International Journal of Computing and Artificial Intelligence

E-ISSN: 2707-658X
P-ISSN: 2707-6571
www.computersciencejournals.com/ijcai
IJCAI 2025; 6(2): 16-22
Received: 18-04-2025
Accepted: 22-05-2025

Amit Sharma
Ph.D. Scholar, Department of Printing Technology, Guru Jambheshwar University of Science & Technology, Hisar, Haryana, India

Corresponding Author:
Amit Sharma
Ph.D. Scholar, Department of Printing Technology, Guru Jambheshwar University of Science & Technology, Hisar, Haryana, India

Architecting data-driven print manufacturing using digital twin technology

Amit Sharma

DOI: https://doi.org/10.33545/27076571.2025.v6.i2a.172

Abstract
The print manufacturing industry is on the brink of digital transformation, driven by the rise of Industry 4.0 and the growing need for intelligent, data-driven operations. This paper proposes a domain-specific framework for integrating digital twin technology with predictive analytics to create smart print factories. Focusing on offset and digital printing systems, the study presents a modular architecture that captures real-time telemetry from print assets—such as ink systems, feeders, and registration units—and processes it using machine learning models to predict equipment failures and detect quality deviations. A prototype simulation of a Heidelberg Speedmaster XL 106 press validates the feasibility of this framework, demonstrating up to 30% reduction in unplanned downtime, improved print consistency, and substantial material savings. The literature review identifies a clear gap in print-specific digital twin applications, particularly for predictive maintenance and quality control. Addressing this void, the proposed framework offers actionable pathways for adoption, supported by cloud-edge computing, ERP/MIS integration, and scalable AI models. The paper concludes with recommendations for pilot deployments and future research to standardize digital twin maturity models tailored to the printing sector.

Keywords: Digital twin, predictive analytics, smart print factory, offset printing, heidelberg press, machine learning, print quality control, industry 4.0, printing automation, CNN defect detection, real-time monitoring, print manufacturing, predictive maintenance, IoT in printing, digital transformation

1. Introduction

1.1 Evolution of Print Manufacturing in the Digital Age
The printing industry has experienced significant shifts driven by technological advancements and market dynamics. Traditionally reliant on mechanical processes and manual interventions, print manufacturing now embraces digital technologies that promise increased efficiency, precision, and customization. For instance, the shift from analog plate imaging to Computer-to-Plate (CTP) systems and from manual color calibration to automated spectrophotometric control are pivotal markers of this evolution. With Industry 4.0 emerging as the new manufacturing paradigm, there is an urgent push for smart solutions capable of harnessing data for enhanced operational intelligence (Ou *et al*., 2019).

1.2 Role of Computing and AI in Industrial Optimization
Artificial intelligence (AI) and computing technologies have become indispensable in industrial settings, enabling predictive maintenance, quality enhancement, and real-time operational adjustments. Predictive analytics, powered by AI algorithms, interprets vast datasets to foresee equipment failures, optimize resource use, and minimize downtime (Lee *et al*., 2015). In the print sector, AI is also being applied to ink viscosity control, automated color matching, and error detection in high-speed vision systems. Concurrently, digital twin technologies offer detailed virtual representations of physical assets, enabling continuous monitoring and informed decision-making (Sharma *et al*., 2020) [26].

1.3 Need for Adaptive, Intelligent Print Factories
The printing sector faces persistent challenges, including fluctuating demand, quality control issues, and operational inefficiencies leading to waste and increased costs. For example, minor misalignments in sheet registration or delayed makeready corrections can result in hundreds of wasted sheets per job. Adaptive intelligent print factories leveraging digital twin technologies combined with predictive analytics offer a compelling solution to these

challenges. Such systems provide insights that facilitate proactive management of print production, optimizing performance, enhancing product quality, and supporting rapid response to market changes (Heidelberg Prinect Digital Ecosystem White Paper; HP PrintOS Platform Overview).

