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Integration of Edge AI and Digital Twins in Industrial Systems: A Review of Trends and Architectures

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***Abstract*—The amalgamation of the Edge Artificial Intelligence (Edge AI) and Digital Twin (DT) technologies is changing the industrial systems by facilitating faster intelligence, real-time monitoring, and more dependable decision-making. The edge AI performs local processing of data with low latency, whereas digital twins generate virtual models of machines and processes to assist in the analysis, prediction, and optimization. They both improve the efficiency and reliability of operations and automation in Industry 4.0 and IIoT. The current review intends to draw attention to modern trends, architectures, and applications, which combine Edge AI with digital twin systems in manufacturing, energy, logistics, and smart infrastructure. Some of the main research trends are on how to enhance scalability, security, interoperability and data management in interrelated industrial ecosystems. Notwithstanding this, there are still challenges which include fragmented architectures, lack of resources, privacy issues and lack of common standards to large scale deployment. It should focus on lightweight AI models and standard frameworks and federated methods of learning in future work. Comprehensively, this review offers a brief insight into the ability of Edge AI and Digital Twins to work together to create more intelligent, autonomous, and sustainable industrial systems.**

***Keywords*— Edge AI, Digital Twin, Industrial Internet of Things (IIoT), Industry 4.0, Intelligent Architectures.**

I. INTRODUCTION

Global concern with sustainability has driven companies to rethink their business model and seek new ways to operate and face this challenge. Industry 4.0 (I4.0) has shown itself capable of contributing to the development or reformulation of organizational processes to make them more competitive and sustainable. Thus, drivers for the development of corporate sustainability via I4.0. To this end, boosting elements that enable organizational processes to become more sustainable via I4.0. Based on these elements, six drivers were systematized and proposed strategy; product and process design; energy and material resources; people; smart production; and supply chain [1]. Each driver was discussed in light of the scientific literature to generate recommendations for companies to develop the economic, social, and environmental dimensions of sustainability. Digital Twin is at the forefront of the industry 4.0 revolution facilitated through advanced data analytics and the Internet of Things (IoT) connectivity [2]. IoT has increased the volume of data usable from manufacturing, healthcare, and smart city environments [3]. The IoT's rich environment, coupled with data analytics, provides an essential resource for predictive maintenance and fault detection to name but two and also the future health of manufacturing processes and smart city developments

Devices with limited resources will interact with the surrounding environment and users. Many of these devices will be based on machine learning models [4] to decode meaning and behavior behind sensors' data, to implement accurate predictions and make decisions. The bottleneck will be the high level of connected things that could congest the network. Hence, the need to incorporate intelligence on end devices using machine learning algorithms [5]. Deploying machine learning on such edge devices improves the network congestion by allowing computations to be performed close to the data sources [6]. The main techniques that guarantee the execution of machine learning models on hardware with low performances in the Internet of Things paradigm, paving the way to the Internet of Conscious Things. The architecture, and requirements on solutions that implement edge machine learning on Internet of Things devices is presented [7], with the main goal to define the state of the art and envisioning development requirements.

Digital Twins is one of the effective technology solutions to deal with such problems. Digital Twins are available for Industrial Systems, but many people are not aware that Digital Twins can be utilized to simulate and model the existing Smart City as well [8]. Nowadays, some of the Smart Cities are set up using Digital Twin Technology to better understand and serve the Smart City purpose. Amravati is one of the Smart Cities in Andhra Pradesh in India which has been set up and maintained using Digital Twin Technology [9]. Fabin Dembski, et al, have discussed in detail in their paper "Urban Digital Twins for Smart Cities and Citizens. Digital Twin (DT) technology [10] a virtual model of the real world, which gathers information continuously, simulates the real-life scenarios, and allows real-time control, optimization, and predictive decision making [11]. Edge AI have become one of the key tools of machine maintenance optimization. Digital Twins (DTs) offer the opportunities of real-time monitoring and simulation, which allows optimizing production processes and maintenance strategies [12]. They enable predictive maintenance by reducing downtime and prolonging the lifespan of the machinery with the help of virtual testing and simulation, and they combine IoT, AI, and machine learning to establish precise digital copies, improving the decision-making process that is based on data and operation efficiency.

A. *Structure of the Paper*

The paper is structured as follows as: Section II reviews Digital transformation performance in Industry 4.0. Section III the Edge AI Overview in Industries, Section IV concludes the approaches of digital twins in future, Section V review the recent studies and Section VI Shows the Conclusion and Future Insights.

