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Cloud-based digital twins: How simulations can predict failures in industry

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Abstract. The relevance of this study stems from the increasing complexity of industrial systems and the need to process large data streams in real time to ensure reliable monitoring, predict technical failures, and support decision-making. The aim of the work was to identify typical architectural configurations of digital twins in cloud environments and determine how the distribution of analytical functions across architectural levels affects the efficiency of such systems in production settings. The research methodology was based on a critical analysis of interdisciplinary sources using content analysis, comparative analysis, and SWOT analysis, which enabled thematic structuring of the material according to architectural, algorithmic, and organisational-regulatory parameters. As a result, it was established that a multi-level digital twin model provides a universal foundation for describing architectures in mechanical engineering, energy, and automated manufacturing. Hybrid solutions that transferred part of the analytics to the edge layer offered increased resilience to network failures and better adaptation to changes in the technical condition of assets. It was found that system efficiency depended not only on the topology of computational tasks but also on the ability of analytical models to process streaming data, maintain accuracy amid data drift, and remain interpretable in critical decision-making contexts. It was shown that key barriers to implementation remained the fragmentation of approaches to functional decomposition, the absence of unified standards, and sensitivity to unstable interactions between components. Based on cross-industry comparison, a typology of digital twin architectures was developed, taking into account the nature of analytics distribution and its integration with cloud infrastructure. The results provide a conceptual foundation for further empirical research aimed at practical verification of the stability, adaptability, and scalability of digital twins in production environments

Keywords: data stream processing; simulation-based forecasting; industrial IoT systems; predictive analytics; hybrid infrastructure

Introduction

The need for effective management of equipment condition has grown due to the increasing complexity of engineering systems and reliance on automated components. Standardised maintenance did not allow for timely responses to individual deviations in asset behaviour. Consequently, digital twins have been considered as a tool for early failure prediction based on simulation analytics in cloud environments. Their implementation is complicated by fragmented architectures, the absence of standardised synchronisation, and data heterogeneity, which creates methodological uncertainty in deploying such systems in production environments.

Previous research has outlined a wide range of digital twin applications across various sectors, from smart manufacturing to urban infrastructure and healthcare. For instance, M. Singh *et al.* (2022) conducted a cross-industry analysis of digital twin implementation, emphasising their ability to integrate physical and virtual components to support decision-making. The study proposed the digital twin as an adaptive element of system management, yet the question of structural implementation in cloud environments remained largely unexplored. In the study by M. Javaid *et al.* (2023), the pivotal role of digital twins in shaping Industry 4.0 was highlighted, with a focus on maintenance automation and predictive analytics. However, the examples provided mainly described conceptual models without verification in unstable industrial conditions.

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Meanwhile, D. Yang *et al.* (2021) analysed the development of digital twins in industry, smart cities, and healthcare, highlighting problems of data fragmentation and weak integration with the Internet of Things (IoT). Despite broad thematic coverage, the study lacked systematic categorisation of architectural approaches, limiting its practical value for technical modelling.

Other researchers, such as T.Y. Melesse *et al.* (2021), emphasised the absence of a unified data model, complicating the application of digital twins in complex production systems. Among the key challenges remained the formation of a single information structure capable of encompassing physical variables, operational data, and their cloud-based representation. M. Attaran & B.G. Celik (2023) highlighted the importance of overcoming scalability and cybersecurity challenges in implementing digital twins in cloud environments. They stressed the strategic significance of continuous monitoring and automated system adaptation, yet left unaddressed the algorithmic implementation of models amid data drift.

Some publications focused on regional implementation of digital twins. For example, Ukrainian researcher V. Doroshenko (2021) studied the digitalisation of foundry and metallurgical production, demonstrating limited adaptation of simulation models to specific conditions. In the publication by O. Boiko *et al.* (2024), the benefits of edge-cloud architectures in hybrid energy systems were analysed, indicating the promise of decentralised computational configurations for digital twins. Despite technical relevance, the study did not consider the full cycle of synchronising the digital copy with the physical asset. Conversely, M. Bulgakov & O. Melnyk (2025) demonstrated the effectiveness of digital twins for forecasting and optimising the operation of a ship's energy system in real time, emphasising the importance of aligning digital models with dynamic control parameters.

International discourse has also addressed key problems in digital twin architecture. S. Khan *et al.* (2022) pointed to uncertainty in the methodology for validating digital twin models in industrial processes. Proposed evaluation criteria did not cover the interaction of models with cloud infrastructure. In S. Ma *et al.* (2022), the issue of integrating digital twins into energy-intensive production was raised, where reliability and timeliness of forecasts were particularly crucial. The authors stressed the need for accurate representation of production dynamics but did not explore methods to achieve this under distributed analytics.