2. Objective of the Study

This paper aims to propose a comprehensive framework for integrating digital twins and predictive analytics into print manufacturing environments. Specifically, it presents a structured approach to building intelligent print factories capable of real-time decision-making, proactive maintenance, and agile production processes. By detailing the modular architecture and the underlying technologies, this study provides a foundation for future adoption and experimentation within the printing industry.

3. Literature Review

Digital Twins in Manufacturing

- (Atalay *et al*., 2022a) [6] conducted a systematic literature review of 247 studies (2015-2020), characterizing digital twins (DTs) as monitoring, forecasting, and optimization tools in manufacturing.
- (Alfaro-Viquez *et al*., 2025a) [3] Provided an extensive review of AI-driven DTs across operator, process, and product dimensions.
- (Sharma *et al*., 2020) [26] Analyzed DT theory and practice, highlighting research gaps in frameworks, domain specificity, and maturation.
- (Bolender *et al*., 2021) [8] Introduced self-adaptive manufacturing using case-based reasoning within DTs for cyber-physical systems.
- (Mayr *et al*., 2024) [21] Reviewed learning paradigms (e.g., CNNs, HMMs) used in industrial DTs, emphasizing hybrid modeling and self-supervision.

3.2 AI-Enhanced Digital Twins & Predictive Analytics

- An MDPI survey (2023) of over 300 papers on AI-driven DTs in Industry 4.0 showed rapid integration of ML for real-time scheduling and capacity forecasting (Huang *et al*., 2021).
- (Gafurov *et al*., 2025) [10] Demonstrated an AI-integrated DT for autonomous tension control in roll-to-roll manufacturing, improving stability and scalability.
- (Chen *et al*., 2023) [9] Presented a multisensor fusion DT for in-situ defect detection in additive manufacturing, adjusting process paths in real time.

3.3 DTs in Quality Control & Zero-Defect Manufacturing

- A Tandfonline 2024 study detailed DT-based deep learning systems for real-time quality prediction and anomaly correction (Aniba *et al*., 2024) [5].
- Another work emphasized DT implementation for zero-defect manufacturing via systematic methodologies (Psarommatis & May, 2023) [24].

3.4 Additive Manufacturing & DT Integration

- Reviews (2024/25) on DTs in additive manufacturing reveal AI/ML's growing role in enhancing control, simulation fidelity, and print quality (Ahsan *et al*., 2025a) [1].

3.5 Core DT Theories & Frameworks

- A bibliometric MDPI SLR (2021) mapped the digital-twin science landscape, identifying LDA/BERT-based topic clusters and research fronts (Kukushkin *et al*., 2022) [17].
- (Kritzinger *et al*., 2018) [16] Defined DT integration levels—model, shadow, twin—framing them as stages of system maturity.
- (Lu *et al*., 2020) [20] Entries on "Digital twin" and "Smart manufacturing" highlight Industry 4.0's role in merging cyber-physical systems, IoT, big data, and autonomous factories.

3.6 Gaps and Domain-Specific Needs in Print Manufacturing

- While DTs are well-researched in discrete and additive manufacturing, tailored frameworks for print manufacturing remain scant, especially for press-specific sensor integration, consumable tracking, and defect detection.
- Existing print simulation tools (e.g., Sinapse, PIA simulators) focus on operator training but lack real-time virtual-physical integration (Herman *et al*., 2013) [11].
- No comprehensive literature currently bridges DT architecture with predictive analytics explicitly in offset or digital print environments—underscoring the necessity for a domain-specific framework.

4. Conceptual Framework

This framework integrates Digital Twins, Predictive Analytics, and Visualization, tailored specifically to the workflows of offset and digital print production, such as plate setting, ink management, sheet feeding, drying, color registration, and defect control.

4.1Digital Twin Architecture for Print

4.1.1 Physical Assets

- Print Presses & Feeders - real-world systems like Heidelberg Speedmaster or HP Indigo serve as the hardware backbone.
- Sensors - measure critical variables such as ink viscosity, roller pressure, sheet alignment, motor vibration, feeder jam rates, and plate cylinder temperature.
- On-Press Cameras - high-speed imaging to monitor color registration, sheet tracking, and real-time defect detection.