II. Foundations of Industry 4.0 and Digital Transformation

Industry 4.0 promotes digital transformation [13] and more intelligent operations via the use of technologies like IoT [14] and AI. For increased productivity, it makes real-time data, automation, and sophisticated analytics possible.

A. *Industry 4.0: Key Drivers and Technologies*

Integrating cutting-edge digital technology, Industry 4.0, the fourth industrial revolution, is revolutionising business and industry. Cloud computing, automation, artificial intelligence (AI), big data analytics, and the Industrial Internet of Things (IIoT) [15] are some of its main forces. These technologies make predictive maintenance, process optimization, and mass customization possible, which allow smart factories where machines, sensors, and systems communicate with each other in real-time. Although 5G connections and advanced robots allow transferring data in real time and producing goods quickly, cloud platforms allow flexible and scalable operations [16]. The digital twins, which are copies of the assets and processes, assist in workflow optimization and product innovation. When combined, these technologies improve quality, efficiency, and flexibility, giving organisations a competitive edge in the digital economy and facilitating quick adaptation to emerging difficulties and shifting markets as shown in Figure 1.

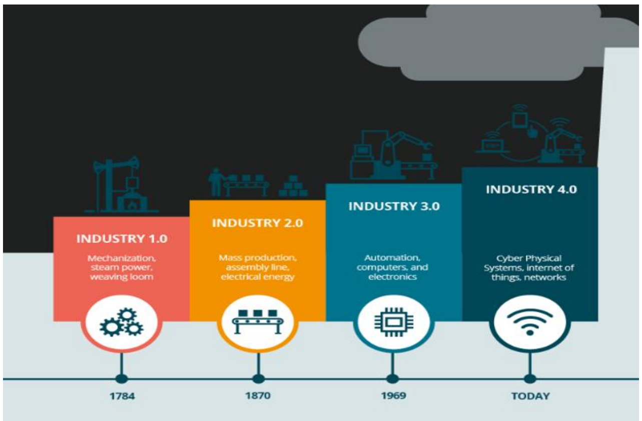

Fig. 1. Industry 1.0 to 4.0 Evaluation

B. *Industrial IoT and Cyber-Physical Systems*

Foundation of contemporary industrial automation is made up of Cyber-Physical Systems (CPS) and the Industrial Internet of Things (IIoT) [17], which allow for the smooth integration of computer controls and physical processes. It is difficult for traditional industrial automation systems (IASs), which are mostly programmed using IEC 61131 standards on PLCs, to meet the complexity and flexibility demands of today. IIoT and CPS are meant to deal with these, as they allow real-time monitoring, control, and data exchange through the incorporation of sensors, actuators, and computer devices into real equipment. This integration supports distributed, flexible and reconfigurable automation systems needed to create Industry 4.0 [18]. The object-oriented programming, model-driven development and a shift toward application-focused, rather than device-focused, methodologies make possible better software design and system integration [19]. Software development, electronics, mechanics, and so on are unified by the standards, including IEC 61131 version 3.0, and the new approaches to use UML/SysML modelling.

C. *Role of AI and Data Analytics in Industrial Systems*

The industrial systems [20] of the modern world are highly dependent on artificial intelligence (AI) and data analytics to facilitate the concept of intelligent production, especially in complex industry processes such as metallurgy and petrochemicals. They enable the analysis, optimization of industrial processes, which involve complex chemical and physical reactions and real-time continuous running. Big data is utilized by AI to enhance the quality of products and decisions and operate more efficiently, as well as reduce the impact on the environment and energy consumption. Advanced analytics make predictive maintenance, process control, and autonomous system management possible, helping companies to adapt fast to the alterations in the market and resources [21]. The world is also feeling the effects of AI-based solutions in manufacturing, in terms of innovation, sustainability, and flexibility. Such integration is necessary to spread digitalization and intelligence in the production environment and transform traditional industrial processes into intelligent, competitive and efficient systems.