Despite active discussion in the scientific community, the question of effective integration of digital twins into cloud computing environments for early detection of technical failures in industrial systems remained unresolved. Existing approaches did not cover the full interaction cycle between the digital model, sensor infrastructure, and data processing tools, complicating practical use in complex production environments. This highlighted the need for research aimed at identifying technological prerequisites and limitations for applying digital twins in cloud environments to model and predict industrial failures. The aim of this study was to comprehensively analyse digital twin architectures in cloud environments, focusing on the distribution of analytical functions across system levels and their impact on the efficiency of predicting technical failures.

Materials and Methods

The methodological basis of the study was founded on a critical analysis of interdisciplinary literature concerning cloud implementation of digital twins in industry. The research was theoretical in nature and aimed to create a generalised conceptual framework by comparing technical approaches presented in current scientific and applied analytics. Particular attention was paid to the interaction of digital models with IoT infrastructure, data stream processing, artificial intelligence (AI), as well as system adaptability and scalability.

The source base included 44 documents: peer-reviewed journal articles, review publications, industry reports from leading technology companie such as Siemens (2023), official documentation for industrial solutions including Azure Digital Twins and AWS IoT Greengrass, and regulatory documents such as ISO No. 23247-1 (2021), ISO No. 23247-2 (2021), and IEC No. 62890:2020 (2020). Sources were selected based on their relevance to cloud-based digital twins, the presence of structured descriptions of architectures, algorithms, or application scenarios, publication period (2020-2025), and verified scientific or technical credibility.

The analysis was conducted in several stages. Initially, texts were coded according to themes: architecture, algorithms, industrial context, and implementation challenges. In the second stage, thematic content analysis was applied, examining each document according to a three-level structural grid: architectural level – structure of digital twins, data processing methods, placement of computational nodes; algorithmic level – classification, forecasting, anomaly detection methods, computational requirements, and cloud infrastructure compatibility; organisational level – scaling barriers, cybersecurity, managerial trust in models, regulatory compliance. Analysis was performed manually using Google Sheets and Miro for building comparison matrices. Each source element was tagged according to: source type, technical focus, relevance to cloud themes, and application sector. Structured data allowed identification of recurring implementation patterns for digital twins and clarified interconnections between architecture, algorithms, and application conditions.

Systematic comparison of sources using standardised criteria and content coding enabled quantitative counting of references to specific architectures, functional components, and application sectors. Comparative evaluation of architecture performance was based on aggregated data regarding effectiveness in applied scenarios, considering cloud tool configurations, algorithm adaptability, and industrial requirements. SWOT (Strengths, Weaknesses, Opportunities, Threats) analysis of analytical algorithms was built on identified technical characteristics and limitations, taking into account computational complexity, interpretability, and resilience to data changes. To ensure internal reliability, cross-validation was conducted: models mentioned in at least three independent sources were marked as stable. Conflicting or rarely described solutions were additionally checked for compliance in other documents or cross-industry analyses, preventing overestimation of unique solutions with limited applicability.

Functional decomposition of digital twin architecture served as a logic for classifying material. Sensor, logical, analytical, and interface levels were studied separately, focusing on their integration in cloud infrastructure. Dependencies between task types (forecasting, classification, anomaly detection) and resource requirements (latency, computational power, fault tolerance) were clarified in parallel. A limitation of the study was the absence of empirical model verification: all analytical conclusions were derived from secondary sources. This imparts a conceptual nature to the results, which require further validation in applied settings.

Results

Content analysis of architectural approaches to digital twins. The deployment of digital twins in industrial systems using cloud technologies can follow various architectural approaches, which influence the functionality, adaptability, and scalability of the digital model (Siemens, 2023). The choice between centralised, distributed, or hybrid models depends on the nature of production processes, the volume and frequency of data flow, and the requirements for processing speed. In centralised architectures, which traditionally rely on full data processing in the cloud, there was a tendency for increased latency in information exchange between the physical object and its digital replica. In such cases, modelling layers – from data collection to analytics – were concentrated in remote infrastructure, providing high computational power but placing additional demands on network reliability (Rovere *et al.*, 2022).