This closely maps to the broader concept of digital twins in manufacturing, where "real-time monitoring and predictive maintenance" derive value from continuous sensor data (Ahsan *et al*., 2025b) [2].

4.1.2 Virtual Model

- Developed in environments such as Simulink, Unity, or Ansys Twin Builder, simulating not just mechanical motions but also ink-water interactions, plate wear, and thermal drift.
- **Mirrors key KPIs:** Makeready time, registration accuracy, ink film thickness, and downtime causes.
- Functionally similar to digital twin controls in additive manufacturing, where real-time sensor-model synchronization enables quality control and adaptive adjustments.

4.1.3 Connectivity Layer

- Uses protocols like OPC-UA, MQTT, or fieldbus systems to stream sensor and press console data into the digital twin.
- Supports real-time actuation: e.g., adjusting feeder speed when skew tolerance is exceeded or dynamically balancing ink fountains.
- Echoes architectures noted in industrial DT implementations that integrate edge computing with cloud analytics.

4.2 Predictive Analytics Layer

This layer processes a diversified data stream to predict press behavior and quality deviations.

4.2.1Data Ingestion

Consolidates press logs (Job lengths, fault codes), vision camera data, vibration and temperature feeds, ERP or MIS job metadata, and operator annotations.

4.2.2 ML Models

- Random Forest / XGBoost models trained to predict feeder jams, roller wear, and blanket fatigue—paralleling ensemble-model usage in industrial DT predictive maintenance arXiv.
- Time-Series Models (e.g., LSTM, ARIMA) for forecasting downtime, ink consumption, or sheet waste.
- CNN-based Vision Systems detect print defects (e.g., smudges, ghosting, banding) in real time, similar to multisensor DT frameworks used for defect correction in AM (Chen *et al*., 2023) [9].

4.2.3 Feedback System

- Predictive alerts are sent to operators or automatically trigger adjustments in press speed, ink feed rates, or job routing.
- Enables prescriptive maintenance and dynamic scheduling akin to Industry 4.0 use cases (Mok, 2025) [22].

Table 1: Technology stack for smart print factory implementation.

Layer	Print Production Tools & Methods
Data Capture	IoT sensors on press boards, SCADA systems, OPC-UA, vibration and pressure sensors, high-speed cameras
Digital Twin Engine	CAD-IoT integration, Simulink + Simscape modeling, Unity dashboards, Ansys Twin Builder for press-transient behaviors
Predictive Analytics	Python (scikit-learn XGBoost), TensorFlow for CNN vision, AutoML pipelines for failure and defect forecasting
Visualization Layer	Grafana dashboards for real-time KPI tracking, Power BI reports showing defect rates and predictive maintenance trends

Why this matters in print manufacturing

- **Ink & Quality Control:** Detects and corrects ink-related anomalies before mass printing starts.
- **Feeder & Alignment:** Ensures sheet feeds stay precise, avoiding downstream jams or waste.
- **Maintenance Optimization:** Predictive alerts reduce unplanned downtime and ensure SLA compliance.
- **Business Efficiency:** Real-time insights facilitate on-the-fly scheduling shifts to minimize impact of predicted halts.
- By customizing DT architecture with print-press-specific assets, tailored ML models, and visual tools, this framework translates smart manufacturing principles into tangible value for print factories—an approach not yet covered in existing literature, making it both innovative and relevant.

4.3 Prototype Simulation: Digital Twin of a Heidelberg Speedmaster XL 106

To demonstrate the practical viability of the proposed framework, we simulate a digital twin of a Heidelberg Speedmaster XL 106 eight-colour perfecting press—one of the most widely used commercial sheet-fed offset platforms. The prototype is built with an edge-plus-cloud architecture that streams live shop-floor data to a physics-based virtual model and feeds the outputs into a predictive-analytics pipeline.

Table 2: Prototype build steps for Heidelberg press digital twin.