III. Edge Artificial Intelligence (Edge AI)

The Edge AI is the implementation of artificial intelligence algorithms and models onto the edge devices, i.e. smartphones, sensors, and IoT devices [22], to run the processing of data locally, without accessing the centralized cloud servers. This method minimizes bandwidth and latency demand as minimal volumes of data have to be sent to remote servers, and real-time decision-making is improved. The Edge AI enhances the privacy and security of the personal information because the sensitive data are stored locally, which minimizes the risk of being exposed to possible breaches. It can be applied particularly in the case of applications where fast and dependable responses are needed like autonomous automobiles, medical diagnostics, and industrial control [23]. Edge AI has such characteristics as decentralized computing, the ability to scale to accommodate increasing amounts of data generated by a large number of interconnected devices, and the ability to be much more resilient to single points of failure than traditional centralized AI systems. Edge AI is pivotal in managing the increasing data flow generated by the expanding Internet of Things (IoT) [24]. Edge AI is the mixture of AI cloud and Edge Computing, as shown in Figure 2.

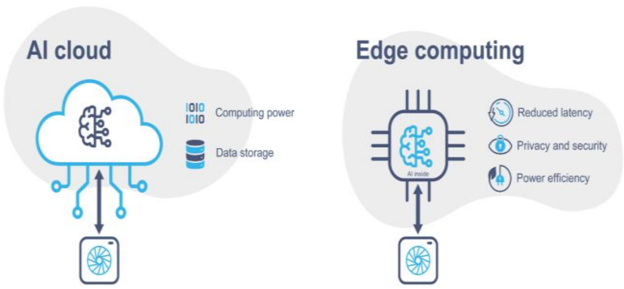

Fig. 2. Edge AI

A. Advantages of Edge AI in Industrial Systems

Industrial system Edge AI enhances operating efficiency and safety as it allows faster, safer, energy-efficient local real-time data processing. The edge AI hardware and software support real-time network edge processing and decision-making. Hardware platforms are usually specialized processors such as GPUs, TPUs, FPGAs, and ASICs designed to perform well on purposes of AI. These processors may often be integrated into edge servers, embedded systems and Internet of Things devices [25]. These devices provide processing power, necessary to run with low latency and using low energy, as depicted in Figure 3, at data sources. Software based platforms include edge-operating systems, development tools and AI frameworks that enable simpler instalment and operation of AI models and optimization on the edge.

Fig. 3. Edge AI in Industry

1) Low Latency and Real-Time Processing

In the industrial context, edge AI has a significant advantage since data can be processed locally by source rather than being transmitted to centralized cloud servers [26]. Real-time decision-making is implemented in order to control the machinery and detect the failures promptly, which is possible due to the minimal time delay reduction [27]. In manufacturing, it results in a higher level of reactiveness and faster execution of jobs; research has indicated that application of Edge AI could shorten time of completion by up to 21 percent. This skill is important in automated industrial environments to ensure that they are safe and efficient.

2) Energy Efficiency and Cost Optimization

A second advantage of Edge AI in the industrial setting is that it leads to energy savings and cost decrease. Local processing of data will reduce the amount of raw data that needs to be transferred to the cloud [28], hence the bandwidth requirement is also reduced, as well as the related network cost. Moreover, the adoption of energy-saving edge devices will minimize reliance on energy-consuming cloud infrastructures [29]. It is also used in predictive maintenance enabled by this localized computation power such that it prevents unexpected delays and expensive maintenance and optimization of the total cost of operations and energy usage in industrial environments.

3) Data Security and Privacy

Edge AI improves data security and privacy by transferring only non-sensitive insights to external servers while retaining sensitive industrial data on local property. This localized data processing reduces the possibility of illegal access or data breaches while the data is being sent. It is especially crucial for industrial operations to preserve sensitive information and adhere to data privacy laws [30]. Moreover, Edge AI will guarantee that crucial information remains secure and confidential as well as allowing continuous industry operations, which will enable reliable work in environments with fewer or less safe access to central information centers.

IV. Future Directions of Edge-AI and Digital Twins.

The development of autonomous, explainable, sustainable, standardized, and human-centric intelligent systems for the next Industry 5.0 is the main goal of Edge AI and digital twins as shown in Figure 4.

