categorizing the results into three primary phases: Product Design, Process Optimization, and Predictive Maintenance. This subdivision, deemed the most natural based on the literature review conducted, facilitates a systematic categorization of the applications of GAI in manufacturing (Figure 2). Moreover, another critical area where AI can provide substantial benefits is decision-making, thanks to its capability to analyze large datasets and identify significant patterns. Challenges and limitations in these areas will be addressed in subsequent sections. Data-driven approaches offer promising alternatives by leveraging increased data accessibility and parallel computing power. However, they often depend on vast amounts of labeled data, presenting challenges in obtaining such data through experiments or simulations. To fully harness the power of data-driven approaches while addressing the limitations of physics-based modeling and experimental data, the use of Mechanistic-AI becomes essential (Mozaffar et al., 2022). Within the realm of DTs in manufacturing, GAI holds immense potential for optimization across various domains.

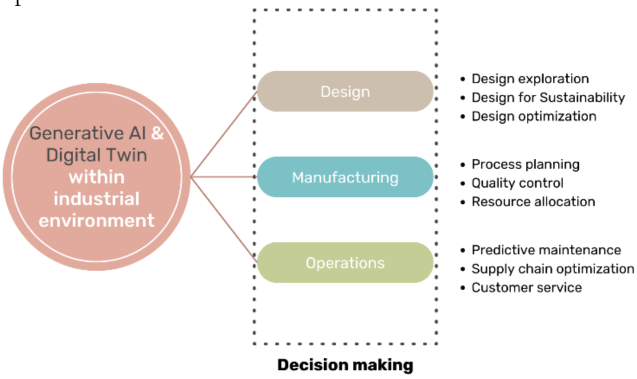

Figure 2. Use cases for GAI and DT integration, Figure Created by Author

4.1 Product Design

GAI is a powerful tool which can be employed in the design phase. GAI can be used to analyze existing product data and manufacturing constraints (GAI-powered design for manufacturability). GAI algorithms can then generate alternative design options optimized for manufacturability. This not only reduces production complexity but also potentially leads to more efficient use of materials and resources (Xu et al., 2023). Machine learning algorithms trained on historical data from past production runs can predict potential manufacturability issues based on specific design features. This allows designers to receive real-time feedback during the design process, enabling them to adjust features for smoother production integration. (Barricelli et al., 2019; Xu et al., 2023). User data collected through surveys, app interactions, or social media can be fed into the DT. GAI algorithms can then analyze this data to identify user preferences, weaknesses, and desired functionalities. These insights can then be used to inform design iterations, leading to products that better meet user needs (Barricelli et al., 2019; Tao et al., 2018a). Textual user reviews and social media conversations can be analyzed by GAI algorithms using sentiment analysis techniques. This can reveal user opinions, identify emerging trends, and highlight areas for design improvement. This real-time feedback loop allows designers to continuously adapt and refine their designs based on user needs (Parapanova et al.; F. Tao, Cheng, et al., 2018). GAI algorithms can also analyze design options within the DT and suggest modifications that minimize environmental impact (GAI for eco-design optimization). This could involve suggesting lighter materials, more energy-efficient components, or designs that facilitate easier disassembly and recycling. GAI-powered optimization can lead to the development of more sustainable products with a reduced environmental footprint. (Xiang et al., 2020). By analyzing historical data and design parameters, GAI algorithms can predict the resource consumption (e.g., energy, materials) associated with different design options during the manufacturing process. This allows designers to identify areas for resource optimization and make informed decisions that minimize environmental impact (Saadi and Yang, 2023). GAI algorithms can analyze design options within the DT and suggest modifications that minimize environmental impact. This could involve suggesting lighter materials, more energy-efficient components, or designs that facilitate easier disassembly and recycling. GAI-powered optimization can lead to the development of more sustainable products with a reduced environmental footprint (Mathern et al., 2019). By analyzing historical data and design parameters, GAI algorithms can predict the resource consumption (e.g., energy, materials) associated with different design options during the manufacturing process. This give the possibility of the identification of areas for resource optimization and making informed decisions that minimize environmental impact.