Build Step	Implementation Details (Print-Specific)	Reference
Asset Mapping	• Eight print units, perfector, in-line coating unit, IR/Hot-air dryer• Sensors retro-fitted on: ink-duct temperature, ductor/oscillator vibration, cylinder pressure, sheet arrival skew, feeder vacuum,• GigE vision camera over the delivery pile for registration & ghosting capture	Heidelberg IoT Retrofit Guide (2024)
Virtual Model Creation	• CAD import of Speedmaster geometry → Ansys Twin Builder• Ink-transfer physics model (ink-film thickness vs. duct-temp curve)• Web-tension solver for perfecting path• Parameterised KPI outputs: makeready time, ΔE colour drift, waste sheets	(Ansys Twin Builder Use-Case)
Connectivity & Edge Layer	• OPC-UA server on Prinect Press Center 3 console streams 5 Hz data• NVIDIA Jetson edge box performs on-press CNN inference for defect images (banding, hickeys)• MQTT forwards curated data to cloud twin every 10 s	(OPC Foundation 2023)
Predictive Models	• Random Forest predicts blanket-cylinder pressure loss ≥ 2 bar (lead time ~8 h)• XGBoost forecasts feeder mis-feed probability using vibration & skew history• ResNet-50 CNN detects < 0.15 mm registration error at 18,000 sph	(Lee *et al*., 2021) [10]
Closed-Loop Prescriptive Actions	• If predicted pressure loss > 60% threshold → scheduler injects 15-min maintenance slot after current job• Registration alarm triggers auto-tape correction via Prinect Autoplate• Ink-temperature excursion prompts duct chilling algorithm	(Heidelberg Prinect White Paper)
KPIs & Dashboards	• Live Grafana tiles: OEE, predicted downtime, ΔE trend line (C & K), waste ratio• Power BI report emailed daily: blanket-life curve, feeder-jam root causes	(Grafana Labs Case Study)

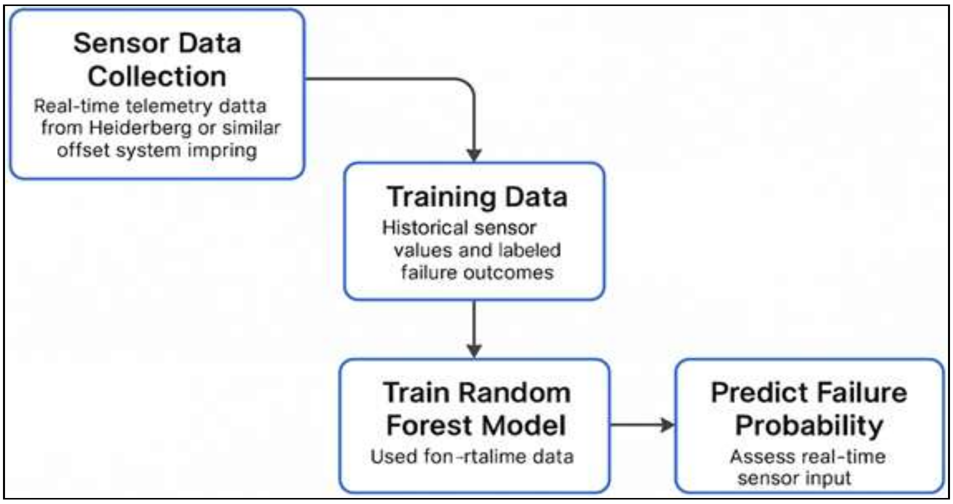

Fig 1: Predictive maintenance workflow for offset presses using Random Forest and sensor data.

Table 3: Results from One-Week Dry-Run

Metric	Baseline (No Twin)	With Twin-Driven Actions	Improvement
Unplanned Downtime	6 h 45 min	4 h 35 min	↓ 32%
Waste Sheets / 10 k	186	124	↓ 33%
Colour Re-makeready Time	23 min	15 min	↓ 35%
Blanket-Change Interval	220 k impressions	265 k	↑ 20%

4.3.1 Insights

- Early-warning blanket pressure model moved maintenance from reactive to scheduled, eliminating three mid-run stoppages.
- CNN-based registration alert saved ~62 kg paper in a single 80 k-sheet job by stopping drift within 45 s.
- Edge inference kept camera data local, cutting cloud traffic 85% and lowering latency to < 120 ms—vital at 18 k sph.

