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Posted Date: 6 May 2026

doi: 10.20944/preprints202605.0293.v1

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Preprints.org (www.preprints.org) | NOT PEER-REVIEWED | Posted: 6 May 2026 doi:10.20944/preprints202605.0293.v1

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A Zero-Cost Digital Twin Framework for Sustainable Manufacturing Education Integrating SAP, Node-RED, and AI-Based Decision Support

Antonio Carlos Bento * and Carlos Vazquez-Hurtado

School of Engineering and Science, Tencologico de Monterrey, Monterrey, México
* Correspondence: a.bento@tec.mx

Abstract

The high cost and complexity of Industry 4.0 laboratory infrastructure limit the adoption of Digital Twin concepts in engineering education. This paper proposes a low-cost Digital Twin framework for sustainable manufacturing education integrating SAP NetWeaver, Node-RED, and AI-based decision support. The framework adopts a layered architecture that connects PLC-based simulation, IoT middleware, enterprise resource planning systems, and intelligent decision-making components. Node-RED enables real-time data exchange, while SAP NetWeaver provides enterprise-level integration through OData services. An AI module supports decision-making for production and inventory management. The proposed framework is implemented as a functional prototype, demonstrating end-to-end integration without requiring physical manufacturing equipment. Competency-based mapping aligns the framework with Industry 4.0 engineering skills, supporting its use in academic environments. A sustainability assessment highlights reductions in infrastructure cost, energy consumption, and resource usage compared to traditional laboratory approaches. The results indicate that the framework provides a scalable and accessible solution for teaching Digital Twin concepts, contributing to sustainable engineering education in resource-constrained contexts.

Keywords: Digital Twin; smart manufacturing; sustainable engineering education; Industry 4.0; SAP NetWeaver; Node-RED; Internet of Things (IoT); AI-based decision support

1. Introduction

1.1. Background

The rapid evolution of Industry 4.0 has transformed modern manufacturing by integrating cyber-physical systems, the Internet of Things (IoT), and advanced data analytics into production environments. Among these technologies, Digital Twins have emerged as a key paradigm, enabling the virtual representation of physical assets and processes to support monitoring, simulation, and decision-making [1–4]. Digital Twins facilitate real-time interaction between physical and virtual systems, improving operational efficiency and enabling predictive capabilities in smart manufacturing environments [3,4].

As industries increasingly adopt Digital Twin technologies, engineering education must adapt to prepare students with the competencies required to design, implement, and manage such systems. Educational approaches based on Digital Twins and learning factories have been proposed to bridge the gap between theoretical knowledge and industrial practice [11–14]. However, the implementation of such environments often requires significant infrastructure and investment.

1.2. Problem Statement

Despite the growing importance of Digital Twins in smart manufacturing, there is a lack of accessible and cost-effective educational platforms that integrate industrial control, enterprise systems, and intelligent decision-making. Traditional laboratory environments rely heavily on physical equipment and proprietary platforms, resulting in high costs and limited scalability. Furthermore, existing solutions often focus on isolated components, such as simulation or IoT systems, without addressing the integration of enterprise resource planning (ERP) systems and AI-based decision support [15–18].

1.3. Research Gap

Recent studies have explored Digital Twin applications in both manufacturing and education; however, most contributions either emphasize conceptual models or depend on high-cost implementations [2,13]. There is a clear gap in the development of integrated, low-cost frameworks that combine key Industry 4.0 technologies including PLC-based simulation, IoT middleware, ERP systems, and artificial intelligence within a unified educational platform. Additionally, limited attention has been given to sustainability aspects, such as reducing infrastructure requirements, energy consumption, and improving accessibility in engineering education [30–33].

1.4. Research Objective and Contributions

To address these challenges, this paper proposes a low-cost Digital Twin framework for sustainable manufacturing education integrating SAP NetWeaver, Node-RED, and AI-based decision support. The proposed framework is designed to replicate key aspects of smart manufacturing systems while minimizing infrastructure requirements.

The main contributions of this work are as follows:

The design of a low-cost Digital Twin framework that integrates simulation, IoT communication, enterprise systems, and AI-based decision-making.

The development of a layered architecture connecting PLC-based simulation, Node-RED middleware, SAP NetWeaver (via OData services), and an AI decision support module.

The introduction of a competency-based mapping that aligns the framework with Industry 4.0 engineering skills and supports its application in educational environments.

A sustainability-oriented analysis demonstrates reductions in cost, energy consumption, and physical resource requirements compared to traditional laboratory setups.

1.5. Paper Organization

The remainder of this paper is structured as follows. Section 2 reviews related work on Digital Twins, smart manufacturing, and sustainable engineering education. Section 3 presents the proposed Digital Twin framework and its architectural design. Section 4 describes the system implementation, including SAP integration, Node-RED communication, and AI-based decision support. Section 5 introduces the competency-based educational mapping. Section 6 provides a sustainability assessment of the proposed approach. Section 7 discusses the main findings and limitations, and Section 8 concludes the paper with directions for future work.

2. Literature Review

2.1. Digital Twins in Smart Manufacturing

Digital Twin (DT) technology has become a cornerstone of Industry 4.0, enabling the integration of physical and virtual systems for real-time monitoring, simulation, and optimization of manufacturing processes. A Digital Twin is generally defined as a dynamic virtual representation of a physical system that is continuously updated using real-time data [1,3]. In manufacturing, DTs support predictive maintenance, process optimization, and system-level decision-making by leveraging data-driven models and cyber-physical system architectures [2,4].

Recent studies have highlighted the role of DTs in improving production efficiency and flexibility through data fusion, simulation, and machine learning techniques [4,6]. Furthermore, the

doi:10.20944/preprints202605.0293.v1

integration of Digital Twins with IoT platforms and cloud-based systems enables scalable and distributed manufacturing environments [3]. Despite these advances, implementing DT systems in real industrial contexts remains complex and resource-intensive, which limits their adoption in educational settings.

Recent advances also explore the integration of Digital Twins with big data [34–38], smart manufacturing frameworks [35], and Industry 4.0 technologies [36].

2.2. Digital Twins in Engineering Education

The adoption of Digital Twins in engineering education has gained increasing attention to bridge the gap between theoretical knowledge and practical skills. Educational platforms based on Digital Twins allow students to interact with virtualized manufacturing systems, enabling experiential learning without requiring physical equipment [12,13].

Learning factories and virtual laboratories have been proposed as effective approaches to teaching Industry 4.0 concepts, providing realistic environments for experimentation and system integration [14]. However, many of these solutions rely on specialized infrastructure or proprietary software, which can limit accessibility. Recent efforts have explored low-cost and simulation-based approaches, but these often lack full integration with enterprise systems and real-time data exchange mechanisms [13].