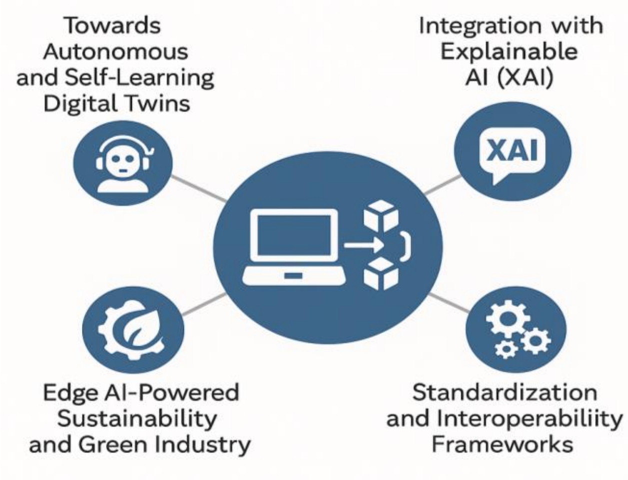

Fig. 4. Future Directions in Digital Twins

A. Towards Autonomous and Self-Learning Digital Twins

Digital twins are being integrated with adaptive control methods and reinforcement learning to become self-learning and autonomous. This increases accuracy and reliability in a dynamic environment because it enables the real-time continuous update and optimization of their physical counterparts[31]. These cyber twins offer secure testing and online training, which enhances automation in the industries.

B. Integration with Explainable AI (XAI)

Explainable AI [32] and digital twins collaborate to increase the clarity in decision making by clarifying the outputs and behaviors of AI models [33]. The result of this integration is an enhancement of adoption in vital industrial applications by helping the stakeholders to understand, trust, and manage automated systems.

C. Edge AI–Powered Sustainability and Green Industry

Edge AI fosters sustainability by reducing carbon emission and promoting green industrial practices by maximizing the use of energy and resources locally [34]. Digital twins based on edge computing encourage environmentally-friendly operations through predictive maintenance and real-time monitoring of the environment.

D. Standardization and Interoperability Frameworks

In order to make them universal, it is important to come up with standardized frameworks of digital twins and edge AI systems [35]. These provide interoperability of devices, platforms and industries, and handle issues of integration, data exchange, and scalability.

V. LITERATURE OF REVIEW

The studies under review analyze the optimization of Edge AI, the frameworks of hardware selection, federation of digital twins, and ICS security through virtualization. These papers point at scaling improvements, real-time processing. Nevertheless, interoperability, validation of deployments, and integration of Edge AI to a large-scale digital twin architecture are still problematic.

Anchitaalagammai et al. (2025) shown the concept of optimization techniques such as quantization, pruning, and NAS are resources that help in considerations for deploying AI models at the Edge as highlighted in the literature. Containerization and microservices also provide a great ecosystem for Edge AI deployments supported by Docker, Kubernetes and KubeEdge which provide scalable infrastructure. Evaluations conducted on various use cases rangingfrom predictive maintenance of industrial IoT, real-time health monitoring as well as autonomous systems, show the performance of these models to improve in terms of model accuracy, inference computation as well as energy efficiency through the enhanced methodologies. Edge AI is set to revolutionize industries like health care, smart cities, and industrial automation despite hitches like data unification and barriers from privacy laws [36].

Conley, Yadav and Yanez (2025) proposed Edge-X, a cost factor evaluation workflow for the effective selection of hardware to host such models, given input parameters. Edge-X prescribes a step-by-step guide for launching an application on an Edge AI device. The workflow is demonstrated using a proof-of-concept gesture recognition application deployed on three target hardware platforms serving as examples of complex, medium, and simple AI integrations on edge devices. The designed workflow shows capability to select appropriate edge devices quickly for any class of a desired application with AI capability [37].

Baek et al. (2024) proposed a methodology with multiple single digital twin systems that can be connected, and the output data of the multiple digital twin systems is federated. Typically, a single digital twin system is developed to digitally mimic a single physical object, system, or single process. Therefore, in the proposed methodology, the large-scale digital twin can be implemented based on federation of multiple single digital twin systems. To federate the multiple single digital twin systems, single digital twin management, validation and federation techniques are required. Therefore, proposed methodology suggests the architecture and functions of the digital twin federation system [38].

Kim, Kim and Park (2024) proposed individual digital twin systems are being created in various areas of smart cities, but the need to federate digital twins created by different entities to create complex digital twins is emerging, but not yet. There is still no implemented system for federating a large number of digital twins, which is necessary to show a colorful and spectacular digital twin system. Therefore, in this paper, they design a system and its interface that enables the federation of various digital twin systems [39].

Surianarayanan, Raj and Niranjan (2023) have shown that Edge AI represented advanced version of edge analytics. With the consistent surge in AI models being produced through the training of AI algorithms (machine and deep learning) on datasets (training, validation and testing) for automating and accelerating a variety of business and people-centric tasks, the AI domain is being seen as a paradigm shift by IT pundits and business executives across the world. With the accumulation of IoT edge devices in their everyday environments (homes, hotels, hospitals, etc.), the computing, which generally happens in nearby and faraway cloud server clusters, moves over to IoT edge devices, which are called as networked embedded systems [40].

