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Data-Driven Digital Twins in Manufacturing Systems: A Critical Investigation Review and Research Gaps and Future Direction

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Abstract

Implementation of Digital Twins, particularly Data-Driven Digital Twins, is transforming the modern manufacturing landscape by facilitating enhanced simulation, optimization and predictive capabilities. This paper investigates the current literature related to Data-Driven Digital Twins in Manufacturing context, tracing its foundations, technologies and applications. A critical analysis of the operational benefits of Data-Driven Digital Twins is conducted through a systematic review of existing publications. Various gaps identified, including the lack of explainability and effective integration of human expertise within Data-Driven Digital Twins, where current models often produce outputs that are difficult for stakeholders to understand, thereby hindering their widespread usability. To address this, this paper proposes a future research direction that explores the effectiveness of an interactive digital interface in improving the insights obtained from data-driven modelling methods embedded within Digital Twin systems.

Keywords
Digital Twin, Data-Drien, Manufacturing systems, Industry 4.0, Human in the loop

1. Introduction

A Digital Twin is a high-fidelity virtual representation of a physical system embodying its characteristics and behavior (Abdoli 2023, Malaibari, et al. 2024). Through using Cyber-Physical System (CPS) and Internet of Things (IoT) components, a bi-directional flow of live data is created between the physical and virtual spaces (Rehman et al. 2025, Abdoli and Ye 2023), with live sensor data, contextual inputs and operational parameters streamed into a virtual model. This enables the creation of a Digital Twin that utilizes the data to optimize operations and monitor performance (Minerva et al. 2020). The insights generated are then transmitted back to the physical system via a closed feedback loop, enabling dynamic adaptation, predictive control and enhanced decision-making. Digital Twin is a core technology of Industry 4.0, with 65% of manufacturing technology decision-makers planning to use or using Digital Twin technology (Ji and Abdoli 2023) to achieve higher efficiency, adaptability and capability.

Data-Driven modelling techniques describe the construction of virtual models using data collected from real-world systems. Statistical methods, Machine Learning (ML) and Artificial Intelligence (AI) techniques are used on both historical and real-time data to identify relationships between system inputs and outputs. Through identifying patterns and trends between parameters, data-driven modelling methods can infer system behavior and extrapolate key insights, assisting with the process monitoring, forecasting and facilitate decision making.

The intersection of these two fields has resulted in the development of Data-Driven Digital Twins, which characterize virtual models of physical systems that were formed through system data analysis. Data-Driven Digital Twins combine the real-time synchronization and virtual model space of Digital Twins with the autonomous learning capabilities of

AI/ML driven models to produce a hybrid system that is capable of evolution, adaptation and intelligent decision-making. By integrating data-driven modelling techniques with the Digital Twin concept, a more comprehensive tool is constructed that is increasingly valuable within complex and dynamic industrial manufacturing environments. This paper seeks to explore the role of Data-Driven Digital Twins in Manufacturing Systems. A critical Literature Review is conducted to detail the evolution, role, technological foundations and applications of these Digital Twin types. Key research gaps are extracted and analyzed from the existing literature, culminating in the proposal of future research directions within the field of Data-Driven Digital Twins in Manufacturing. The contribution of this study to the field will be that the readers will gain valuable insights into the current state of research, practical applications, and the potential for future advancements in this rapidly evolving field.

2. Review Methodology

A systematic search on publication platforms including Google Scholar and web of science was conducted. The key words “Data-based”, “Data-driven”, “Digital Twins”, “Manufacturing”, “AI”, “ML”, “Big Data” were used to narrow down the publications relevant. Literature was then screened to filter out irrelevant sources, and the remaining publications were categorized into topics to ensure a structured analysis. During research, special attention was paid to the case studies and industrial examples explored within the articles.

3. Results

3.1 Foundations of Digital Twins

The concept of Digital Twins was first introduced to describe a virtual replica of a physical system (Grieves 2023) and gained prominence in Product Lifecycle Management (PLM) applications and within aerospace engineering (Negri et al. 2017). A Digital Twin can comprise of 3 main architectural layers, consisting of the Physical System that is the real-world object, the Virtual Representation that is the digital model, and an Interconnection/Exchange of data between the other 2 layers (Cimino et al. 2021 and Leng et al. 2022). Early implementations closely resembled either Digital Shadows or Digital Models rather than Digital Twins, where only static models were explored or there only existed a unidirectional information flow between physical and virtual model (Kritzinger et al. 2018). With advancements of IoT and CPS, Digital Twins have evolved over time to actualize dynamic synchronization through the real-time exchange of data between the physical and virtual model (Cao et al. 2024). Digital Twins have evolved to incorporate intelligent and responsive behavior through leveraging the advancements of data analytics to optimize and predict system behavior. This next phase of Digital Twin evolution facilitates self-optimization and autonomous decision-making, marking the transition from descriptive models to accurate predictive and prescriptive systems with less manual intervention (Minerva et al. 2020).