Hybrid models, combining edge, fog, and cloud functionalities, proved to be more flexible and suitable for adaptation in industrial environments. Critical signal processing occurred at the edge, reducing latency, while the cloud served as a platform for long-term storage and analytics. This load distribution helped reduce traffic and improve system fault tolerance. Some models also envisaged delegating part of the computations to local nodes, with aggregated results subsequently transmitted to the cloud (Borghesi *et al.*, 2021). However, implementing such architectures complicated synchronisation between layers, updating digital replicas, and coordinating local and global forecasts, while also requiring consistency in visualised data, which could hinder result interpretation. For a clearer understanding of the functional characteristics of each architecture, a comparative diagram of their main elements is presented below (Fig. 1).

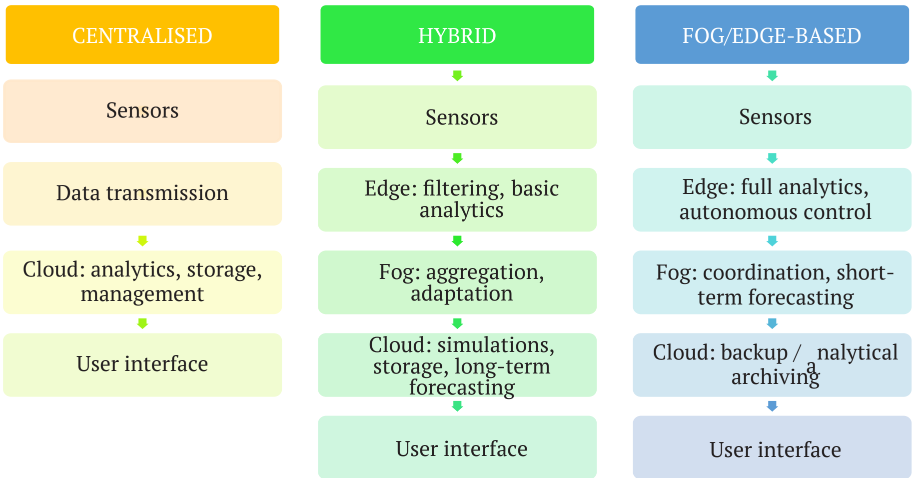

***Figure 1**. Structural differences of three digital twin architectures in a cloud environment*
***Source:** compiled by the author*

The main distinction between approaches lies in the degree of localisation of computational processes and the speed of feedback, which directly affects the flexibility, processing latency, and fault tolerance of digital twins. The multi-layered structure of industrial digital twin architectures typically included sensory, logical, analytical, and interface layers, each with a defined functional role (Siemens, 2023). The sensory layer collected primary signals, the logical layer handled filtering and preliminary processing, the analytical layer built simulation models and assessed risks, and the interface layer provided output and interaction with control systems. However, several concepts showed ambiguity regarding the clear differentiation of these layers, which manifested in varying interpretations depending on the architectural configuration and cloud model features (Onaji *et al.*, 2022). This highlighted the importance of ensuring coherence between functional modules of the digital twin, especially in the context of scaling, synchronisation, and integration with the physical environment. Establishing robust interaction between layers remained a critical factor in overall system effectiveness. Table 1 summarised the data obtained from literature analysis regarding the structural and functional parameters of digital twins implemented using cloud technologies.

***Table 1**. Quantitative distribution of key architectural decisions and functions of digital twins*

Criterion	Category	Number of mentions
Architecture	Hybrid	14
	Cloud-only	20
	Edge-only	13
	Fog/other	6
System levels	2-layer	3
	3-layer	8
	4-layer/multilayer	15
Functional components	Real-time data	28
	Analytics (AI/ML)	33
	Simulations	31
	Model synchronisation	14

***Note:** ML – machine learning*
***Source:** compiled by the author*

Cloud-oriented architectures received the highest frequency of mentions, which may indicate the historical dominance of the centralised approach in the early stages of digital twin deployment. This preference was likely due to the stability, scalability, and relative ease of implementation of cloud infrastructure compared to more complex hybrid or edge solutions. At the same time, the relatively high frequency of mentions of edge architectures, as well as the presence of fog and hybrid approaches, points to the gradual evolution of architectural strategies towards decentralisation and localised computation. This evolution likely stems from the technological need to minimise data processing latency and ensure rapid feedback, particularly in time-critical production scenarios.