Kemnitz et al., (2023) proposed a framework for building and operating AI models at the industrial edge. The center of this framework is the model artifact, a model-generating entity. and analyze three AI model use-cases and user roles involved in industrial AI applications to illustrate the challenges in deploying and operating AI applications in industrial edge scenarios. also propose to structure the AI models into predefined artifacts that enable deployments with only a few clicks. The edge device links sensor data with the model input and returns the model output as feedback back into the industrial process [41].

Bhatt and Kumar (2022) discussed the evolution of industry 4 and emerging I4.0 technology, major drivers and factors impacting the implementation of I4.0 practices. It also covers the paradigm shift in how next-generation industry is getting shifted with the help of I5.0. It highlights the prospects of the development of technologies that is contributing to the transition of Industry 4.0 to Industry 5.0. This provides a high-level overview of industry 4.0, its emergences and emerging technologies and transition from Industry 4.0 to Industry 5.0 [42].

Table I presents some of the most important studies on Edge AI and digital twins, detailing significant contributions in the optimization, hardware choice, and system federation. Although these works enhance efficiency and scalability, problems like interoperability, data problems, and no real-world deployment are still a challenge.

TABLE I. SUMMARY OF KEY STUDIES ON EDGE AI, DIGITAL TWINS, AND INDUSTRY 4.0–5.0

Author (Year)	Key Findings	Methods / Approach	Challenges Addressed	Limitations / Gaps
Anchitaalagammai et al. (2025)	Optimization techniques (quantization, pruning, NAS) and containerized deployments improve model accuracy, inference speed, and energy efficiency in Edge AI.	Survey and evaluation of Edge AI techniques and deployments across predictive maintenance, health monitoring, and autonomous systems.	Edge resource constraints, need for scalable infrastructure, energy efficiency.	Data unification issues; privacy law barriers.
Conley, Yadav & Yanez (2025)	Proposed **Edge-X**, a workflow to quickly select suitable edge hardware and deploy AI applications effectively.	Hardware evaluation workflow demonstrated using gesture recognition on 3 different devices.	Helps in selecting appropriate hardware considering cost and performance.	Limited to proof-of-concept scenarios and specific hardware classes.
Baek et al. (2024)	Demonstrated how multiple single digital twins can be federated to	Proposed a digital twin federation architecture with	Managing multiple digital twins; scaling from single to large systems.	Real-world implementation complexity; lack of tested large-scale DT federation.

	form large-scale digital twin systems.	management, validation, and federation techniques.		
Kim, Kim & Park (2024)	Designed a system enabling federation of digital twins from different entities to build complex city-scale digital twins.	System design and interface architecture for DT federation.	Need for interoperability between independently created digital twins.	No existing large-scale deployed system; still conceptual.
Surianarayanan, Raj & Niranjan (2023)	Edge AI is becoming a major paradigm shift as computation moves from cloud servers to IoT edge devices.	Review of emerging Edge AI trends and IoT-driven model deployment.	Need for faster, localized computation and reduced cloud dependency.	Does not present a specific framework; mostly conceptual overview.
Kemnitz et al. (2023)	Proposed an industrial edge framework using model artifacts for quick AI deployment with minimal user actions.	Framework design + analysis of 3 industrial AI use-cases.	Simplifying AI deployment in industrial environments; linking sensor data to edge models.	Limited validation outside industrial settings; model artifacts still evolving.
Bhatt & Kumar (2022)	Discussed evolution from Industry 4.0 to 5.0 and emerging technologies driving future industrial transitions.	High-level review of Industry 4.0/5.0 technologies and drivers.	Understanding drivers and factors enabling industrial transformation.	Lacks technical depth; does not present implementation-level solutions.

VI. Conclusion and Future Work

The adoption of Edge AI and Digital Twin to industrial systems is a radical change to intelligent, real-time, and resilient operations. Edge AI allows processing data at the network edge with low latency, whilst digital twins offer an abstract view of industrial assets, processes, and systems to make predictive decisions and monitoring. All these technologies can solve some of the most important issues, including system reliability, operational efficiency, scalability, and cybersecurity. The recent literature indicates promising architectures that can be used to combine edge-driven intelligence and twin-based simulation to take advantage of Industry 4.0 and IIoT applications. Nevertheless, available literature is still disjointed, with most being concerned with a particular issue, such as optimization, communications networks, or security, without providing a comprehensive architectural framework. Additionally, there are still problems with interoperability, validation of deployment and standardization which restricts widespread adoption.