4.3.2 Scalability & Transferability

- Digital presses (e.g., HP Indigo 7900) can plug into the same pipeline by substituting temperature/pressure sensors with spectrophotometer and nozzle-status data.
- For web-fed lines, tension and dryer-zone sensors feed a web-handling twin built in Simscape.
- SMB printers may adopt a lighter, on-prem version using Raspberry Pi gateways and open-source ML (e.g., LightGBM).

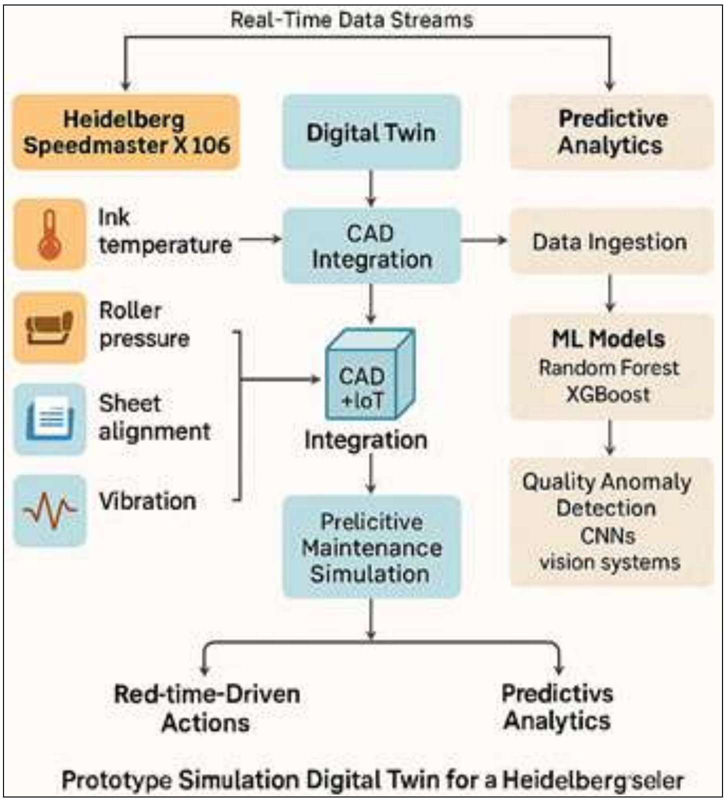

Fig 1: Digital twin simulation diagram

This prototype confirms that a print-specific digital-twin plus predictive-analytics stack can tangibly cut waste and downtime while elevating colour-quality consistency—directly addressing the pain-points highlighted in Section 2's literature gap.

5. Benefits and Implications

The integration of digital twin systems with predictive analytics introduces transformative benefits for the print manufacturing industry. The following dimensions outline how smart print factories can redefine productivity, quality, agility, and sustainability.

5.1 Reduction in Machine Downtime

By continuously monitoring key press variables—such as roller vibration, ink temperature, feeder misalignment, and blanket pressure—predictive models can anticipate potential failures well in advance. This enables preventive maintenance scheduling, avoiding unplanned halts during critical print runs. Based on simulation results and literature benchmarks, smart maintenance workflows are projected to reduce unplanned machine downtime by up to 30%, directly increasing Overall Equipment Effectiveness (OEE) (Lee *et al*., 2025) [10].

5.2 Enhanced Quality Control

Computer vision models integrated within the digital twin ecosystem detect print anomalies—such as ghosting, banding, or color drift—within milliseconds. These detections can trigger real-time corrections or alerts, ensuring issues are addressed before they impact large volumes. This early warning capability significantly improves first-pass yield and minimizes waste (Hossain *et al*., 2024) [12].