4.2 Process Optimization

Within the manufacturing landscape, DTs have emerged as powerful tools for process visualization, monitoring, and planning (Demartini et al., 2021; R. Revetria et al., 2019). However, the integration of GAI with DTs unlocks a new level of optimization potential across various domains. One key area is decision support and lifecycle management. Using historical data and scenario simulations, GAI-powered DTs can give real-time insights. This is important as it enables data driven optimization of production schedules, resource allocation and maintenance strategies which is aimed at improving efficiency while lowering costs at the same time (Sharp et al., 2018). For example (Tao et al., 2018a) discusses the future mode of DT-driven product manufacturing using the example of drive shaft machining. It outlines the various steps involved in the process, including resource allocation, NC code generation, machining plan verification, and real-time monitoring during machining. Furthermore, DTs equipped with deep learning algorithms, such as Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs), significantly enhance quality inspection and fault diagnosis. By analyzing sensor data in real-time, these algorithms can detect defects, anomalies, and potential equipment failures with high accuracy, ensuring product quality and minimizing production downtime. In Wang et al., 2018 GAI contributes to defect prognosis and optimization. Advanced data processing techniques within DTs, including denoising, outlier detection, and imputation, combined with GAI's predictive capabilities, enable accurate defect prediction. This foresight allows for anticipating maintenance needs and optimizing manufacturing processes to minimize waste and maximize efficiency (Zhang and Gao, 2021). DT technology generative models also present intelligent process planning that is exhaustive in manufacturing. Enhancing reliability, transparency and efficiency by synergizing both methods, the stated framework eventually leads to better product quality and manufacturing process improvement like in Xu et al., 2023, where is discusses the challenges posed by traditional process planning methods in manufacturing, highlighting the limitations of human expertise and the need for more efficient and reliable approaches. It presents GAI Models (GAIM) like ChatGPT as hopeful problem solvers because they can function independently within their specific area and learn on their own. The part suggests that one way of handling these worries would be combining a GAIM with DT technology, which is defined as being an integrated simulation system for evaluating & verifying process knowledge along with plans through modelling physical systems. The whole idea behind using DT technologies in this context serves nothing more than making sure everything planned out makes sense practically- this means authenticating what GAI's have provided towards intelligent process planning. DTs integrating GAI aims to address several challenges traditionally faced by the low user-friendliness, limited flexibility and high entry barriers in the process planning systems. DT technology provides validation and reliability support of the produced content, ensuring its accuracy and alleviating the reliability issues often associated with GAI models. This fusion introduces never seen before insights into the applications of Generative AIs in manufacturing sector by giving practical ideas and proposals to beat the limitations of traditional process planning systems. Zotov, 2022 proposes using generative adversarial networks (GANs) within DTs for manufacturing. It introduces a time-domain machining vibration model based on GANs, allowing for knowledge extraction from existing models and data-driven simulation for process optimization. Additionally, the thesis presents a novel GAN analysis solution, comparing generative accuracy and sensitivity maps to identify patterns. Moreover, the proposed simulation model extends to adapt knowledge from a source model to a target environment, enabling information elicitation from both physics-based and data-driven solutions. This method, implemented as the CycleStyleGAN algorithm, is validated in an experimental scenario mimicking a real-world manufacturing knowledge transfer problem, showing significant reduction in required target domain data.