3.2 Types of Digital Twins

Digital Twins are categorized into Physics-Based and Data-Driven Digital Twins [Lee et al.2022]. The Hybrid Digital Twins combines features of data-driven and physics-based models to enhance its capability. Physics-Based Digital Twins utilize physics principles to develop a virtual representation of a physical system. A physics-based modelling process involves defining a target variable and selecting a set of hypotheses that can infer relationships between physical system variables through established physical laws and principal equations. Relevant parameters are applied to these hypotheses through sensor data from the physical system, allowing a virtual model to predict asset behavior under varying conditions. Complex operations such as machine-tool interactions, material deformation and fluid flow can be simulated on this model, allowing to reduce trial-and-errors, predict performance, and optimize process parameters (Lee et al. 2022, Tuegel 2017).

Data-Driven Digital Twins primarily utilize ML such as deep learning models to discover data patterns between input and output variables. By consuming both real-time and historical data from the physical system, data-driven modelling techniques identify correlations between parameters to build behavioral models that infer the system’s behavior based on empirical evidence. The underlying dynamics of a physical system are learnt from the data, rather than predefined equations. AI, ML and Big Data (BD) models used within Data-Driven Digital Twins continuously and evolve as new data is received, allowing adaptive learning (Lee et al. 2022, Wang et al. 2018, Tuegel 2017, Aheleroff et al. 2021).

While Physics-based models provide strong interpretability and asset behavior predictions, they struggle with handling dynamic environments and can be computationally expensive. Data-driven models offer effective solutions in complex systems and are capable of continuous evolution. Hybrid Digital Twins combine the capabilities of both Physics-based and Data-driven models to enhance simulation accuracy whilst maintaining flexibility and scalability. This is done within Hybrid Digital Twins by embedding physical laws into architecture or training process of ML models to facilitate physics-informed ML. The ML is also used to approximate parts of a physics-based simulation that are computationally expensive. Operating in a feedback loop, the Hybrid Digital Twin uses ML to identify patterns and anomalies while the physics-based components simulate the expected behavior (Lee et al. 2022, Badakhshan and Ball 2021).

3.3 Key Technologies in Data-Driven Digital Twins

3.3.1 IoT and Big Data

IoT networks and BD perform a critical role in Data-Driven Digital Twins by providing streams of data and analytical power to facilitate real-time monitoring and autonomous decision making. A network of physical sensors and software collects data from the CPS and exchanges it with Digital Twin via IoT. Through this flow of information, Digital Twin can synchronize with physical system (Minerva et al. 2020).

BD refers to infrastructure that can handle Volume, Velocity, Variety and Value of diverse data sets collected from physical ecosystem. Within these platforms, the data is cleaned, transformed and normalized to remove noise and convert the raw input into a usable format (Zhang et al. 2022, Aheleroff et al. 2021). Multi-source data is aggregated in usable formats to AI/ML models. BD platforms feed the cognition layer within the Digital Twins and enable them to make informed decisions (Aheleroff et al. 2021). Through storing the information, BD provides the historical data sets necessary to compare current system behavior with past performance, thereby supporting the continuous improvement and learning of Data-Driven Digital Twins. Without BD, the Data-Driven Digital Twin lacks the material to develop intelligence to accurately handle and extract insights from physical system information (Tao et al. 2018).

Table 1 is a summary of BD techniques utilized within literature, demonstrating that BD has been used to unify the heterogeneous information for cross-lifecycle insights. All case studies include accompanying AI/ML models, demonstrating the synergy between BD and ML models within Digital Twin to produce insights that optimize production systems.

Table 1. Comparison of the usage of Big Data within the Digital Twin Case Studies

Data Type (reference)	Application	Techniques	Outcomes
IoT sensor data, event logs (Uhlemann et al. 2021)	Real-time data collection for process mining	ML classification, Petri nets	15% faster failure detection in drone assembly line
PLM data, sensor data (Tao et al. 2017)	Integrates design, manufacturing, and service lifecycle data and predictive maintenance algorithms	ANN (Artificial Neural Network)	20% improvement in machining precision; 40% downtime reduction
ERP/MES data, social media (Tao et al. 2018)	Multi-source data for product design and scheduling	AI-driven dynamic scheduling	Optimized production plans; improved demand forecasting
Sensor data, parameter logs, simulations (Zhang 2024)	Surrogate modeling (MARS) to reduce computational load	Genetic Algorithm (GA), TOPSIS	11.95% efficiency gain in SME 3D printer assembly
Energy usage data, EMS logs (Zhang et al. 2022)	Tracks and optimizes energy consumption across product lifecycle	ML	3–10% energy savings in energy-intensive industries
Sensor data, simulation data, shopfloor events (Tuegel 2017)	Combines physics-based models with data-driven insights	Physics informed ML	Improved asset behavior prediction under uncertainty