Future studies must be aimed at creating unified models in which Edge AI and digital twins can be easily integrated into the world of heterogeneous industries. Emphasis needs to be laid on the interoperability standards, lightweight AI models to be used in their implementation to edges, and cross-layers architectures that will be able to scale in real-time. Also, the discussion of integration with 6G, blockchain and federated learning will also improve the secure, adaptive and autonomous industrial ecosystems further.

References

[1] A. B. T. da Rocha, K. B. de Oliveira, M. Espuny, J. S. da Motta Reis, and O. J. Oliveira, "Business transformation through sustainability based on Industry 4.0," *Heliyon*, vol. 8, no. 8, p. e10015, Aug. 2022, doi: 10.1016/j.heliyon.2022.e10015.

[2] J. Thomas, K. V. Vedi, and S. Gupta, "The Effect and Challenges of the Internet of Things (IoT) on the Management of Supply Chains," *Int. J. Res. Anal. Rev.*, vol. 8, no. 3, pp. 874–879, 2021.

[3] A. Fuller, Z. Fan, C. Day, and C. Barlow, "Digital Twin: Enabling Technologies, Challenges and Open Research," *IEEE Access*, vol. 8, pp. 108952–108971, 2020, doi: 10.1109/ACCESS.2020.2998358.

[4] P. Patel, "Predictive Maintenance in HVAC Systems Using Machine Learning Algorithms: A Comparative Study," *Int. J. Eng. Sci. Math.*, vol. 9, no. 11, pp. 118–125, 2024.

[5] S. B. Shah, "Evaluating the Effectiveness of Machine Learning in Forecasting Financial Market Trends: A Fintech Perspective," in *2025 3rd International Conference on Integrated Circuits and Communication Systems (ICICACS)*, 2025, pp. 1–6. doi: 10.1109/ICICACS65178.2025.10968297.

[6] M. Merenda, C. Porcaro, and D. Iero, "Edge Machine Learning for AI-Enabled IoT Devices: A Review," *Sensors*, vol. 20, no. 9, 2020, doi: 10.3390/s20092533.

[7] N. Prajapati, "The Role of Machine Learning in Big Data Analytics: Tools, Techniques, and Applications," *ESP J. Eng. Technol. Adv.*, vol. 5, no. 2, pp. 16–22, 2025, doi: 10.56472/25832646/JETA-V5I2P103.

[8] D. S. Gade, "Disruptive Technologies for Efficient and Sustainable Smart Cities," *Int. J. Manag. Technol. Soc. Sci.*, no. August, pp. 47–64, Aug. 2021, doi: 10.47992/IJMTS.2581.6012.0152.

[9] R. Patel, "Survey of Digital Twin Applications in Predictive Maintenance for Industrial Material Handling Equipment," *Journal, Int. Recent. O F Sci. Technol.*, vol. 9, no. 4, pp. 77–86, 2024.

[10] Vikas Prajapati, "Exploring the Role of Digital Twin Technologies in Transforming Modern Supply Chain Management," *Int. J. Sci. Res. Arch.*, vol. 14, no. 3, pp. 1387–1395, Mar. 2025, doi: 10.30574/ijsra.2025.14.3.0792.

[11] R. Sharma, "Digital Twins as Enablers of Sustainable and Resilient Industry 5 . 0 Infrastructure : A Review," *Proc. 2025 12th Int. Conf. Comput. Sustain. Glob. Dev. Bharati Vidyapeeth's Inst. Comput. Appl. Manag. (BVICAM), New Delhi*, no. May, 2025.

[12] R. Fildansyah, A. Nampira, and M. Muhtadi, "The Effect of Digital Twin and Edge AI on Industrial Machine Maintenance Optimization in Karawang," *West Sci. Interdiscip. Stud.*, vol. 3, pp. 941–949, 2025, doi: 10.58812/wsis.v3i06.1988.

[13] N. Malali, "The Impact of Digital Transformation on Annuities: Personalization, Investment Strategies, and Regulatory Challenges," *J. Glob. Res. Math. Arch.*, vol. 11, no. 12, pp. 01–07, 2024.

[14] S. Garg, "Next-Gen Smart City Operations with AIOps & IoT : A Comprehensive look at Optimizing Urban Infrastructure," *J. Adv. Dev. Res.*, vol. 12, no. 1, 2021.