4.3 Predictive Maintenance

The convergence of GAI and DTs ushers in a new era of predictive maintenance capabilities. GAI algorithms leverage operational data to meticulously forecast potential equipment failures. In the field of GAI, a more accurate method for predicting remaining useful life is encouraged in the development of mainframe predictive maintenance, including deep learning techniques such as Auto-encoders, Deep Belief Networks, Convolutional Neural Networks, and Recurrent Neural Networks (Wang et al., 2020). 6G networks will gradually introduce new challenges and require new, innovative solutions, for instance, through GAI, to meet the needs of developing scaling and synchronic DTs that can support the complex infrastructure in future networks (Tao et al., 2023). Such a collaborative use of GAI and DTs in predictive maintenance will work toward enhancing operational efficiency and reliability while, at the same time, also driving forward improvements of the technologies that underpin Industry 4.0, essentially making industrial systems more resilient and intelligent. This connected relationship between GAI and DTs supports a preventive maintenance approach. There is a noticeable drop in downtime and asset life span elongation by a factor (Booyse et al., 2020; Tao et al., 2023; Wang et al., 2020b). Furthermore, precise forecasts of future faults lead to better distribution of resources and time management, thus removing unnecessary repairs (Errandonea et al., 2020). By reducing the number of instances where machinery breaks down unexpectedly and making them last longer, such systems also cut down overall maintenance costs significantly. the capability to model various situations as well as stress conditions enables early identification of potential dangers and subsequent risk mitigation (Aivaliotis et al., 2019). The above paragraph has made it clear that merging GAI and DT models is able to bring out their full potential in optimizing for design production, and maintenance operations. This act alone gives an upper hand among its competitors in the sector. However, one must be aware of the fact there are obstacles, challenges, and hazards coupled with these integrations. The next paragraph analyses these blocks and provides solutions for successful implementation.

4.4 Generative AI and Decision Making

GAI presents a significant potential for revolutionizing decision-making processes within the manufacturing domain, particularly in the realm of DT models. Drawing upon insights from seminal articles such as those by (Castañé et al.; Corici et al., 2023; Emmert-Streib, 2023), there emerges a collective recognition of the transformative impact of integrating GAI into DT frameworks, aimed at augmenting decision-making capabilities in manufacturing settings. Through the utilization of GAI techniques encompassing generative modelling, optimization, and machine learning, DTs are endowed with the capacity to dynamically generate and refine system configurations, simulate diverse production scenarios, and forecast optimal courses of action. This interaction leads to self-governing exploration of wide-ranging solution spaces allowing quick responses to changing manufacturing conditions and encouraging proactive decision-making. Besides, the focus on responsible AI by initiatives such as the ASSISTANT Project highlights the need for decisions made to be based on ethical considerations as well as being under human supervision in order to create reliance and safety in automated decision support systems (Castañé et al.). Combining DT and GAI results in machine learning models that can improve decision-making processes, enabling rapid responses in varying conditions, and encouraging proactive strategies. The relationship between DT and GAI allows users to optimize their production systems, operate intricate networks, and deal with strategic managerial issues. This cooperation empowers all parties involved to choose what they believe is best with all the required information at their disposal while being sure of their actions.

5. Challenges for Shaping DT & GAI

Despite the promise of DT and GAI integration for sustainable product life cycle management, several obstacles hinder their effective implementation. Challenges such as data interoperability, scalability, and organizational resistance pose significant barriers to realizing the full potential of these technologies.

5.1 Data-Centric Challenges

Creating accurate DTs necessitates a comprehensive dataset encompassing product information, materials, and manufacturing processes (Abusohyon et al., 2021). Inconsistent or limited data can lead to inaccurate simulations and hinder GAI algorithms (Grieves, 2016b). Addressing this challenge requires establishing robust data collection and management practices throughout the design and manufacturing lifecycle (Tao et al., 2018b). DT accuracy and Replicability: Ensuring DTs accurately replicate their physical counterparts is crucial. Potential errors in replicating tasks can lead to discrepancies between the digital and physical worlds, impacting the reliability of predictive maintenance (Wenqiang Yang et al., 2022). Effective predictive maintenance through DTs requires readily available, relevant data. Failure to integrate existing maintenance efforts with DT methodologies can lead to data incompatibility issues (Falekas and Karlis, 2021). Achieving ultra-high synchronization and fidelity data between virtual and physical spaces necessitates advancements in modelling and transmission technologies (Wenqiang Yang et al., 2022). Building complex models that account for numerous variables and interactions while minimizing cumulative error requires highly sophisticated techniques and algorithms (Das et al., 2023a). Complex DT simulations and GAI-powered design optimization can be computationally intensive. This can be a barrier for smaller companies or those lacking robust computing infrastructure (Tao et al., 2023). Cloud-based solutions and advancements in hardware technology offer potential solutions by providing access to more powerful computing resources.