HT simulation data, experimental data (Yao et al. 2021)	Accelerates material design via data-driven ICME	Neural Network Potentials	Faster material innovation cycles
IoT sensor, event logs (Aheleroff et al. 2021)	Trains RL agents for real-time scheduling	Deep RL (DQN, PPO)	20% faster task allocation in robot cells

3.3.2 Machine Learning and Artificial Intelligence

AI focuses on developing systems that can replicate human intelligence to perform tasks. As a subset of AI, the ML algorithms are centered around deriving patterns and relationships from data. AI/ML models constitute the cognition layer of the Digital Twin, analyzing the historical and real-time sensor data stored to recognize patterns and make data-informed decisions without the necessity of domain knowledge, traditional rule-based systems or explicit programming (Wang et al. 2022). AI/ML models can transform beyond static simulation into an intelligent system that autonomously actuates and learns continuously. The insights or control signals generated by the models are validated within simulations in the virtual model to test their effectiveness. Validated insights are then translated into actuation signals, which are then transmitted back to the physical system to effect a physical change (Park et al. 2021, Zhang and Xu 2023) Due to the capacity for learning within AI/ML models, the Data-Driven Digital Twin can adapt and evolve to new operational states, thereby reducing the reliance on domain expertise and making the Twin system comprehensive and flexible (Table 2).

Table 2. Capabilities of AI/ML Models in literature of Data-Driven Digital Twins in Manufacturing

Model	Algorithm	Capabilities (Reference)
SL	ANN	Analyzed relationships between failure logs and productivity data to predict throughput (Chryssolouris et al. 2020)
	Support Vector Machine (SVM)	RBF kernels mapped non-linear relationships between equipment behavior and failure signals (Wang et al. 2018)
	RF	Aggregated predictions from multiple decision trees, used feature importance and real-time voting to identify root causes and classify defects (Wang et al.2022)
	CNNs	Extracts spatial features from visual data (Chryssolouris et al. 2020)
	RNNs/LSTMs	Captures temporal dependencies in sequences, enables time-series modelling (Tao et al 2018)
UnSL	k-Means Clustering	Grouped unlabeled data by similarity, clustered anomalies (Zhang et al. 2022)
Reinforcement Learning (RL)	Deep Q-Networks (DQN)	Learn control strategies through interaction in simulated environments (Schluse et al. 2018)
	PPO	Refined a RL policy within the DT to balance exploration and exploitation (Aheleroff et al. 2021)
Hybrid	Physics based ML	Integrates domain knowledge into learning; reduces data needs and enhances interpretability (Lee et al. 2022)
	GA	Solves multi-objective optimization problems (Zhang 2024)
Probabilistic	Bayesian Networks	Captures probabilistic dependencies, reasoning under uncertainty (Wang et al.2022)

The level of dynamism offered by AI/ML models is what distinguishes Data-Driven Digital Twins from static and Physics-Based Models, which are limited to pre-programmed behaviors and hence, lack real-time adaptability. For example, Random Forests (RF) were proved to aggregate multiple decision trees to classify manufacturing defects in real-time (Wang et al.2022), which negated the necessity for manual recalibration of threshold values within the Digital Twin system. Similarly, DQN autonomously learnt control strategies through iterative simulation and reward feedback (Aheleroff et al. 2021), which could not be done in traditional physics-based models. Hence, AI/ML models transform Digital Twins from passive virtual models into intelligent systems.

Table 2 summarizes the AI/ML algorithms that were explored within the literature, including the type of model, the associated algorithm and their key capabilities within the manufacturing context.

CNNs are-suited for extracting spatial features from visual inspection datasets. LSTM models are typically used to model temporal dependencies for time-series data, useful for predictive maintenance. Unsupervised models (e.g., k-Means clustering) fit well for unlabeled data, thereby assisting to detect operational anomalies or failure modes. Lastly, RL techniques can be applied for iterative improvement of control strategies (Schluse et al. 2018, Park et al. 2021). AI/ML generates the decision logic within the Digital Twin translated into actionable insights that are applied onto the physical system.