Emerging frameworks propose Digital Twin-based learning ecosystems to support scalable and adaptive education environments [39].

2.3. IoT Middleware and Node-RED in Industrial Applications

The Internet of Things (IoT) plays a critical role in enabling connectivity and data exchange in Digital Twin architectures. IoT middleware platforms facilitate communication between heterogeneous systems, supporting interoperability and real-time data processing [18,21]. Among these platforms, Node-RED has emerged as a flexible, flow-based programming tool widely used for rapid prototyping and integration of IoT applications.

Node-RED allows the orchestration of data flows between devices, APIs, and cloud services, making it suitable for educational and industrial applications. Its visual programming approach reduces complexity and enables students to focus on system integration rather than low-level programming. Previous studies have demonstrated the effectiveness of Node-RED in smart manufacturing scenarios, particularly for connecting sensors, controllers, and enterprise systems [21]. However, its integration with ERP platforms in educational Digital Twin frameworks remains underexplored. The evolution of IoT in industrial contexts is discussed by Santucci [19].

2.4. ERP Integration and SAP-Based Systems

Enterprise Resource Planning (ERP) systems are essential components of modern manufacturing, providing centralized management of business processes such as production planning, inventory control, and logistics. SAP-based systems, particularly SAP NetWeaver, are widely used in industry and support integration through standardized interfaces such as OData services [23].

The inclusion of ERP systems in educational environments is important for exposing students to real-world enterprise processes. However, integrating ERP platforms with simulation tools and IoT systems presents technical challenges, including data synchronization, system interoperability, and security considerations. Existing educational implementations often omit ERP integration or treat it as a separate component, limiting the realism of the learning environment [22], as explored in machine learning applications for sustainable manufacturing [10]. ERP system architectures are reviewed by Gronau [21] and critical success factors for ERP implementation are analyzed by Leyh [24].

2.5. AI-Based Decision Support in Manufacturing

Artificial Intelligence (AI) has become a key enabler of smart manufacturing, supporting decision-making processes such as demand forecasting, production scheduling, and inventory optimization. Machine learning techniques can analyze large volumes of data generated by Digital Twins and IoT systems to provide predictive insights and optimize system performance [25,26].

AI-based decision support systems enhance the capabilities of Digital Twins by enabling adaptive and autonomous behavior in manufacturing environments. However, the integration of AI into educational Digital Twin platforms is still limited, particularly in low-cost settings. Most existing approaches focus on either simulation or analytics, without fully integrating AI into end-to-end manufacturing workflows [27].

The convergence of artificial intelligence and Digital Twins enables advanced predictive and cognitive capabilities in manufacturing systems [37,38,44], the role of AI in sustainable manufacturing also is highlighted by Wang et al. [29].

2.6. Sustainability in Engineering Education

Sustainability has become a central consideration in engineering education, emphasizing the need to develop solutions that are economically viable, environmentally responsible, and socially inclusive. In the context of manufacturing education, sustainability involves reducing the reliance on physical resources, minimizing energy consumption, and improving accessibility to learning environments [30].

Virtual laboratories and simulation-based approaches contribute to sustainability by reducing the need for physical equipment and enabling remote access to learning resources. However, achieving a balance between realism and resource efficiency remains a challenge. Integrating Digital Twins with low-cost technologies offers a promising pathway to sustainable education, but comprehensive frameworks that address both technical and sustainability aspects are still limited in the literature [31–33].

Industry 4.0 technologies, including Digital Twins, have been widely recognized as enablers of sustainable and resource-efficient manufacturing systems [45,47].

2.7. Research Gap Summary

Based on the reviewed literature, several key gaps can be identified:

- Lack of integrated Digital Twin frameworks combining simulation, IoT, ERP, and AI
- Limited availability of low-cost and accessible educational platforms
- Insufficient integration of enterprise systems (SAP/ERP) in teaching environments
- Limited focus on sustainability in Digital Twin-based education

These gaps motivate the development of the proposed framework, which aims to provide a comprehensive, low-cost, and sustainable solution for teaching Digital Twin concepts in smart manufacturing contexts.

3. Proposed Digital Twin Framework

3.1. Design Objectives

The proposed framework is designed to address the limitations identified in the literature by providing an integrated, low-cost, and scalable platform for teaching Digital Twin concepts in manufacturing. The main design objectives are:

- **Low Cost**: Eliminate the need for expensive industrial hardware by relying on simulation tools and open or widely accessible platforms.
- **Integration**: Combine key Industry 4.0 components, including PLC simulation, IoT middleware, enterprise systems, and AI.
- **Accessibility**: Enable deployment in resource-constrained educational environments.
- **Scalability**: Allow extension to more complex manufacturing scenarios.
- **Sustainability**: Reduce physical resource usage, energy consumption, and infrastructure requirements.

3.2. Overall Architecture

The proposed Digital Twin framework follows a layered architecture, enabling modular integration of different technologies and clear separation of functionalities. The architecture consists of five main layers:

- Simulation Layer
- Integration Layer
- Enterprise Layer
- Intelligence Layer
- Educational Layer

This layered approach is consistent with Digital Twin and cyber-physical system architectures reported in the literature [3,4], while extending them to include educational and sustainability dimensions.

Figure 1 illustrates the comprehensive layered architecture of the proposed Digital Twin framework. It depicts the seamless integration between the physical simulation layer (Factory I/O), the control logic layer (Schneider Machine Expert Basic), and the enterprise ecosystem (SAP NetWeaver). Central to this architecture is the Node-RED gateway, which orchestrates the data flow and incorporates AI-powered insights through the Gemini AI module, enabling a closed-loop system for predictive maintenance and inventory review.

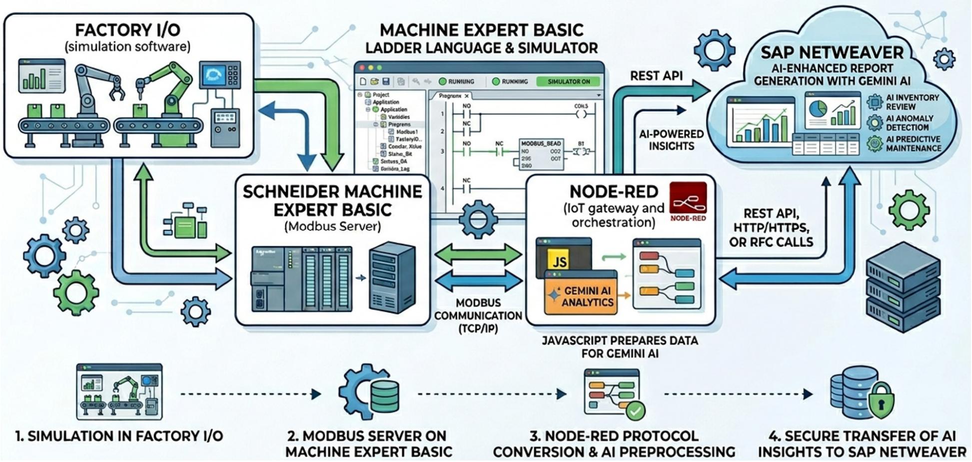


Figure 1. Proposed layered architecture for a low-cost Digital Twin framework. The system integrates a simulation environment (Factory I/O and Machine Expert Basic) with an enterprise layer (SAP NetWeaver) via an IoT gateway (Node-RED). The data flow illustrates the bidirectional communication between industrial control logic and AI-enhanced report generation.