5.2 Integration Challenges

Combining DT and GAI tools with the current design software and manufacturing systems can get complicated. Establishing a standard data format and creating interoperable platforms are vital for ensuring that these technologies are smoothly integrated, and their benefits maximized (Tao et al., 2023). While they provide powerful tools, human expertise remains essential for data interpretation, design decisions, and overseeing the design process. Effective collaboration between engineers, designers, and data scientists is crucial to leverage the full potential of GAI and DTs in product design (Borangiu et al., 2020b). The integration of vast amounts of operational data raises security and privacy concerns. Robust cybersecurity measures and ethical considerations regarding data ownership and usage are paramount (Lee et al., 2013). Maintaining data integrity and confidentiality is also crucial for applications in critical infrastructure (Liu et al., 2023). Both DTs and GAI for asset maintenance require significant investments in technology and infrastructure, potentially posing a barrier for small and medium-sized enterprises (Booyse et al., 2020). Integrating these technologies with existing maintenance and IT infrastructure can be challenging for companies, potentially leading to stakeholder resistance to adopting new technologies (Aivaliotis et al., 2019). Besides managing high-dimensional and noisy data, a common challenge in data-driven approaches like deep learning, is essential for deriving actionable insights in prognostic decision-making (Wang et al., 2020). For this both approaches have limitations. Physics-based models can be computationally expensive and lack reusability, while data-driven models may suffer from overfitting and lack knowledge of system physics (Wang et al., 2020). Hybrid approaches offer a potential solution but increase complexity.

6.Discussion and Conclusions

6.1 Opportunities for Future Development

Future research should focus on advancing the maturity of General Artificial Intelligence (GAI) and Digital Twin (DT) systems by fine-tuning algorithms, enhancing data handling capabilities, and improving communication interfaces between GAI and DT configurations. As these technologies evolve, they will become integral to a wider range of industries, promoting sustainable practices across various sectors. Transdisciplinary partnerships involving data science, engineering, sustainability studies, and industry practitioners are crucial for optimizing the integration of GAI and DT technologies to achieve sustainability objectives. Standardized frameworks are necessary to incorporate GAI and DT systems into sustainable product life cycle management. Models for data collection, publication, and copyright must address safety and ethical considerations to ensure reliability and efficiency. Clear guidelines for data collection, processing, and utilization are essential to maintain transparency and accountability. Traceability features that log decision-making processes will enhance transparency and facilitate audits. Addressing potential biases in GAI algorithms is vital for ensuring fair outcomes. This involves developing methods to detect, evaluate, and mitigate biases, incorporating fairness constraints in algorithm design, and conducting regular bias assessments. Establishing ethical guidelines for GAI and DT technologies is crucial to prevent misuse and ensure socially responsible deployment. This includes setting boundaries for applications that might raise ethical concerns and promoting positive societal impacts. Developing and adhering to safety standards is critical to prevent harm caused by GAI and DT systems. Rigorous testing, validation procedures, and the implementation of fail-safes and redundancies will enhance system safety and mitigate risks. A uniform approach to these considerations involves creating standardized protocols and guidelines that can be adopted globally, fostering collaboration between regulatory bodies, industry stakeholders, and academic institutions. Incorporating DT-based software systems provides businesses with an opportunity to integrate GAI into production lines. These systems often include tools for data analysis and visualization, which can be augmented using GAI for deeper insights and predictive capabilities. As these programs develop, their impact on eco-friendly manufacturing processes will be substantial.