3.4 Applications of Data-Driven Digital Twins in Manufacturing

3.3.1 Predictive Maintenance

Attaching IoT sensors to the physical system allows continuous stream of data such as temperature, vibration and pressure to be recorded from production components and machinery (Wang and Abdoli 2025). ML algorithms embedded within the Digital Twin compare the real-time data to the historical data to detect data trends that typically precede equipment failures. Consequently, machine maintenance can be scheduled just-in-time or prior to any physical breakdowns, thereby reducing downtime and lowering operational costs. Beyond this, enabling predictive maintenance within a manufacturing system also extends equipment lifespan, enhances asset reliability and optimizes production planning. This work used Recurrent Neural Networks (RNNs) analyzed CNC machine vibration logs to detect anomalies that predicted bearing failures, enabling pre-emptive maintenance procedures to be carried out (Schluse et al. 2018). Similarly, LSTMs modeled the efficiency drop within rotating equipment to predict the remaining useful life for turbines and motors (Wang et al. 2018). A study conducted on power transformers, the ML algorithms within Digital Twin correlated real-time thermal and electrical data with historical records to predict transformer failures, led to a 40% reduction in unplanned downtime, and a 20% decrease in repair costs by early intervention (Tao et al. 2017).

3.3.2 Process Optimization and Dynamic Scheduling

Unlike traditional optimization methods, Data-Driven Digital Twins do not rely on fixed process parameters and predetermined physical relationships. Instead, the integration of AI/ML models enables the incorporation of live data streams from the shop floor to develop a context-aware system that can make dynamic adjustments. Within the virtual environment, multiple 'what-if' scenarios can be simulated before changes are implemented onto physical system, wherein specific ML algorithms can identify optimal routing and scheduling practices. The feedback loop between Data-Driven Digital Twin and physical system allows dynamic adjustment of machine and process parameters, thereby improving throughput with minimal human intervention. In a case study of a 3D printer assembly line, a Digital Twin model with Multi-Criteria Decision Making (TOPSIS) and GA were developed to optimize the production layouts by dynamically adjusting resource allocations and schedules, improving production efficiency by 11.95% (Zhang 2024). A Deep Q-Network (DQN) trained within a Digital Twin was able to optimize Automated Guided Vehicles (AGVs) within a manufacturing system, leading to a 25% improvement in material delivery times and a 15% reduction in energy usage (Schluse et al. 2018). RL agents continuously analyzed real-time sensor data, including the position, speed and battery status of the Autonomous Mobile Robots (AMRs) to learn optimal paths and task assignments. Using rewards for efficient behaviors, the model simulated scenarios within Digital Twin to determine operation patterns that ultimately reduced AMR travel distance by 17% (Kim et al.2023). In another case, the Proximal Policy Optimization (PPO) algorithm was used to train scheduling agents to respond to machine downtime and task-variations. Thousands of production scenarios were simulated, creating a test bed for the trained agents to reallocate tasks across available machines to avoid bottlenecks (Aheleroff et al. 2021). Consequently, idle time was reduced, and machines were fully utilized.

3.3.3 Quality Control and Fault Detection

When Data-Driven Digital Twins are paired with high-resolution images, manufacturers can closely monitor product features to identify defective products during production. Algorithms specializing in advanced computer vision techniques process image and sensor data to identify scratches, misalignment and deformations in real-time. This approach has proven effective in an electronics manufacturing system, where a CNN-based Digital Twin was trained on datasets containing defects. Using high-resolution images, the algorithm was able to identify micro-cracks in solder joints with over 95% accuracy (Wang et al. 2018). Thus, Digital Twins could identify surface anomalies and inconsistencies with greater accuracy. A Digital Twin can simulate unhappened fault scenarios or variations that may occur under different operating conditions, providing a data-rich basis to generate synthetic defect data based on historical ones. According to Chryssolouris et al. (2020), the synthetic data sets created by Digital Twin can be used to train embedded ML models to detect trends associated with product quality issues. ML models are exposed to fault scenarios without having actual defective products, so reducing reliance on physical prototypes. This enhances Digital Twin's ability to improve the production line's quality. This concept was used to simulate surface and orientation irregularities, where virtual defect scenarios were used as training data sets for CNN models, which achieved 100% accuracy when detecting orientation for robotic pick-and-place operations.

3.3.4 Product Lifecycle Management

Data-Driven Digital Twins enhance product lifecycle management by facilitating seamless data integration across all stages of a product, from design to disposal. As a holistic system with access to real-time data, historical data and process machine parameters, the Digital Twin evolves alongside the product with the added benefits of a simulation space and a record of all previous information. These features create a closed-loop model that allows manufacturers, assemblers, and supply chain manager to track product performance under different operational conditions (Puniani and Abdoli 2025)), simulate to identify design flaws early on and identify past failures to inform iterative improvements to the product.