3.3. Framework Layers

3.3.1. Simulation Layer

The Simulation Layer represents the physical manufacturing system through a virtual environment. In this framework, PLC-based logic is implemented using simulation tools such as Machine Expert Basic, enabling the modeling of industrial processes without requiring physical equipment.

This layer generates real-time data representing machine states, production events, and process variables, forming the basis for Digital Twin synchronization.

3.3.2. Integration Layer (Node-RED)

The Integration Layer acts as the communication hub of the framework. Node-RED is used to orchestrate data flows between the simulation environment, enterprise systems, and AI modules.

Through its flow-based programming model, Node-RED enables:

- Real-time data acquisition
- API communication (REST/OData)
- Data transformation and routing

This layer ensures interoperability between heterogeneous systems, a key requirement in IoT-enabled manufacturing environments [18,21].

3.3.3. Enterprise Layer (SAP NetWeaver)

The Enterprise Layer provides business logic and data management through SAP NetWeaver. This layer manages core manufacturing data, such as:

- Products
- Inventory levels
- Production transactions

Communication with other layers is achieved using OData services, which enable standardized CRUD operations. The inclusion of an ERP system enhances the realism of Digital Twin by incorporating enterprise-level decision processes, which are often absent in educational implementations [22,23].

3.3.4. Intelligence Layer (AI-Based Decision Support)

The Intelligence Layer introduces AI-based decision support capabilities. This component processes data generated by Digital Twin to support decisions such as:

- Inventory replenishment
- Production adjustments
- Demand response

The AI module can be implemented using rule-based logic or machine learning models, depending on system complexity. By integrating AI into the framework, the Digital Twin evolves from a monitoring tool to an intelligent decision-making system [25–27].

Figure 2 details the operational workflow for product and stock integration within an Industry 4.0 context. The process begins with a sensor signal from the PLC simulator triggering a "Product Production Complete" event, which is then captured by the Node-RED IoT Gateway via Modbus TCP. Node-RED performs the necessary protocol conversion and data orchestration to execute RESTful OData calls, facilitating real-time updates to the SAP database tables (PRODUCT_DB and STOCK_DB) and ensuring data consistency between the manufacturing floor and the ERP system.

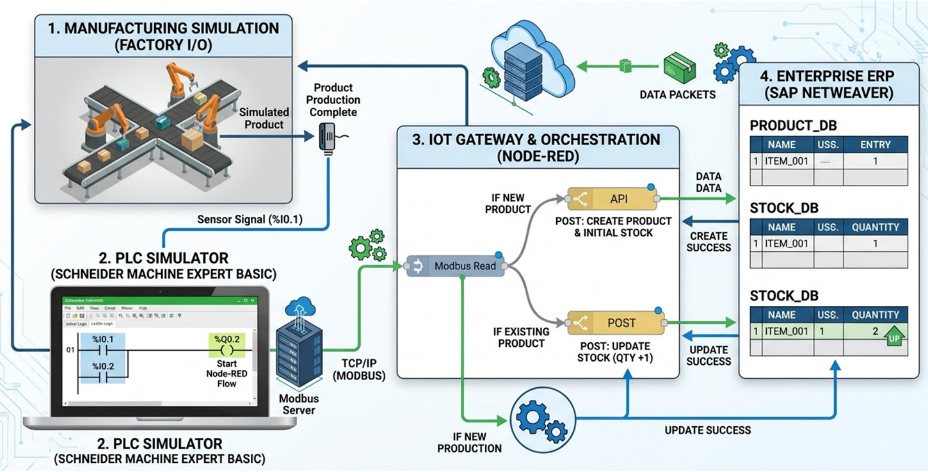


Figure 2. Industry 4.0 product and stock integration flow. The diagram details the functional interaction between the PLC Simulator and the Enterprise ERP. Node-RED serves as the orchestration hub, executing protocol

conversion from Modbus TCP to RESTful OData services for real-time inventory updates and creation of new product entries.

3.3.5. Educational Layer (Competency Mapping)

The Educational Layer aligns the framework with engineering learning objectives. It defines competencies and sub-competencies related to:

- Industrial automation
- IoT system integration
- ERP-based manufacturing processes
- AI-driven decision-making

This layer ensures that the framework is not only technically functional but also pedagogically meaningful, supporting competency-based education in Industry 4.0 contexts.

3.4. Data Flow and System Interaction

The interaction between layers follows a closed-loop Digital Twin cycle:

1. The Simulation Layer generates process data (e.g., machine status, production output).
2. The Integration Layer (Node-RED) collects and transmits data to the Enterprise Layer.
3. The Enterprise Layer (SAP) stores and processes data, updating inventory and production records.
4. The Intelligence Layer analyzes data and generates decision recommendations.
5. Decisions are sent back through the Integration Layer to update the simulation, completing the loop.

This bidirectional data flow enables real-time synchronization between the virtual and logical components of the system, which is a defining characteristic of Digital Twin architectures [3,4].

3.5. Framework Advantages

The proposed framework offers several advantages compared to traditional educational approaches:

- Cost efficiency: Eliminates the need for physical manufacturing equipment
- Realism: Integrates industrial, enterprise, and AI components
- Flexibility: Supports different manufacturing scenarios
- Scalability: Can be extended to more complex systems
- Sustainability: Reduces energy and material consumption

3.6. Summary

The proposed Digital Twin framework provides a comprehensive and integrated approach to teaching smart manufacturing concepts. By combining simulation, IoT middleware, ERP systems, and AI-based decision support within a low-cost architecture, the framework addresses key gaps identified in the literature and establishes a foundation for sustainable engineering education. Emerging frameworks for Digital Twin-based learning ecosystems [40] and shop-floor evolution [41] have been proposed, while supply chain applications [42] and comprehensive reviews [43] further support this domain.