6.2 Conclusions

The integration of Generative Artificial Intelligence (GAI) and Digital Twins (DTs) represents a transformative approach to managing products throughout their life cycles. However, realizing the full potential of this integration requires addressing several challenges. These challenges include ensuring the quality and accuracy of data inputs, managing substantial computational demands, and maintaining the need for skilled human oversight. Despite these hurdles, the potential benefits of combining GAI and DTs are substantial. Advanced production methods and more environmentally friendly processes can be achieved through these technologies. The ongoing development and refinement of GAI and DT technologies are crucial for overcoming current limitations and achieving sustainable product life cycle management. By addressing these obstacles and fostering innovation, GAI and DTs can significantly contribute to more sustainable industrial practices.

References

Abusohyon, I.A.S., Crupi, A., Bagheri, F., Tonelli, F., 2021. How to set up the pillars of digital twins technology in our business: Entities, challenges and solutions. Processes 9.

Aivaliotis, P., Georgoulias, K., Arkouli, Z., Makris, S., 2019. Methodology for enabling digital twin using advanced physics-based modelling in predictive maintenance, in: Procedia CIRP. Elsevier B.V., pp. 417–422.

Barricelli, B.R., Casiraghi, E., Fogli, D., 2019. A survey on digital twin: Definitions, characteristics, applications, and design implications. IEEE Access.

Bert Baeck, 2023. Unlocking a Digital Twin and Scalable AI Models Through Fit-For-Purpose Reliable Data. Society of Petroleum Engineers.

Booyse, W., Wilke, D.N., Heyns, S., 2020. Deep digital twins for detection, diagnostics and prognostics. Mech Syst Signal Process 140.

Castañé, G., Dolgui, A., Kousi, N., Meyers, B., Thevenin, Simon, Vyhmeister, E., Östberg, P.-O., Thevenin, S, Ostberg, P.-O.¨, The ASSISTANT project: AI for high level decisions in manufacturing. The ASSISTANT project: AI for high level decisions in manufacturing. Int J Prod Res 2023, 61.

Corici, M., Buhr, H., Magedanz, T., 2023. Generative Twin for 6G and Beyond 5G Networks: Vision, Challenges and Architecture, in: International Conference on 6G Networking, 6GNet 2023. Institute of Electrical and Electronics Engineers Inc.

Das, N., Kotal, A., Roseberry, D., Joshi, A., 2023b. Change Management using Generative Modeling on Digital Twins, in: Proceedings - 2023 IEEE International Conference on Intelligence and Security Informatics, ISI 2023. Institute of Electrical and Electronics Engineers Inc.

Demartini, M., Orlandi, I., Tonelli, F., Anguitta, D., 2017. A manufacturing value modeling methodology (MVMM): A value mapping and assessment framework for sustainable manufacturing, Smart Innovation, Systems and Technologies.

Demartini, M., Tonelli, F., Pacella, M., Papadia, G., 2021. A Review of Production Planning Models: Emerging features and limitations compared to practical implementation, in: Procedia CIRP. Elsevier B.V., pp. 588–593.

Emmert-Streib, F., 2023. What Is the Role of AI for Digital Twins? AI (Switzerland) 4, 721–728.

Falekas, G., Karlis, A., 2021. Digital twin in electrical machine control and predictive maintenance: state-of-the-art and future prospects. Energies (Basel).

Grieves, M., 2016b. Origins of the Digital Twin Concept.

Lee, J., Lapira, E., Bagheri, B., Kao, H. an, 2013. Recent advances and trends in predictive manufacturing systems in big data environment. Manuf Lett 1, 38–41.

Liu, J., Zhou, Y., Li, Yu, Li, Yong, Hong, S., Li, Q., Liu, X., Lu, M., Wang, X., 2023. Exploring the Integration of Digital Twin and Generative AI in Agriculture, in: Proceedings - 2023 15th International Conference on Intelligent Human-Machine Systems and Cybernetics, IHMSC 2023. Institute of Electrical and Electronics Engineers Inc., pp. 223–228.