Tao et al. (2017) explores the cross-lifecycle assistance offered by Data-Driven Digital Twins. Specifically, in the design Phase, the Twin can integrate not just historical defect data, but also customer feedback and real-world usage data, to refine product designs. In a bicycle design case study, the virtual model was able to use environmental and usage data to simulate real-world stress testing on preliminary designs, reducing the cost of physical prototyping by 30%. During the manufacturing phase, a drive shaft manufacturing case study was used to demonstrate how Digital Twin was able to optimize machining parameters. Comparing real-time CNC machine data with virtual simulations, CNC parameters were optimized and led to a 15% reduction in tool wear and a 20% improvement in machining precision. Not only was the current output enhanced, but the resultant data was stored and tracked for future design and process iterations. Lastly, as the virtual model collects data on the product's performance, key insights related to the component wear and failure modes of the product are recorded. This data stored within Digital Twin helps manufacturers decide and improve end-of-life strategies, including the decision to refurbish, recycle or re-purpose.

3.5 Critical Summary

Table 3 demonstrates a critical analysis on Literature related to Data-Driven Digital Twins. In the reviewed literature, case studies dominate the methodologies explored, with many demonstrating the practical benefits of the Twins in improving efficiency and cost reductions. A consistent finding is the role of Data-Driven Digital Twins as enablers for operational optimization without physical risk. Several publications show success in replicating production scenarios to train ML models to optimize logistics and planning processes. All the Case Studies reviewed demonstrate the substantial improvements in efficiency, precision and maintenance. ML and hybrid modelling are prevalent techniques that are proven to enhance real-time decision making, predictive maintenance and the accuracy of simulation. Several limitations were highlighted in the reviewed literature. Many case studies demonstrated success in controlled environments but failed to adequately address challenges of scalability or diverse manufacturing systems (Uhlemann et al 2021, Butala and Duhovnik 2021, Zhang et al 2024). Many publications note that high-quality, real-time data is critical (Zhang et al. 2024, Zhang et al. 2022), however, synthetic or simulation-generated data were used (Schluse et al. 2018, Chryssolouris et al. 2020), which fails to fully replicate real-world variability. The cost and computational barriers of Data-Driven Digital Twins are also highlighted, where techniques like hybrid modelling (Lee et al. 2022) and high-throughput simulations (Yao et al. 2021) are noted to demand significant resources which can limit SME accessibility. Issues regarding legacy system compatibility (Zhang et al. 2022), data interoperability (Hohmann and Sauer 2024) and diminishing explainability of AI/ML insights (Wang et al. 2018, Aheleroff et al. 2021) were also observed within the Literature. Moreover, conceptual frameworks such as those explored in (Lee et al. 2022, Tao et al, 2018) lack empirical validation and real-time performance metrics (Hohmann and Sauer 2024).

Table 3. Critical review of Literature on Data-Driven Digital Twin Methods, Techniques and Outcomes

Approach(reference)	Application	Techniques Used	Outcome and limitations
Case study (Uhlemann et al. 2021)	Smart factory simulation	IoT sensors, ML, Process mining, Petri nets, MLE	Enabled real-time DT generation with high fidelity to actual production dynamics; captured operational bottlenecks and rare failure patterns for predictive control.
Literature review (Badakhshan and Ball 2021)	Strategic and operational decision- making	Thematic and conceptual analysis	Highlighted a disconnect between DT insights and actual operational decisions; noted absence of standard metrics and integration pathways.
Case study (Butala and Duhovnik 2021)	DT planning for discrete manufacturing	5-step DT planning method, Siemens Plant Simulation, SimTalk	Demonstrated improvements in layout and process efficiency
Literature review, expert interviews (Hohmann and Sauer 2024)	DT framework for industrial settings	Ontology modeling, data categorization, API development	Developed a modular DT framework emphasizing semantic interoperability
Case study (Zhang 2024)	SME production optimization	Hybrid simulation, MARS, GA, TOPSIS	Achieved +11.95% efficiency increase; aided real-time decision-making. Resource-intensive for SMEs
Conceptual framework (Lee et al. 2022	Smart manufacturing modelling	Physics-informed ML, hybrid models	Improved model explainability and physical plausibility.
Conceptual framework (Schluse et al. 2018)	Simulation training for ML	SL, RL, synthetic data	Established DTs as safe, repeatable environments for ML training.
Case study (Tao et al. 2017)	Product design, manufacturing, and service	Real-time monitoring, predictive maintenance, virtual verification	Lifecycle-wide optimizations:15% tool wear, -40% downtime Requires high implementation costs and continuous data synchronization
NASA concept and case study (Negri and Macchi 2017)	Predicting emergent behaviour	DT instance	Enabled early detection of complex interactions in aerospace systems. Limited to high-budget applications; not easily transferable to other industries.
Case study (Zhang et al. 2022,)	Sustainable manufacturing in energy- intensive manufacturing BD, ERP/ MES/ EMS integration	IoT, ML, BD	Reported -3% energy in first month, up to 10% annual savings. However, this has Long ROI period and their integration complexity with legacy systems.
Literature review (Wang et al. 2018)	Quality control, predictive maintenance	CNNs, AEs, RNNs, RBMs	Deep learning excels in pattern recognition for defects/faults.
Review and concept integration (Yao et al. 2021)	Smart design of advanced materials	High-throughput simulations, ML, digital thread	Accelerated discovery cycles. High computational demands and SME deployment costs.