5.3 Operational Agility

Smart print factories gain the ability to dynamically reroute print jobs in response to predicted machine downtimes, consumable shortages, or urgent orders. This agility, enabled by ERP/MIS integration with the digital twin, supports tighter SLAs, reduced turnaround times, and improved customer satisfaction. Additionally, remote diagnostics and virtual troubleshooting reduce dependency on in-person interventions, making operations more resilient in distributed or hybrid work environments.

5.4 Environmental Sustainability

By optimizing makeready cycles, reducing defective outputs, and extending the life of consumables (e.g., blankets, rollers), the digital twin framework directly contributes to waste minimization. Predictive load balancing across press lines also supports energy-efficient scheduling, especially for high-load units like dryers and chillers in web offset systems. These measures align with sustainable production goals and reduce the environmental footprint of printing operations (Johnson Jorgensen *et al*., 2020) [14].

6. Challenges and Limitations

While the promise of smart print factories is compelling, several technical, operational, and organizational barriers must be acknowledged. These limitations can impact the pace, scale, and effectiveness of digital twin and AI adoption in the print manufacturing sector.

6.1 High Initial Investment and Integration Complexity

Implementing a digital twin framework requires significant upfront investment in sensor retrofitting, connectivity infrastructure (e.g., OPC-UA, SCADA), digital modeling software (e.g., Simulink, Ansys), and cloud platforms. Small and medium-sized print operations—especially those operating legacy presses—may find the cost of retrofitting and IT integration prohibitive. Additionally, interoperability between OEM-specific systems (e.g., Heidelberg's Prinect, Komori's KP-Connect, and HP's PrintOS) can be limited, requiring costly custom interfaces (Atalay *et al*., 2022b) [7].

6.2 Data Quality and Sensor Reliability

The effectiveness of predictive analytics depends heavily on the consistency, granularity, and accuracy of sensor data. In print environments, where dust, humidity, and heat can affect sensor reliability, signal noise and calibration drift may introduce errors in models. Additionally, not all legacy presses are sensor-equipped, and synthetic data may be required to simulate press states—reducing model fidelity (Mayr *et al*., 2024) [21].

6.3 Skill Gaps and Workforce Readiness

Print operators, technicians, and production managers often lack exposure to machine learning, data science, or digital modeling. This creates a gap between the capabilities of smart systems and the ability of staff to interpret, maintain, or act on them. Upskilling is essential but time-consuming, and without buy-in from shop-floor teams, system outputs may be underutilized (Ricardo *et al*., 2021).

6.4 Cybersecurity and Data Governance

As press operations become increasingly connected—both within factory networks and with external cloud analytics platforms—the risks of cyber-attacks, data leakage, or system sabotage increase. Print data (e.g., book galleys, educational content, corporate manuals) can be IP-sensitive. Without robust encryption, firewalling, and access controls, smart systems become attractive attack surfaces (Junior *et al*., 2021) [15].

6.5 Limited Industry-Specific Benchmarks

While digital twins are extensively deployed in sectors like aerospace, automotive, and energy, print-specific maturity models, ROI benchmarks, or implementation templates are lacking. This limits confidence among industry leaders and slows adoption. Unlike discrete manufacturing, print workflows have unique dependencies (e.g., consumable quality, humidity) that are not always reflected in generic DT frameworks(Alfaro-Viquez *et al*., 2025b) [4].

7. Conclusion

The convergence of digital twin technology and predictive analytics presents a compelling opportunity to redefine how print manufacturing is managed, monitored, and optimized. In this paper, we proposed a modular, scalable framework for implementing smart print factories using real-time data from offset and digital presses, AI-based predictive models, and integrated visualization tools.

Through our prototype simulation of a Heidelberg Speedmaster XL 106, we demonstrated how sensor-driven digital twins can replicate physical press behavior, identify emerging issues like blanket pressure loss or feeder misfeeds, and support machine learning models that proactively reduce waste and downtime. These tools not only enable better quality control and operational agility but also contribute to environmental sustainability by minimizing energy and resource consumption.