[15] S. Dodda, N. Kamuni, P. Nutalapati, and J. R. Vummadi, "Intelligent Data Processing for IoT Real-Time Analytics and Predictive Modeling," in *2025 International Conference on Data Science and Its Applications (ICoDSA)*, 2025, pp. 649–654. doi: 10.1109/ICoDSA67155.2025.11157424.

[16] M. Z. Yaqub and A. Alsabban, "Industry-4.0-Enabled Digital Transformation: Prospects, Instruments, Challenges, and Implications for Business Strategies," *Sustainability*, vol. 15, no. 11, 2023, doi: 10.3390/su15118553.

[17] G. Sarraf, "Resilient Communication Protocols for Industrial IoT : Securing Cyber- Physical-Systems at Scale," *Int. J. Curr. Eng. Technol.*, vol. 11, no. 6, pp. 694–702, 2021.

[18] M. R. R. Deva, "Advancing Industry 4.0 with Cloud-Integrated Cyber-Physical Systems for Optimizing Remote Additive Manufacturing Landscape," in *2025 IEEE North-East India International Energy Conversion Conference and Exhibition*

(NE-IECCE), IEEE, Jul. 2025, pp. 1–6. doi: 10.1109/NE-IECCE64154.2025.11182940.

[19] K. Thramboulidis, "A cyber–physical system-based approach for industrial automation systems," *Comput. Ind.*, vol. 72, pp. 92–102, Sep. 2015, doi: 10.1016/j.compind.2015.04.006.

[20] K. M. R. Seetharaman, "Sustainable Manufacturing Practices in the Apparel Industry: Balancing Innovation and Environmental Responsibility," *Tech. Int. J. Eng. Res.*, vol. 11, no. 12, pp. 908–914, 2024.

[21] T. Yang, X. Yi, S. Lu, K. H. Johansson, and T. Chai, "Intelligent Manufacturing for the Process Industry Driven by Industrial Artificial Intelligence," *Engineering*, vol. 7, no. 9, pp. 1224–1230, Sep. 2021, doi: 10.1016/j.eng.2021.04.023.

[22] V. Shah, "Analyzing Traffic Behavior in IoT-Cloud Systems : A Review of Analytical Frameworks," *Int. J. Sci. Res. Comput. Sci. Eng. Inf. Technol.*, vol. 9, no. 3, pp. 877–885, 2023.

[23] A. Santoso and Y. Surya, "Maximizing Decision Efficiency with Edge-Based AI Systems: Advanced Strategies for Real-Time Processing, Scalability, and Autonomous Intelligence in Distributed Environments," *J. Comput. Soc. Dyn. Res. Artic. Q. J. Emerg. Technol. Innov.*, no. November, p. 9, 2024.

[24] S. Amrale, "Anomaly Identification in Real-Time for Predictive Analytics in IoT Sensor Networks using Deep," *Int. J. Curr. Eng. Technol.*, vol. 14, no. 6, pp. 526–532, 2024.

[25] A. S. George, A. S. H. George, and T. Baskar, "Edge Computing and the Future of Cloud Computing: A Survey of Industry Perspectives and Predictions," *Partners Univers. Int. Res. J.*, vol. 2, no. 2, pp. 19–44, 2023, doi: 10.5281/zenodo.8020101.

[26] S. Thangavel, K. Narukulla, and R. Sundaram, "Edge-Enabled Distributed Computing for Low-Latency IoT Applications: Architectures, Challenges, and Future Directions," *Int. J. Emerg. Res. Eng. Technol.*, vol. 3, no. 1, pp. 28–41, 2022, doi: 10.63282/3050-922x.ijeret-v3i1p104.

[27] E. Dmitrieva, G. Thakur, P. K. Prabhakar, A. Prakash, A. Vyas, and Y. L. Prasanna, "Edge Computing and AI: Advancements in Industry 5.0- An Experimental Assessment," *BIO Web Conf.*, vol. 86, 2024, doi: 10.1051/bioconf/20248601096.

[28] B. R. Ande, "Enhancing Cloud-Native AEM Deployments Using Kubernetes and Azure DevOps," *Int. J. Commun. Networks Inf. Secur.*, vol. 15, no. 8, 2023.

[29] M. S. Tokarik and R. C. Richman, "Life cycle cost optimization of passive energy efficiency improvements in a Toronto house," *Energy Build.*, vol. 118, pp. 160–169, Apr. 2016, doi: 10.1016/j.enbuild.2016.02.015.