4. Research Gaps

4.1 Limited Implementations of Data-Driven Digital Twins

There is still a large gap in realization of Data-Driven Digital Twins in real-life due to the complexity and multi-layered operations of manufacturing systems (Du et al. 2023). Many Case Studies and theoretical models investigated within the studied literature only utilize small-scale, single operation production lines to model the effectiveness of their selected algorithms or data-driven frameworks. For instance, Uhlemann et al (2021), (Butala and Duhovnik 2021) focus on proof-of-concept case studies that operate under tightly controlled settings. Similarly, (Hohmann and Sauer 2024) and (Lee et al. 2022) explore the theoretical construction of Data Driven Digital Twins but fail to address how these models would perform within a real-life factory, which contain operational complexity (Abdoli 2023) and data invariability. These limitations are supported by a recent literature review, which discovered that 55% of Data-Driven Digital Twin case studies were from academic labs rather than real-world industrial applications (Badakhshan and Ball 2021). Moreover, the simulations conducted, such as in sources (Badakhshan and Ball 2021) and (Zhang et al.2024), utilize structured and curated data sets, failing to capture challenges presented within processing real-world data. These designed datasets do not adequately reflect complexities of real-life manufacturing systems which often have interconnected system dependencies, multiple system layers, noisy or incomplete data, interacting departments or subsystems and operational constraints.

There is a limited proposal of frameworks that completely model Data-Driven Digital Twins on a factory-wide scale with multiple production lines, or various machines and equipment. This sentiment is echoed in (Uhlemann et al 2021), whereby there is explicit acknowledgment of the limited scalability of its theoretical 5-step Digital Twin planning method beyond demonstration environments. While (Schluse et al. 2018) has promising results regarding the efficiency gains of optimization algorithms, its solution is only applied to a single SME production system. Hence, the scalability and usability of its methodology across various manufacturing systems is still unverified. Many studies implemented do not include the integration of real-time sensor data into their AI/ML models, thereby limiting the exposure of their models to variant, noisy, incomplete and unpredictable data sets. Many papers, including (Butala and Duhovnik 2021) and (Tao et al.2017), discuss AI-enhanced optimization but do not evaluate their model's performance underneath conditions with sensor noise, data interruptions and real-time uncertainty. Papers [Uhlemann et al 2021, Tuegel 2017) underscore that empirical demonstrations in multi-line, large-scale production environments are largely absent within literature. Without consideration of these unexpected circumstances, complexities and variabilities, the utilization of Data-Driven Digital Twins cannot be fully realized. Moreover, without testing complex manufacturing environments, the reliability and efficacy of the suggested frameworks cannot be proven.

In summary, scalable data-driven frameworks that operate under uncertain and variable conditions are a research gap that must explored to facilitate comprehensive Digital Twins that can effectively operate in real-world manufacturing systems.

4.2 Security in Data-Driven Digital Twins

With the integration of data-driven modelling techniques, Digital Twin systems have become increasingly reliant on digital infrastructure, hence security, integrity and privacy of these virtual systems must be considered. However, the literature studied paid less attention to the introduced vulnerabilities onto Digital Twins (Butala and Duhovnik 2021) (Tao et al.2017, Aheleroff et al. 2021, Chryssolouris et al. 2020). A core feature of Data-Driven Digital Twins is continuous flow of data between physical and virtual systems; however, this creates an attack surface from which malicious software can pose serious cyber threats (Lee et al. 2022, Zhang et al. 2022). With existing studies relying on curated data sets and controlled testbeds like in papers (Wang et al. 2018, Aheleroff et al. 2021), the impact of how compromised data sets can distort an AI/ML model's decision-making, is not explored. Without effective study into security measures such as role-based access controls, encryption and data validation, malicious inputs can be introduced into Digital Twin, resulting in erroneous insights and incorrect decisions, largely undetected with ramifications on physical system. AI/ML and BD models are prone to Data Poisoning, Model Inversion, Adversarial and Data Snooping attacks, which can result in reverse-engineering of confidential proprietary information, faulty predictions/diagnoses and theft (Hohmann and Sauer 2024) (Schluse et al. 2018) (Kim et al.2023). Given the ramifications of cyber-attacks, further research must be conducted to develop secure-by-design