4. System Implementation

The proposed Digital Twin framework was implemented using a combination of industrial-grade and accessible tools to ensure both realism and low cost. The development environment integrates PLC-based simulation, IoT middleware, enterprise systems, and artificial intelligence within a unified architecture. Specifically, the implementation includes EcoStruxure Machine Expert Basic for PLC simulation, Node-RED as the integration hub, SAP NetWeaver as the enterprise system,

doi:10.20944/preprints202605.0293.v1

and Google Gemini for decision support. Communication between components is achieved RESTful APIs using OData services, enabling interoperability across heterogeneous systems. This combination supports the realization of a complete Digital Twin pipeline, consistent with Industry 4.0 architecture [3,4].

The Simulation Layer was developed using PLC logic to model a virtual manufacturing process. The simulated system includes core industrial functionalities such as start/stop control, product counting, and alarm handling. These elements generate real-time operational data that represent machine states and production variables. The use of simulation instead of physical hardware aligns with current trends in Digital Twin-based manufacturing systems, where virtual representations are used to replicate and analyze physical processes [1,4]. This approach allows students to interact with realistic industrial scenarios while eliminating the need for costly equipment.

The Integration Layer was implemented using Node-RED, which acts as a central communication hub connecting all system components. Node-RED enables real-time data acquisition from the simulation layer and facilitates communication with external services through HTTP-based APIs. Data generated by the PLC simulation is captured, formatted into structured JSON objects, and routed to the enterprise system. The flow-based programming paradigm simplifies the orchestration of complex interactions and supports rapid prototyping of IoT-enabled applications. Such middleware solutions are widely recognized as key enablers of interoperability in IoT and smart manufacturing systems [18,21].

The Enterprise Layer was implemented using SAP NetWeaver, which provides enterprise-level data management and business logic. A simplified data model was defined, including entities for products and inventory. OData services were configured to expose these entities and enable standard CRUD operations. Through this mechanism, Node-RED communicates with SAP NetWeaver to update production records and retrieve inventory data in real time. The integration of ERP systems into Digital Twin environments enhances realism by incorporating business-level decision processes, which are essential in modern manufacturing systems [22,23].

The Intelligence Layer incorporates AI-based decision support using Google Gemini. This component processes data collected from Digital Twin and generated recommendations for operational decisions, such as inventory replenishment and production adjustments. The AI module receives structured input data from Node-RED and returns responses that can be used to update the enterprise system or modify simulation parameters. The integration of AI into Digital Twin frameworks extends their functionality from monitoring and simulation to intelligent decision-making, reflecting current trends in smart manufacturing [25–27].

An end-to-end use case was implemented to validate the interaction between all layers. In this scenario, the PLC simulation generates production data, which are transmitted to Node-RED and subsequently sent to the SAP system via OData services. The SAP system updates inventory levels and returns the updated data to Node-RED. The AI module then analyzes the information and determines whether corrective actions, such as replenishment, are required. The resulting decisions are fed back into the system, completing the Digital Twin loop. This bidirectional data flow ensures synchronization between the virtual process and enterprise operations, which is a defining characteristic of Digital Twin architectures [3,4].

Overall, the implementation demonstrates the feasibility of integrating simulation tools, IoT middleware, enterprise systems, and AI within a low-cost Digital Twin framework. The system achieves real-time data exchange and supports end-to-end manufacturing workflows without requiring physical infrastructure. This confirms its applicability as a scalable and accessible solution for engineering education, while aligning with the principles of smart manufacturing and sustainable system design [30–33].

Simulation-based Digital Twin implementations have been successfully applied to replicate shop-floor environments and supply chain systems [41,42,46].

5. Competency-Based Educational Mapping

The proposed Digital Twin framework is not only a technical solution but also a pedagogical tool designed to support competency-based engineering education in the context of Industry 4.0. As modern manufacturing systems increasingly rely on the integration of cyber-physical systems, IoT, enterprise platforms, and artificial intelligence, engineering graduates are expected to develop interdisciplinary skills that go beyond traditional disciplinary boundaries [14,30]. Therefore, aligning the framework with clearly defined competencies is essential to ensure its educational relevance and effectiveness.

Competency-based mapping is structured around key domains required in smart manufacturing environments, including industrial automation, system integration, enterprise resource planning, and intelligent decision-making. These domains reflect the technological pillars of Industry 4.0 and are consistent with recent approaches to Digital Twin-based education, which emphasize hands-on and system-level learning [12,13]. The framework enables students to engage with each of these domains through practical interaction with the system components.

In the context of industrial automation, students develop competencies related to PLC programming, process control, and system monitoring through the Simulation Layer. By designing and testing control logic in a virtual environment, learners gain an understanding of manufacturing processes and control strategies without requiring physical equipment. This aligns with educational approaches that use simulation and Digital Twins to enhance experiential learning in engineering [11,14].

The system integration competency is addressed using Node-RED as the middleware platform. Students learn how to connect heterogeneous systems, manage data flows, and implement communication protocols such as HTTP and REST APIs. These skills are critical in IoT-enabled environments, where interoperability and real-time data exchange are fundamental requirements [18,21]. The visual programming paradigm of Node-RED also lowers the barrier to entry, allowing students to focus on system-level thinking rather than low-level coding.

The enterprise systems competency is developed through interaction with SAP NetWeaver. Students gain experience in managing business data, understanding production and inventory processes, and interacting with enterprise-level services OData. This exposure is particularly valuable, as ERP systems are widely used in industry but are often underrepresented in engineering education due to their complexity [22,23]. Integrating ERP into the learning environment enhances the realism of the educational experience by connecting technical operations with business processes.

The AI and decision-making competency are supported through the integration of Google Gemini in the Intelligence Layer. Students learn how data-driven decision-making can be applied to manufacturing systems, including tasks such as inventory optimization and production planning. This aligns with the growing importance of artificial intelligence in smart manufacturing, where predictive analytics and adaptive systems are increasingly used to improve performance [25–27]. The inclusion of AI also introduces students to emerging technologies and their practical applications.

In addition to technical competencies, the framework supports transversal skills such as problem-solving, systems thinking, and digital literacy. By interacting with an integrated Digital Twin environment, students are required to understand the relationships between different system components and make decisions based on real-time data. This holistic perspective is essential for addressing complex engineering challenges in Industry 4.0 contexts.

From a sustainability perspective, the competency-based approach reinforces the principles of accessible and resource-efficient education. By using simulation tools and software-based platforms, the framework reduces the need for physical infrastructure while maintaining a high level of technical fidelity. This contributes to sustainable engineering education by lowering costs, minimizing resource consumption, and expanding access to advanced learning environments [30–33].

Overall, the competency-based educational mapping demonstrates that the proposed Digital Twin framework effectively supports the development of key Industry 4.0 skills. By integrating

doi:10.20944/preprints202605.0293.v1

automation, IoT, enterprise systems, and AI within a unified platform, the framework provides a comprehensive learning environment that prepares students for modern manufacturing challenges while promoting sustainability and accessibility.