[30] R. R, "Advancing Predictive Maintenance with Edge AI and IoT Integration in Industrial Systems," *Int. J. Sci. Res. Eng. Trends*, vol. 11, no. 2, pp. 2155–2160, 2025, doi: 10.61137/ijsret.vol.11.issue2.407.

[31] H. S. Berg, D. Menges, T. Tengesdal, and A. Rasheed, "Digital twin syncing for autonomous surface vessels using reinforcement learning and nonlinear model predictive control," *Sci. Rep.*, vol. 15, no. 1, p. 9344, 2025, doi: 10.1038/s41598-025-93635-9.

[32] Y. Macha and S. K. Pulichikkunnu, "An Explainable AI System for Fraud Identification in Insurance Claims via Machine-Learning Methods," *Int. J. Adv. Res. Sci. Commun. Technol.*, vol. 3, no. 3, pp. 1391–1400, Jul. 2023, doi: 10.48175/IJARSCT-11978X.

[33] A. Sharma, E. Kosasih, J. Zhang, A. Brintrup, and A. Calinescu, "Digital Twins: State of the art theory and practice, challenges, and open research questions," *J. Ind. Inf. Integr.*, vol. 30, p. 100383, Nov. 2022, doi: 10.1016/j.jii.2022.100383.

[34] R. Patel, "Sustainability and Energy Management: Trends and Technologies for a Greener Industrial Future," *Int. J. Adv. Res. Sci. Commun. Technol.*, vol. 4, no. 1, pp. 886–898, Jul. 2024, doi: 10.48175/IJARSCT-19200E.

[35] S. Acharya, A. A. Khan, and T. Päivärinta, "Interoperability levels and challenges of digital twins in cyber–physical systems," *J. Ind. Inf. Integr.*, vol. 42, p. 100714, Nov. 2024, doi: 10.1016/j.jii.2024.100714.

[36] J. V Anchitaalagammai, S. Kavitha, R. Buurvidha, T. S. Santhiya, M. D. Roopa, and S. S. Sankari, "Edge Artificial Intelligence for Real-Time Decision Making using NVIDIA Jetson Orin, Google Coral Edge TPU and 6G for Privacy and Scalability," in *2025 International Conference on Visual Analytics and Data Visualization (ICVADV)*, 2025, pp. 150–155. doi: 10.1109/ICVADV63329.2025.10960953.

[37] J. Conley, N. Yadav, and P. Yanez, "Edge-X: Cost Factor Evaluation Workflow for Model Deployment on Edge AI Devices," in *2025 IEEE Conference on Artificial Intelligence (CAI)*, 2025, pp. 669–674. doi: 10.1109/CAI64502.2025.00123.

[38] M.-S. Baek, E. Jung, Y. S. Park, and Y.-T. Lee, "Federated Digital Twin Implementation Methodology to Build a Large-Scale Digital Twin System," in *2024 IEEE International Symposium on Broadband Multimedia Systems and Broadcasting (BMSB)*, 2024, pp. 1–2. doi: 10.1109/BMSB62888.2024.10608284.

[39] H. Kim, D. H. Kim, and C.-W. Park, "Designing Systems and Interfaces to Enable Federation of Digital Twins," in *2024 15th International Conference on Information and Communication Technology Convergence (ICTC)*, 2024, pp. 1699–1700. doi: 10.1109/ICTC62082.2024.10826840.

[40] C. Surianarayanan, P. Raj, and S. K. Niranjan, "The Significance of Edge AI towards Real-time and Intelligent Enterprises," in *2023 International Conference on Intelligent and Innovative Technologies in Computing, Electrical and Electronics (IITCEE)*, 2023, pp. 1–6. doi: 10.1109/IITCEE57236.2023.10090926.

[41] J. Kemnitz *et al.*, "An Edge Deployment Framework to Scale AI in Industrial Applications," in *2023 IEEE 7th International Conference on Fog and Edge Computing (ICFEC)*, 2023, pp. 24–32. doi: 10.1109/ICFEC57925.2023.00012.

[42] K. Bhatt and S. M. Kumar, "Way Forward to Digital Society – Digital Transformation of Msmes from Industry 4.0 to Industry 5.0," in *2022 Fourth International Conference on Emerging Research in Electronics, Computer Science and Technology (ICERECT)*, 2022, pp. 1–6. doi: 10.1109/ICERECT56837.2022.10060517.