Data-Driven Digital Twin frameworks, which integrate security considerations at developmental stage rather than as an afterthought. Literature on Industrial IoT/CPSs suggests that Digital Twin frameworks that contain built-in cyber protection mechanisms and authentication protocols is a starting point to develop robust systems to safeguard industrial systems from external threats (Negri and Macchi 2017, Tuegel 2017, Tao et al, 2018). Future research must also consider how AI/ML security measures can be adapted for a manufacturing context, where real-time data flow and continuous learning can impede on traditional security paradigms (Yao et al. 2021, Wang et al.2022).

4.3 Explainability in Data-Driven Digital Twins

Explainability in the context of AI/ML refers to the degree in which the reasoning and decisions of AI/ML model can be understood by humans through the provision of explanations for suggested decisions or outcomes. Many Data-Driven Digital Twins frameworks explored within literature suggest ’black-box’ AI/ML techniques which lack transparency such as DQN, SVM and RN (Hohmann and Sauer 2024) (Zhang et al. 2024), Wang et al. 2018). Most of the existing literature focuses on the recommendation of frameworks to support Data-Driven Digital Twins or for how to select and standardize models for widespread usage, however, few discuss the presentation of these outputs in such a way that is easily understood. This is evidential in studies (Butala and Duhovnik 2021) and (Tao et al.2017), which detail a framework for intelligent control and optimization using ML but make no mention of explainability and interpretability in their decision outputs. With manufacturing decisions largely centered around quality, safety and efficiency, this omission is critical as full transparency into reasoning behind why systems have made certain recommendations is vital.

Explainability is crucial in ensuring that AI/ML insights can be trusted with confidence, as humans are less likely to trust decisions that they cannot understand. While the autonomy of a manufacturing system improves overall efficiency, without providing the cause within the data that prompted the model to make a certain prediction, the reliability of output cannot be assured. This diminishes the trust that stakeholders may have in the Digital Twin system, reducing their willingness to adopt and rely on it. Explainability also ensures accountability and traceability. If Data-Driven systems lack explainability, decisions are no longer traceable and do not provide enough depth to allow managers to resolve the issues effectively. Without a full understanding of the logic behind insights, blame and accountability may also be placed solely on the AI/ML system, thereby making ethical, regulatory legal responsibilities complex. Furthermore, AI/ML models are liable to misclassify, develop bias and instability (Lee et al. 2022). Explainability is therefore required to ensure that others can diagnose any biases, issues or flaws in the logic to tune models, as Digital Twin systems evolve continuously with new data.

A recent survey confirms that many existing ML models are considered ’black-box’, whereby they do not provide any human-understandable explanations for their predictions. Furthermore, XAI remains an underdeveloped field with less than 10% applied in manufacturing settings (Tariq er al. 2023). This may be due to how computationally expensive explainable models are, and their lack of scalability across manufacturing applications. Additionally, there was no standardized framework into how technical explanations should be produced that provide the most clarity for non-technical users. Nevertheless, it was specified that manufacturing systems require explainability as areas of incomplete problem formalization always arise and, in those instances, interpretability and explainability is paramount to providing trustworthiness, causality, transferability, confidence, fairness and accessibility for users. The employment of XAI allows the ’reverse-engineering’ of opaque models to output human understandable insights in natural language that effectively detail the causational factors that resulted in the decision.

Research in explainability of Data Driven Digital Twin frameworks is crucial in manufacturing, where decisions have serious financial, operational and safety implications. To facilitate explainability in manufacturing applications, domain-specific XAI methods should be developed that are tailored to specific industrial processes. Other post-hoc methods such as LIME, counterfactual explanations and SHAP should be explored to provide local explanations that explain individual predictions. Further research should be conducted to evaluate methods to display insights in an intuitive and visual manner for end-users.