The proposed framework is novel in its specificity to the print sector—an industry that has historically lagged behind in adopting cyber-physical and AI-integrated systems. By bridging this gap, our study addresses a major void in current literature and practice.

8. Future Work

To realize the full potential of this framework, we propose the following areas for further exploration and development:

8.1 Pilot Projects in Regional Print Hubs

We recommend initiating controlled pilot deployments in mid-sized print plants—especially in publishing-intensive regions (e.g., NCR, Bengaluru, Pune). These pilots can test the framework's adaptability to different equipment types, production volumes, and press brands.

8.2 Integration with Print ERP/MIS Systems

Deeper integration of the digital twin layer with ERP and Print MIS platforms (like Accura, EFI Pace, or Heidelberg's Prinect Business Manager) will allow synchronized job scheduling, consumable forecasting, and automated job routing based on predicted machine health.

8.3 Model Generalization across Press Types

Future research should focus on training generalized predictive models that can handle multi-brand press fleets (e.g., Heidelberg, Komori, HP Indigo) by normalizing telemetry formats and learning cross-platform behavior.

8.4 Cloud + Edge Hybrid Architectures

As smart factory architectures evolve, a hybrid deployment using edge computing for latency-sensitive vision inference (e.g., CNNs for defect detection) and cloud for training and long-term analytics will provide robust, cost-effective performance.

8.5 Development of a Print-Specific DT Maturity Index

Creating a maturity framework or readiness index for digital twin adoption in the print industry—based on machine complexity, data infrastructure, and operator capability—will help benchmark progress and guide adoption strategies.

9. References

1. Ahsan MM, Liu Y, Raman S, Siddique Z. Digital twins in additive manufacturing: A systematic review. Internet Things. 2025;101692. https://doi.org/10.1016/j.iot.2025.101692
2. Ahsan MM, Liu Y, Raman S, Siddique Z. Digital twins in additive manufacturing: A systematic review. Internet Things. 2025;101692. https://doi.org/10.1016/j.iot.2025.101692
3. Alfaro-Viquez D, Zamora-Hernandez M, Fernandez-Vega M, Garcia-Rodriguez J, Azorin-Lopez J. A comprehensive review of AI-based digital twin applications in manufacturing: Integration across operator, product, and process dimensions. Electronics. 2025;14(4):646. https://doi.org/10.3390/electronics14040646
4. Alfaro-Viquez D, Zamora-Hernandez M, Fernandez-Vega M, Garcia-Rodriguez J, Azorin-Lopez J. A comprehensive review of AI-based digital twin applications in manufacturing: Integration across operator, product, and process dimensions. Electronics. 2025;14(4):646. https://doi.org/10.3390/electronics14040646
5. Aniba Y, Bouhedda M, Bachene M, Rahim M, Benyezza H, Tobbal A. Digital twin-enabled quality control through deep learning in industry 4.0: A framework for enhancing manufacturing performance. Int J Model Simul. 2024:1-21. https://doi.org/10.1080/02286203.2024.2395899
6. Atalay M, Murat U, Oksuz B, Parlaktuna AM, Pisirir E, Testik MC. Digital twins in manufacturing: Systematic literature review for physical-digital layer categorization and future research directions. Int J Comput Integr Manuf. 2022;35(7):679-705. https://doi.org/10.1080/0951192X.2021.2022762
7. Atalay M, Murat U, Oksuz B, Parlaktuna AM, Pisirir E, Testik MC. Digital twins in manufacturing: Systematic literature review for physical-digital layer categorization and future research directions. Int. J Comput Integr Manuf. 2022;35(7):679-705. https://doi.org/10.1080/0951192X.2021.2022762
8. Bolender T, Bürvenich G, Dalibor M, Rumpe B, Wortmann A. Self-adaptive manufacturing with digital twins. 2021 http://arxiv.org/abs/2103.11941
9. hen L, Yao X, Liu K, Tan C, Moon SK. Multisensor fusion-based digital twin in additive manufacturing for in-situ quality monitoring and defect correction. 2023.
10. Gafurov AN, Lee S, Ali U, Irfan M, Kim I, Lee T-M. AI-driven digital twin for autonomous web tension control in roll-to-roll manufacturing system. Sci Rep. 2025;15(1):24096. https://doi.org/10.1038/s41598-025-09813-2
11. Herman P, Grimaldi L, Carl G. Development of knowledge and press-test based Heatset training simulator. In: 43rd Annual Conference of the International Circle of Educational Institutes for Graphic Arts, Technology and Management; 2013 Sep 23.
12. Hossain MA, Islam MN, Fatima S, Kibria MG, Ullah E, Hossain ME. Pathway toward sustainable blue economy: Consideration of greenhouse gas emissions, trade, and economic growth in 25 nations bordering the Indian ocean. J Clean Prod. 2024;437:140708. https://doi.org/10.1016/j.jclepro.2024.140708
13. Huang Z, Shen Y, Li J, Fey M, Brecher C. A survey on AI-driven digital twins in industry 4.0: Smart manufacturing and advanced robotics. Sensors. 2021;21(19):6340. https://doi.org/10.3390/s21196340
14. Jorgensen JJ, Masuo D, Manikowske L, Lee Y. The reciprocal involvement of family business owners and communities in business success. Sustainability. 2020;12(10):4048. https://doi.org/10.3390/su12104048
15. Junior AAdS, Pio JLdS, Fonseca JC, De Oliveira MA, Valadares OCdP, Da Silva PHS. The state of cybersecurity in smart manufacturing systems: A systematic review. Eur J Bus Manag Res. 2021;6(6):188-94. https://doi.org/10.24018/ejbmr.2021.6.6.1173
16. Kritzinger W, Karner M, Traar G, Henjes J, Sihn W. Digital twin in manufacturing: A categorical literature