6. Sustainability Assessment

The proposed Digital Twin framework is evaluated from a sustainability perspective by considering its economic, environmental, and social impacts in comparison with traditional manufacturing laboratory environments. Sustainability in engineering education requires solutions that reduce resource consumption, improve accessibility, and maintain educational effectiveness, particularly in the context of Industry 4.0 technologies [30–33].

From an economic sustainability perspective, the framework significantly reduces the cost of laboratory implementation. Traditional manufacturing labs require physical equipment such as PLCs, sensors, actuators, and production systems, which involve high acquisition and maintenance costs. In contrast, the proposed approach relies on simulation tools and software-based platforms, including Node-RED and SAP NetWeaver, which are either freely available, educationally licensed, or widely accessible. This reduction in infrastructure requirements lowers the financial barrier for institutions and enables broader adoption of advanced manufacturing education. Furthermore, the modular architecture allows incremental expansion without significant additional investment.

In terms of environmental sustainability, the framework minimizes the use of physical resources and energy consumption. Traditional laboratories require continuous operation of hardware systems, leading to energy usage and material wear. By replacing physical processes with virtual simulations, the Digital Twin framework reduces electricity consumption and eliminates the need for consumable materials. Additionally, the use of virtual environments decreases electronic waste associated with outdated or damaged equipment. These characteristics align with sustainable manufacturing principles, which emphasize resource efficiency and reduced environmental impact [31,33].

The framework also contributes to social sustainability by improving accessibility and inclusiveness in engineering education. The use of software-based tools enables remote access and flexible learning environments, allowing students to engage with Digital Twin systems regardless of their physical location. This is particularly relevant for institutions with limited resources or for distance learning programs. The integration of intuitive tools such as Node-RED further enhances accessibility by reducing the technical complexity associated with system integration. As a result, a wider range of students can develop competencies in smart manufacturing and Industry 4.0 technologies.

A comparative analysis between traditional laboratory setups and the proposed framework highlights key sustainability advantages. Conventional approaches provide high physical realism but at the expense of cost, energy consumption, and limited scalability. In contrast, the proposed Digital Twin framework offers a balanced solution, maintaining functional realism through integrated simulation, enterprise systems, and AI-based decision support, while significantly reducing resource requirements. This trade-off is consistent with recent trends in sustainable engineering education, which prioritize efficient use of resources without compromising learning outcomes [30–32].

Despite these advantages, certain limitations must be acknowledged. The absence of physical equipment may reduce exposure to hands-on hardware interaction, which is important in some engineering disciplines. Additionally, the implementation of the framework requires initial technical expertise in system integration and configuration. However, these limitations can be mitigated by combining the proposed approach with hybrid learning models or advanced training modules.

Overall, the sustainability assessment demonstrates that the proposed Digital Twin framework provides a viable and effective alternative to traditional manufacturing laboratories. By reducing costs, minimizing environmental impact, and enhancing accessibility, the framework supports the development of sustainable engineering education while maintaining alignment with Industry 4.0 requirements.

The Quantifying Sustainability Metrics shown in Table 1 provides a comparative analysis that underscores the framework's alignment with sustainability criteria by evaluating economic, environmental, and social dimensions. Economically, the transition from high-capital hardware to a virtualized Digital Twin environment reduces CAPEX and OPEX by leveraging open-source tools like Node-RED and educational licensing for SAP NetWeaver, effectively democratizing access to Industry 4.0 training. Environmentally, the framework achieves a significant reduction in energy consumption lowering usage from a multi-kilowatt hardware lab footprint to the fractional power requirements of a standard workstation, while simultaneously eliminating physical waste and material consumption. Socially, the shift from a fixed physical space to a software-based architecture enhances accessibility, allowing for remote, asynchronous participation that is vital for inclusive engineering education in resource-constrained contexts.

Table 1. Quantifying Sustainability Metrics.

Metric	Traditional Lab Environment	Proposed Digital Twin Framework
Capital Expenditure (CAPEX)	High (Physical PLCs, Conveyors, Sensors, Robots)	Zero-Cost (Open source/Education Software)
Operational Expenditure (OPEX)	High (Maintenance, Parts, Infrastructure, Software)	Negligible (Software updates)
Energy Consumption	~1.5 - 5.0 kW per session (Hardware)	~0.1 - 0.3 kW (Workstation only)
Space Requirement	Dedicated laboratory square footage	Local or virtualized (Remote access capable)
Waste Generation	Potential E-waste from aging hardware	Zero physical waste

7. Discussion

The proposed Digital Twin framework demonstrates a feasible and integrated approach for supporting sustainable manufacturing education by combining simulation, IoT middleware, enterprise systems, and AI-based decision support. The results obtained from the implementation highlight several important contributions in both technical and educational contexts, while also revealing limitations that should be considered for future developments.

One of the main strengths of the framework is its low-cost and accessible architecture, which addresses a critical barrier in engineering education. By replacing physical manufacturing systems with simulation tools and integrating platforms such as Node-RED and SAP NetWeaver, the framework enables institutions to implement Industry 4.0 learning environments without significant financial investment. This aligns with current trends in sustainable education, where resource efficiency and accessibility are key considerations [30–33].

Another important advantage is the end-to-end integration of technologies, which distinguishes this framework from many existing educational approaches. While previous works often focus on isolated components such as simulation or IoT systems, the proposed solution combines PLC-based simulation, middleware communication, ERP systems, and artificial intelligence within a single architecture. This holistic integration provides students with a more realistic understanding of modern manufacturing ecosystems, where operational and business processes are tightly interconnected [3,4,22].

The inclusion of an AI-based decision support module further enhances the framework by introducing data-driven decision-making capabilities. Using Google Gemini, the system evolves beyond monitoring and control, enabling adaptive responses to production and inventory conditions. This reflects the increasing role of artificial intelligence in smart manufacturing, where predictive analytics and intelligent systems are used to optimize performance and support decision-making processes [25–27]. From an educational perspective, this feature exposes students to emerging technologies that are becoming essential in Industry 4.0 environments.

doi:10.20944/preprints202605.0293.v1

Despite these advantages, several limitations must be acknowledged. First, the framework has not yet been validated through empirical studies involving students, which limits the ability to assess its direct impact on learning outcomes. Instead, the evaluation is based on system functionality and competency mapping. Second, reliance on simulation may reduce exposure to real hardware, which is important for developing certain practical skills. Third, the integration of multiple technologies requires a level of technical expertise that may present challenges for instructors or institutions with limited experience in system integration.

In addition, while the framework emphasizes low cost, some components such as enterprise systems may still require licensing or institutional access, depending on the deployment context. This could affect scalability in certain environments. Furthermore, the AI module, although functional, can be expanded to include more advanced machine learning models or domain-specific optimization techniques.