Mateev, M., 2023. Predictive Analytics Based on Digital Twins, Generative AI, and ChatGPT, in: Proceedings of World Multi-Conference on Systemics, Cybernetics and Informatics, WMSCI. International Institute of Informatics and Cybernetics, pp. 168–174.

Mathern, A., Ek, K., Rempling, R., 2019. Sustainability-driven structural design using artificial intelligence. ABSE 1058–1065.

Mozaffar, M., Liao, S., Xie, X., Saha, S., Park, C., Cao, J., Liu, W.K., Gan, Z., 2022. Mechanistic artificial intelligence (mechanistic-AI) for modeling, design, and control of advanced manufacturing processes: Current state and perspectives. J Mater Process Technol.

Parapanova, V., Eriksson Supervisor, Y., Söderlund, C., Westin, J., User-Centered Design in Digital Twins: Insights Based on Industrial Designers' Activities.

Rathore, M.M., Shah, S.A., Shukla, D., Bentafat, E., Bakiras, S., 2021. The Role of AI, Machine Learning, and Big Data in Digital Twinning: A Systematic Literature Review, Challenges, and Opportunities.

Revetria, R., Tonelli, F., Damiani, L., Demartini, M., Bisio, F., Peruzzo, N., 2019. A real-time mechanical structures monitoring system based on digital Twin, IOT and augmented reality, in: Simulation Series.

Saadi, J.I., Yang, M.C., 2023. Generative Design: Reframing the Role of the Designer in Early-Stage Design Process. Journal of Mechanical Design 145.

Sharp, M., Ak, R., Hedberg, T., 2018. A survey of the advancing use and development of machine learning in smart manufacturing. J Manuf Syst 48, 170–179.

Tao, F., Cheng, J., Qi, Q., Zhang, M., Zhang, H., Sui, F., 2018a. Digital twin-driven product design, manufacturing and service with big data. International Journal of Advanced Manufacturing Technology 94, 3563–3576.

Tao, F., Zhang, M., Liu, Y., Nee, A.Y.C., 2018b. Digital twin driven prognostics and health management for complex equipment. CIRP Annals 67, 169–172.

Tao, Z., Xu, W., Huang, Y., Wang, X., You, X., 2023. Wireless Network Digital Twin for 6G: Generative AI as A Key Enabler.

Wang, G., Ledwoch, A., Hasani, R.M., Grosu, R., Brintrup, A., 2019. A generative neural network model for the quality prediction of work in progress products. Applied Soft Computing Journal 85.

Wang, J., Ma, Y., Zhang, L., Gao, R.X., Wu, D., 2018. Deep learning for smart manufacturing: Methods and applications. J Manuf Syst 48, 144–156.

Wang, Y., Zhao, Y., Addepalli, S., 2020. Remaining useful life prediction using deep learning approaches: A review, in: Procedia Manufacturing. Elsevier B.V., pp. 81–88.

Wenqiang Yang, Xiangyu Bao, Yu Zheng, 2022. Digital Twin Approach to Build Predictive Maintenance Model and Its Case Study. ASME 2022 International Design Engineering Technical Conferences and Computers and Information in Engineering Conference.

Xiang, F., Huang, Y. yuan, Zhang, Z., Zuo, Y., 2020. Digital twin driven energy-aware green design, in: Digital Twin Driven Smart Design. Elsevier, pp. 165–184.

Xu, Q., Zhou, G., Zhang, C., Chang, F., Cao, Y., Zhao, D., 2023. Generative AI and digital twin integrated intelligent process planning: A conceptual framework.

Yandrapalli, V., 2023. Revolutionizing Supply Chains Using Power of Generative AI, International Journal of Research Publication and Reviews.

Zhang, J., Gao, R.X., 2021. Deep Learning-Driven Data Curation and Model Interpretation for Smart Manufacturing. Chinese Journal of Mechanical Engineering (English Edition).

Zotov, E., 2022. StyleGAN-based machining digital twin for smart manufacturing.