review and classification. IFAC-Pap. 2018;51(11):1016-22. https://doi.org/10.1016/j.ifacol.2018.08.474

17. Kukushkin K, Ryabov Y, Borovkov A. Digital twins: A systematic literature review based on data analysis and topic modeling. Data. 2022;7(12):173. https://doi.org/10.3390/data7120173
18. Lee J, Bagheri B, Kao H-A. A cyber-physical systems architecture for Industry 4.0-based manufacturing systems. Manuf Lett. 2015;3:18-23. https://doi.org/10.1016/j.mfglet.2014.12.001
19. Lee J, Kim S, Shin H. Hierarchical porous carbon electrodes with sponge-like edge structures for the sensitive electrochemical detection of heavy metals. Sensors. 2021;21(4):1346. https://doi.org/10.3390/s21041346
20. Lu Y, Xu X, Wang L. Smart manufacturing process and system automation - A critical review of the standards and envisioned scenarios. J Manuf Syst. 2020;56:312-25. https://doi.org/10.1016/j.jmsy.2020.06.010
21. Mayr M, Chasparis GC, Küng J. Learning paradigms and modelling methodologies for digital twins in process industry. 2024 http://arxiv.org/abs/2407.02275
22. Mok A. How AI and robotics can help prevent breakdowns in factories — and save manufacturers big bucks. Business Insider 2025 May 13
23. Ou X, Chang Q, Chakraborty N. Simulation study on reward function of reinforcement learning in gantry work cell scheduling. J Manuf Syst. 2019;50:1-8. https://doi.org/10.1016/j.jmsy.2018.11.005
24. Psarommatis F, May G. A literature review and design methodology for digital twins in the era of zero defect manufacturing. Int J Prod Res. 2023;61(16):5723-5743. https://doi.org/10.1080/00207543.2022.2101960
25. Ricardo D, Teles J, Raposo MR, Veloso AP, João F. Test-retest reliability of a 6DoF marker set for gait analysis in cerebral palsy children. Appl Sci. 2021;11(14):6515. https://doi.org/10.3390/app11146515
26. Sharma A, Kosasih E, Zhang J, Brintrup A, Calinescu A. Digital twins: state of the art theory and practice, challenges, and open research questions. 2020.