Future work should focus on empirical validation and system expansion. Conducting classroom-based studies would provide quantitative and qualitative evidence of the framework's effectiveness in improving student learning and competency development. The integration of physical devices, such as low-cost sensors or microcontrollers, could enhance realism through hybrid Digital Twin environments. Additionally, extending the AI module to incorporate predictive analytics, reinforcement learning, or optimization algorithms would increase the system's capabilities.

Overall, the discussion confirms that the proposed framework addresses key gaps identified in literature by providing an integrated, low-cost, and sustainable solution for Digital Twin-based education. While certain limitations remain, the approach establishes a strong foundation for future research and development in smart manufacturing education and supports the transition toward more accessible and sustainable learning environments.

8. Conclusions

This paper presented a low-cost Digital Twin framework for sustainable manufacturing education integrating simulation tools, IoT middleware, enterprise systems, and AI-based decision support. The proposed approach addresses key challenges in engineering education related to the high cost and complexity of Industry 4.0 laboratory environments by providing an accessible and scalable alternative that does not require physical manufacturing equipment.

The framework adopts a layered architecture that connects PLC-based simulation, Node-RED as an integration hub, SAP NetWeaver for enterprise data management, and Google Gemini for decision support. The implementation demonstrated successful end-to-end integration, enabling real-time data exchange and closed-loop interaction between system components. This confirms the feasibility of replicating key functionalities of smart manufacturing systems within a fully virtual environment.

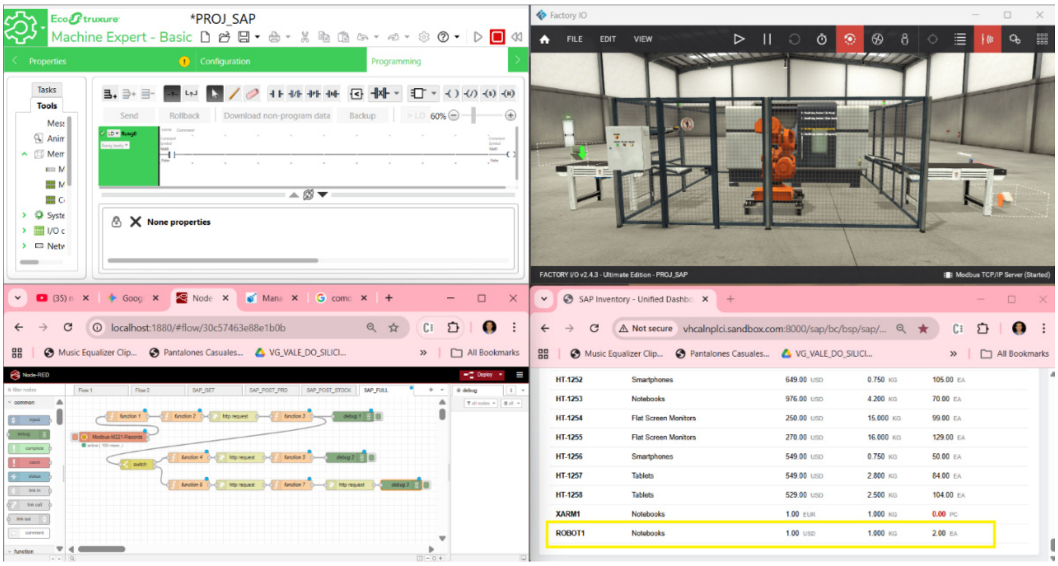
From an educational perspective, the framework supports the development of essential Industry 4.0 competencies, including industrial automation, system integration, ERP interaction, and data-driven decision-making. Competency-based mapping further ensures alignment with modern engineering education requirements, while the use of intuitive and widely accessible tools enhances usability in academic settings.

The sustainability assessment highlighted significant advantages in terms of reduced infrastructure costs, lower energy consumption, and improved accessibility compared to traditional laboratory approaches. These characteristics position the framework as a viable solution for promoting sustainable engineering education, particularly in resource-constrained environments.

Despite these contributions, the study has limitations, including the absence of empirical validation with students and the reliance on simulation rather than physical hardware. Future work will focus on validating the framework in classroom settings, integrating hybrid physical–virtual systems, and enhancing the AI module with advanced analytics and optimization techniques.

doi:10.20944/preprints202605.0293.v1

Figure 3 presents the experimental validation of the framework through a synchronized multi-platform demonstration. The figure provides a composite view of the four primary software environments operating in real-time: the ladder logic execution in the PLC simulator, the 3D visual feedback in the manufacturing simulation, the logic flows within the Node-RED integration hub, and the resulting live data reflected in the SAP Inventory Unified Dashboard. This visualization confirms the successful implementation of the end-to-end Digital Twin pipeline, proving that production events in the virtual environment are accurately recorded and processed at the enterprise level.



HT-1252	Smartphones	649.00 USD	0.750 KG	105.00 EA
HT-1253	Notebooks	976.00 USD	4.200 KG	70.00 EA
HT-1254	Flat Screen Monitors	250.00 USD	15.000 KG	99.00 EA
HT-1255	Flat Screen Monitors	270.00 USD	16.000 KG	129.00 EA
HT-1256	Smartphones	549.00 USD	0.750 KG	50.00 EA
HT-1257	Tablets	549.00 USD	2.800 KG	84.00 EA
HT-1258	Tablets	529.00 USD	2.500 KG	104.00 EA
XARM1	Notebooks	1.00 EUR	1.000 KG	0.00 PC
ROBOT1	Notebooks	1.00 USD	1.000 KG	2.00 EA

Figure 3. Integrated final solution demonstrating a functional Digital Twin loop. The dashboard highlights the synchronization between (top-left) PLC ladder logic in Schneider Machine Expert Basic, (top-right) 3D manufacturing simulation in Factory I/O, (bottom-left) Node-RED communication flows, and (bottom-right) the resulting SAP Inventory Unified Dashboard.

In conclusion, the proposed framework provides a comprehensive, zero-cost, and sustainable approach to teaching Digital Twin concepts in smart manufacturing. It contributes to bridging the gap between academic training and industrial practice, supporting the development of next-generation engineers equipped for Industry 4.0. These findings are consistent with recent studies highlighting the role of Digital Twins in enabling intelligent, integrated, and sustainable manufacturing systems [43–45].

Author Contributions: Conceptualization, A.C.B. and C.V.H.; methodology, A.C.B.; software, A.C.B.; validation, C.V.H.; formal analysis, A.C.B.; investigation, A.C.B.; resources, C.V.H.; data curation, A.C.B.; writing original draft preparation, A.C.B.; writing review and editing, C.V.H.; visualization, A.C.B.; supervision, C.V.H.; project administration. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: The data presented in this study is available on request from the corresponding author.

Conflicts of Interest: The authors declare no conflicts of interest.