Regarding system structure, the prevalence of multilayer architectures reflected the need for specialised distribution of functions across sensory, logical, analytical, and interface layers. Such organisation increased modularity and flexibility but also created challenges related to data integration and synchronisation between layers. The functional distribution showed clear dominance of simulation and analytical modules, confirming the orientation of digital twins towards modelling complex scenarios and failure prediction. Meanwhile, less frequent mention of synchronisation mechanisms between physical and digital objects may indicate both the technical difficulty of implementing this function and the theoretical underdevelopment of issues related to real-time model consistency.

The reviewed approaches emphasised the importance of aligning the update frequency of the digital replica with the dynamics of the physical object. Considerable variability was found in update rates, ranging from periodic data collection to near real-time synchronisation. In practice, this introduced risks of predictive errors, particularly when there was a delay between the actual state of the object and its digital counterpart (Jia *et al.*, 2022). Implementing bidirectional interaction, where analytical results affect the physical process, required high reliability, action logging, and verification of permissible automated interventions. Some conceptual models also considered behavioural scenarios of changes in the production environment and the role of the user in the interaction cycle with the digital twin (Kuo *et al.*, 2021). These approaches envisaged flexible interfaces, communication layers, and adaptive logic, which, combined with modularity principles, increased system scalability. This is especially important for technical diagnostics and real-time failure prediction in industrial environments.

Thus, architectural approaches to implementing digital twins in a cloud environment demonstrated significant diversity at both structural and functional levels. Variability in model selection and integration with physical objects highlighted the need for adaptive solutions capable of accounting for the contextual conditions of production. At the same time, methodological uncertainty remained regarding standardisation of synchronisation principles, load distribution, and consistency between layers.

Comparative effectiveness of digital twins in applied sectors. A review of publications on digital twins revealed a concentration of research in six key sectors: urban environments, manufacturing, engineering, automotive, aerospace, and medicine. As shown in Figure 2, the largest share of publications focused on urban scenarios (47%), while other sectors showed lower activity: manufacturing – 17%, engineering – 12%, automotive – 8%, and aerospace and medicine – 1% each.

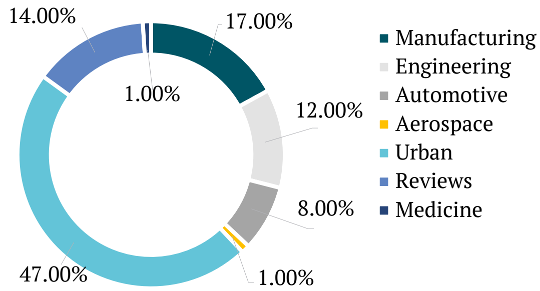

***Figure 2**. Distribution of digital twin publications by application sector as of 2024*
***Source:** compiled by the author based on C. Dilmegani (2025)*

The greatest attention was on urban applications, encompassing smart city concepts, energy networks, transport infrastructure, and digital modelling of complex socio-technical systems. In this context, digital twins were used to monitor critical objects (transformers, power units, sewage systems, road interchanges) and manage their operation in real time. Models were implemented for infrastructure degradation prediction, traffic simulation, anomaly detection in loads, and emergency response scenario modelling. In highly inertial urban systems, long-term time series were predominantly used, requiring cloud processing of large historical datasets (Yu *et al.*, 2022). Critical components, however, required partial offloading of computations to the edge to minimise latency.

In the manufacturing sector, digital twins were primarily used to optimise automated lines, control robotic units, and improve process accuracy in high-precision engineering. Sensor monitoring included load, rotational speed, vibrations, and other mechanical activity indicators (Can & Turkmen, 2023). The focus was on detecting deviations in drive and actuator performance and generating forecasts for preventive maintenance. Hybrid architectures, in which preliminary analytics were performed locally and aggregated data sent to the cloud for long-term simulations, proved effective. However, coordination issues between layers sometimes reduced the stability of digital model updates.

In engineering, covering complex objects with long lifecycles (e.g., bridges, dams, turbines), digital twins enabled analysis of structural loads, deformations, vibration resonances, and other physical characteristics. Research primarily focused on static and semi-dynamic scenarios, allowing identification of wear processes. Accurate simulations facilitated predictions of residual object life and reconstruction feasibility. Cloud services were mainly used for data accumulation and scenario modelling, while real-time processing was not critical. The automotive sector used digital twins to monitor vehicle components, including engines, braking systems, batteries, and navigation systems. This domain combined real-time processing with high-frequency data updates, complicating the balance between local computations and cloud analytics. Early failure detection algorithms and assessments of operating conditions' impact on vehicle health were widely applied. Network limitations and issues with standardising data formats across digital twin components complicated practical deployment.