4.4 Facilitation of Humans in the Loop

The existing research largely focuses on integration of autonomous decision making directly into Digital

Twin's control and feedback system (Zhang et al. 2024) (Tao et al.2017) (Kim et al.2023). However, the dynamic nature of production results in novel situations that may require contextual evaluation, ethical consideration, and complex decision-making. Consequently, the element of human oversight within these autonomous systems is still essential in ensuring that the Digital Twin system is resilient in real-world variability (Tao et al.2019). Manufacturing systems are often subject to unusual events that occur rarely, such as novel defects or sudden infrastructure failures. Additionally, the interlinked processes and variables in manufacturing systems result in complex cause-and-effect relationships and dependencies that data alone cannot capture (Butala and Duhovnik 2021) (Lee et al. 2022). This is especially relevant within Industry 4.0 smart factories, where interconnected processes interact in both cyber and physical domains. In such environments, AI/ML models trained on historical data struggle to interpret context and may misclassify new events (Uhlemann et al 2021, Chryssolouris et al. 2020). This highlights the necessity of incorporating human input within data driven frameworks to refine model outputs, interpret anomalies, apply qualitative expertise and guide algorithms in instances where the data is ambiguous or incomplete.

In critical manufacturing areas such as medical device manufacturing, autonomous decision-making introduces ethical or moral challenges. In traditional systems, when a human operator makes a mistake, the responsibility is traceable, whereas liability is harder to define when AI/ML models are used (Wang et al. 2018, Aheleroff et al. 2021). Implicit bias for optimization can conflict with ethical considerations such as environmental impact, worker safety, quality control, and product integrity.

There is a lack of checkpoints allowing humans to correct biases and contribute to system improvement (Hohmann and Sauer 2024) (Schluse et al. 2018), Uhlemann et al 2021, Tuegel 2017, Tao et al, 2018). Human domain expertise is imperative in validating the AI/ML insights and providing a feedback loop to models to ensure that decisions continue to align with ethics, goals and standards.

A future research direction to explore is the integration of human-in-the-loop frameworks. Interactive interfaces and visuals should be explored that allow humans to interact, verify, validate and potentially intervene the outputs data-driven models. Further research must also be conducted on how to incorporate human ethical judgement and qualitative feedback into AI/ML models.

4.5 Data Standardization

The existing case studies relied on narrowly scoped data sources in their suggested frameworks with datasets that were curated or collected from a single proprietary system, machine type or production line (Butala and Duhovnik 2021) (Schluse et al. 2018). Therefore, the existing literature has shortcomings in account for the integration of heterogeneous data sources as a common characteristic of manufacturing systems. This gap is supported by other publications (Wang et al.2022, Zhang et al. 2022), which acknowledged this challenge too. In manufacturing systems, data is produced by various sources such as MES, ERP, SCADA, sensors, IoT devices, and cameras, with difference in format, quality, granularity and labelling. A lack of standardization between sources of information results in processing difficulties that can affect efficiency, reliability, and scalability of the Digital Twin (Lee et al. 2022, Wang et al. 2018, Oyekan et al.2020). With AI/ML models requiring consistently structured data, these differences in the semantics of data result in increased pre-processing complexity that diminishes the autonomous and scalable operation of the models. These inconsistencies can cause domain shifts within AI/ML models, resulting in poor performance of the model when it is applied to different machines within the manufacturing system (Raissi, et al.2018). If data cannot be easily joined, aggregated or queried across different input streams, Big Data systems can become inefficient, fragile and less scalable due to fragmented insights (Badakhshan and Ball 2021, Zhang et al. 2022, Aheleroff et al. 2021). Furthermore, since non-uniform data requires data parsing, cleaning and standardizing, the data can result in bottlenecks that reduce the ability of AI/ML models to develop insights efficiently. This is not ideal where decisions must be made quickly to ensure efficient production, profitability and reduced downtime (Uhlemann et al 2021, Kim et al.2023).

5. Conclusion and Future Research Direction

Despite the growing advancement and adoption of Data-Driven Digital Twins in manufacturing systems, numerous research gaps hinder its full usability and effectiveness in real-world industrial applications. Therefore, the future direction undertaken will explore methods of promoting trust, reliability and refinement in Data-Driven Digital Twins. This research suggests this future direction as the most critical ones in this context: *How will an interactive digital interface improve the human usability and explainability of the insights obtained from Data-Driven Digital Twins in Manufacturing*?

To address this research question, A pathway can be a web-based approach that can translate Digital Twin outputs into an understandable and actionable format for operators, engineers and managers to use. This interactive interface will be included within the system architecture of the Digital Twin and integrate into the feedback loop to allow human users to provide contextual data, domain knowledge, manual corrections and insight ratings. Context based use case scenarios can be defined in advance and built in the interface to facilitate the interaction of the human with Digital Twin framework. AI/ML models can also benefit from the addition of contextual information and human domain knowledge by considering these inputs in their algorithms, ultimately allowing them to improve the quality of their analyses.

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