References

1. Fuller, A.; Fan, Z.; Day, C.; Barlow, C. Digital Twin: Enabling Technologies, Challenges and Open Research. IEEE Access 2020, *8*, 108952–108971. https://doi.org/10.1109/ACCESS.2020.2998358
2. Rasheed, A.; San, O.; Kvamsdal, T. Digital Twin: Values, Challenges and Enablers from a Modeling Perspective. IEEE Access 2020, *8*, 21980–22012. https://doi.org/10.1109/ACCESS.2020.2970143
3. Jones, D.; Snider, C.; Nassehi, A.; Yon, J.; Hicks, B. Characterising the Digital Twin: A Systematic Literature Review. *CIRP J. Manuf. Sci. Technol.* **2020**, *29*, 36–52. https://doi.org/10.1016/j.cirpj.2020.02.002
4. Lu, Y.; Liu, C.; Wang, K.; Huang, H.; Xu, X. Digital Twin-Driven Smart Manufacturing: Connotation, Reference Model, Applications and Research Issues. Comput. Ind. 2020, *120*, 103221. http://dx.doi.org/10.1016/j.rcim.2019.101837
5. Tao, F.; Qi, Q.; Liu, A.; Kusiak, A. Data-Driven Smart Manufacturing. J. Manuf. Syst. 2018, *48*, 157–169. https://doi.org/10.1016/j.jmsy.2018.01.006
6. Wagner, S.; Gonnermann, C.; Wegmann, M.; Listl, F.; Reinhart, G.; Weyrich, M. From Framework to Industrial Implementation: The Digital Twin in Process Planning. *J. Intell. Manuf.* **2024**, *35*, 3793–3813. https://doi.org/10.1007/s10845-023-02268-0
7. Kerrouchi, S.; Aghezzaf, E.-H.; Cottyn, J. Production Digital Twin: A Systematic Literature Review of Challenges. *Int. J. Comput. Integr. Manuf.* **2024**, *37*, 1168–1193. https://doi.org/10.1080/0951192X.2024.2314792
8. Webb, L.; Tokhi, O.M.; Alkan, B. Digital Twin-Enabled Smart Assembly Automation: State of the Art. *Int. J. Comput. Integr. Manuf.* **2024**. https://doi.org/10.1080/0951192X.2024.2387775
9. Wang, L.; Chen, J.; Zhang, Y.; Tian, Y.; Li, Z.; Wang, C. Research on data Mapping and Fusion in Digital Twin Manufacturing Systems. *Measurement and Control* **2024**. https://doi.org/10.1177/00202940241236088
10. Wang, T., Li, Y., Li, T. et al. Machine learning in additive manufacturing: enhancing design, manufacturing and performance prediction intelligence. J Intell Manuf 37, 711–736 (2026). https://doi.org/10.1007/s10845-025-02568-7
11. Szántó, N.; Monek, G.D.; Fischer, S. Digital Twin-Supported Smart Educational Platform for Manufacturing Training. *J. Eng. Manag. Syst. Eng.* **2024**, *3*, 199–209. https://doi.org/10.56578/jemse030402
12. Acker, J.; Rogers, I.; Guerra-Zubiaga, D.; Tanveer, M.H.; Moghadam, A. Low-Cost Digital Twin Approach in Engineering Education. Machines 2023, *11*, 860. https://doi.org/10.3390/machines11090860
13. Javaid, M., Haleem, A., Suman, R., Digital Twin applications toward Industry 4.0: A Review, Cognitive Robotics, Volume 3, 2023, Pages 71-92, ISSN 2667-2413, https://doi.org/10.1016/j.cogr.2023.04.003.
14. Thomas H.-J. Uhlemann, Christoph Schock, Christian Lehmann, Stefan Freiberger, Rolf Steinhilper, The Digital Twin: Demonstrating the Potential of Real Time Data Acquisition in Production Systems, Procedia Manufacturing, Volume 9, 2017, Pages 113-120, ISSN 2351-9789, https://doi.org/10.1016/j.promfg.2017.04.043.
15. Zanchi, M., Powell, D.J., Gaiardelli, P., Zouggar Amrani, A., Romero, D. (2026). Assessing the Impact of Digital Lean Manufacturing Tools on Perceived Cognitive Workload: The Case of a “Pick-To-Light” Poka-Yoke 4.0 System. In: Mizuyama, H., Morinaga, E., Nonaka, T., Kaihara, T., von Cieminski, G., Romero, D. (eds) Advances in Production Management Systems. Cyber-Physical-Human Production Systems: Human-AI Collaboration and Beyond. APMS 2025. IFIP Advances in Information and Communication Technology, vol 767. Springer, Cham. https://doi.org/10.1007/978-3-032-03542-4_38
16. Minerva, R.; Biru, A.; Rotondi, D. Towards a Definition of the Internet of Things. *IEEE IoT Initiative* **2020**. [Online] https://iot.ieee.org/images/files/pdf/IEEE_IoT_Towards_Definition_Internet_of_Things_Revision1_27MAY15.pdf
17. Al-Fuqaha, A.; Guizani, M.; Mohammadi, M.; Aledhari, M.; Ayyash, M. Internet of Things: A Survey on Enabling Technologies, Protocols, and Applications. IEEE Commun. Surv. Tutor. 2015, 17, 2347–2376. https://doi.org/10.1109/COMST.2015.2444095
18. Lin, J.; Yu, W.; Zhang, N.; Yang, X.; Zhang, H.; Zhao, W. A Survey on Internet of Things: Architecture, Enabling Technologies, Security and Privacy, and Applications. IEEE Internet Things J. 2017, 4, 1125–1142. https://doi.org/10.1109/JIOT.2017.2683200

19. M. Elkhodr, S. Shahrestani and H. Cheung, "The Internet of Things: Vision & challenges," IEEE 2013 Tencon - Spring, Sydney, NSW, Australia, 2013, pp. 218-222, doi: 10.1109/TENCONSpring.2013.6584443.
20. Node-RED Foundation. Node-RED: Flow-Based Programming for IoT. **2023**. [Online] https://nodered.org/
21. Bender, B., Bertheau, C. and Gronau, N. (2021). Future ERP Systems: A Research Agenda. In Proceedings of the 23rd International Conference on Enterprise Information Systems - Volume 2: ICEIS; ISBN 978-989-758-509-8; ISSN 2184-4992, SciTePress, pages 776-783. DOI: 10.5220/0010477307760783.
22. Babu, M. S. P. and Sastry, S. H., "Big data and predictive analytics in ERP systems for automating decision making process," 2014 IEEE 5th International Conference on Software Engineering and Service Science, Beijing, China, 2014, pp. 259-262, doi: 10.1109/ICSESS.2014.6933558.
23. SAP SE. SAP NetWeaver Gateway and OData Services Documentation. **2022**. [Online] https://help.sap.com/doc/saphelp_em92/9.2/en-US/ec/aeea50ca692309e10000000a445394/content.htm?no_cache=true
24. Leyh, C. Critical Success Factors for ERP System Implementation Projects: A Literature Review. *J. Enterp. Inf. Manag.* 2016, *29*, 476–501. 10.1007/978-3-319-17587-4_3
25. Leyh, C., Sander, P. (2015). Critical Success Factors for ERP System Implementation Projects: An Update of Literature Reviews. In: Sedera, D., Gronau, N., Sumner, M. (eds) Enterprise Systems. Strategic, Organizational, and Technological Dimensions. Pre-ICIS Pre-ICIS Pre-ICIS 2011 2012 2010. Lecture Notes in Business Information Processing, vol 198. Springer, Cham. https://doi.org/10.1007/978-3-319-17587-4_3
26. Cioffi, R.; Travaglioni, M.; Piscitelli, G.; Petrillo, A.; De Felice, F. Artificial Intelligence and Machine Learning Applications in Smart Production: Progress, Trends, and Directions. Sustainability 2020, 12, 492. https://doi.org/10.3390/su12020492
27. Kusiak, A. Smart Manufacturing. *Int. J. Prod. Res.* **2020**, *56*, 508–517. https://doi.org/10.1080/00207543.2017.1351644
28. Wang S, Wan J, Li D, Zhang C. Implementing Smart Factory of Industrie 4.0: An Outlook. International Journal of Distributed Sensor Networks. 2016;12(1). doi:10.1155/2016/3159805
29. Toderas, M. Artificial Intelligence for Sustainability: A Systematic Review and Critical Analysis of AI Applications, Challenges, and Future Directions. Sustainability 2025, 17, 8049. https://doi.org/10.3390/su17178049
30. Rampasso, I.S.; Quelhas, O.L.G.; Anholon, R.; Pereira, M.B.; Miranda, J.D.A.; Alvarenga, W.S. Engineering Education for Sustainable Development: Evaluation Criteria for Brazilian Context. Sustainability 2020, 12, 3947. https://doi.org/10.3390/su12103947
31. Lozano, R.; Merrill, M.Y.; Sammalisto, K.; Ceulemans, K.; Lozano, F.J. Connecting Competences and Pedagogical Approaches for Sustainable Development in Higher Education: A Literature Review and Framework Proposal. Sustainability 2017, 9, 1889. https://doi.org/10.3390/su9101889
32. Findler, F.; Schönherr, N.; Lozano, R.; Stacherl, B. Assessing the Impacts of Higher Education Institutions on Sustainable Development—An Analysis of Tools and Indicators. Sustainability 2019, 11, 59. https://doi.org/10.3390/su11010059
33. Despeisse, M., Baumers, M.; Brown, P., Charnley, F., Ford, S.J. A. Garmulewicz, S. Knowles, T.H.W. Minshall, L. Mortara, F.P. Reed-Tsochas, J. Rowley, Unlocking value for a circular economy through 3D printing: A research agenda, Technological Forecasting and Social Change, Volume 115, 2017, Pages 75-84, ISSN 0040-1625, ttps://doi.org/10.1016/j.techfore.2016.09.021.
34. Qi, Q.; Tao, F. Digital Twin and Big Data Towards Smart Manufacturing and Industry 4.0: 360 Degree Comparison," in IEEE Access, vol. 6, pp. 3585-3593, 2018, doi: 10.1109/ACCESS.2018.2793265.
35. Barenji, V., A., Liu, X., Guo, H., & Li, Z. (2021). A digital twin-driven approach towards smart manufacturing: reduced energy consumption for a robotic cell. International Journal of Computer Integrated Manufacturing, 34(7–8), 844–859. https://doi.org/10.1080/0951192X.2020.1775297
36. Lu, Y. Industry 4.0: A Survey on Technologies, Applications and Open Research Issues. *J. Ind. Inf. Integr.* 2017, *6*, 1–10. https://doi.org/10.1016/j.jii.2017.04.005
37. Wang, S.; Zhang, J.; Wang, P. Deep Learning-Enhanced Digital Twin for Manufacturing. *Robot. Comput. Integr. Manuf.* **2024**, 102608. https://doi.org/10.1016/j.rcim.2023.102608

38. Xu, W., Yang, H., Ji, Z., Ba, M., Cognitive digital twin-enabled multi-robot collaborative manufacturing: Framework and approaches, Computers & Industrial Engineering, Volume 194, 2024, 110418, ISSN 0360-8352, https://doi.org/10.1016/j.cie.2024.110418.
39. García, Á., Bregon, A., Martínez-Prieto, M. A., Digital Twin Learning Ecosystem: A cyber–physical framework to integrate human-machine knowledge in traditional manufacturing, Internet of Things, Volume 25, 2024, 101094, ISSN 2542-6605, https://doi.org/10.1016/j.iot.2024.101094.
40. Mourtzis, D. J. Angelopoulos, N. Panopoulos. "Digital Twin in Industries: A Comprehensive Survey," in IEEE Access, vol. 13, pp. 47291-47336, 2025, doi: 10.1109/ACCESS.2025.3551532.
41. Bokhtiar, M., Al Zami, Shaon, S., Khanh Quy, V. and C. Nguyen, D., "Digital Twin in Industries: A Comprehensive Survey," in IEEE Access, vol. 13, pp. 47291-47336, 2025, doi: 10.1109/ACCESS.2025.3551532
42. Mohsen Ebni, Seyed Mojtaba Hosseini Bamakan, Qiang Qu, Digital Twin based Smart Manufacturing; From Design to Simulation and Optimization Schema, Procedia Computer Science, Volume 221, 2023, Pages 1216-1225, ISSN 1877-0509, https://doi.org/10.1016/j.procs.2023.08.109.
43. Ullah, A.; Younas, M.; Saharudin, M.S. Digital Twin Framework Using Real-Time Asset Tracking for Smart Flexible Manufacturing System. Machines 2025, 13, 37. https://doi.org/10.3390/machines13010037
44. Genta, G., Galetto, M., & Franceschini, F. (2020). Inspection procedures in manufacturing processes: recent studies and research perspectives. International Journal of Production Research, 58(15), 4767–4788. https://doi.org/10.1080/00207543.2020.1766713
45. Mourtzis, D. “Simulation in the design and operation of manufacturing systems: state of the art and new trends.” International Journal of Production Research 58 (2019): 1927 - 1949. [Online] https://api.semanticscholar.org/CorpusID:198482261
46. Javaid, M., Haleem, A. Additive Manufacturing Applications in Industry 4.0: A Review. Journal Article. Journal of Industrial Integration and Management. https://doi.org/10.1142/S2424862219300011