Although the aerospace industry accounted for a small share of mentions, it demonstrated high technical complexity in digital models. Research showed the use of high-precision simulation models synchronised with flight parameters, navigation, and structural loads. Due to strict reliability and accuracy requirements, specialised cloud environments were used for deep data processing and post-mission analysis (Moenck *et al.*, 2024). However, the complexity of synchronisation and high implementation costs limited large-scale real-time deployment.

Medicine accounted for the smallest share among applied sectors. Digital twins were used for virtual modelling of physiological processes, simulating treatment responses, and analysing biomechanical structures. Due to high data individualisation and confidentiality requirements, most computations occurred in secure environments with limited cloud access. This complicated scalability but ensured patient-level accuracy. Architectural solutions, typical data sources, and key performance indicators were analysed for each sector, with summary results presented in Table 2.

***Table 2**. Features of digital twin applications in different sectors*

Sector	Typical architecture	Data sources	Performance indicators
Urban	Cloud + Fog	Transport flows, energy consumption	10-15% reduction in energy use, 25% improvement in load forecasting, 15-18% increase in urban service efficiency.
Manufacturing	Edge + Cloud	Vibration, load, noise	25-30% reduction in downtime, 20-25% increase in overall productivity, 10-12% energy savings.
Engineering	Cloud	Computer-aided design models, simulations	35% reduction in design errors, 15-20% shorter development time, 18-20% improved parameter estimation accuracy.
Automotive	Edge + Cloud	Vibration, temperature, load	20% improvement in technical diagnostics, 18% maintenance cost reduction, 10-15% extended service intervals.
Aerospace	Cloud	Flight sensors, acoustic analysis	30-40% improved predictive accuracy, 20-25% reduction in failure risk, 15-20% faster processing of critical signals.
Medicine	Cloud	Imaging, patient biosignals	15% increased diagnostic accuracy, 10-12% shorter preparation time for interventions, 8-10% reduced procedural complication risk.

***Source:** compiled by the author based on W. Yu et al. (2022), O. Can & A. Turkmen (2023), R.D. D'Amico et al. (2023), K. Moenck et al. (2024)*

Comparative analysis showed that digital twin performance largely depended on the production environment, types of signals processed, and time-criticality of responses. These systems were most effective where data was structured, communication channels were stable, and operations were highly repetitive. Cloud technologies ensured scalability and historical data storage but required architectural adaptation to sector-specific conditions: edge solutions prevailed in highly dynamic environments such as aviation and automotive industries, while a centralised cloud approach was appropriate for urban systems and medicine. Therefore, digital twin deployment strategies needed to account for both technical and organisational parameters of each sector.

SWOT analysis of digital twins in cloud infrastructure. In deploying digital twins in cloud environments, analytical algorithms played a key role in providing functional system value. They enabled automated anomaly detection, technical failure forecasting, and data-driven decision support from industrial objects. A SWOT analysis of these algorithms was conducted to outline development opportunities and potential threats in cloud deployment (Fig. 3).

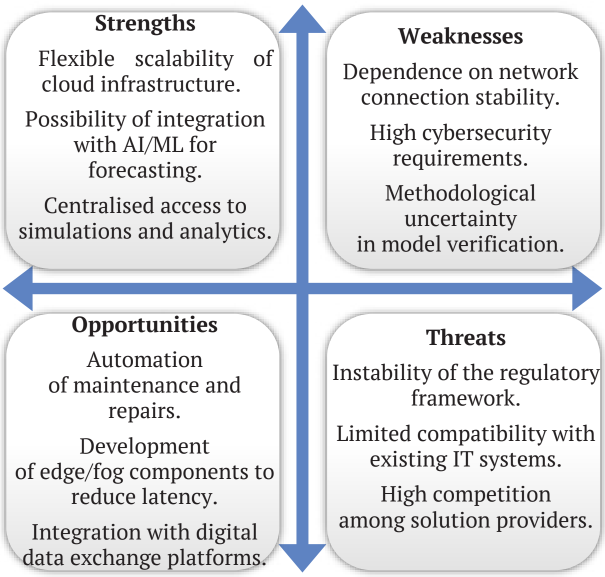

***Figure 3**. SWOT analysis of cloud-based digital twin technology in industry*
***Source:** compiled by the author*

Among strengths, algorithms' ability to process large volumes of multi-sensor data in the cloud was highlighted. This capability combined high-performance modern computing architectures with parallel processing of information streams from heterogeneous sources. Methods such as Random Forest, Support Vector Machines, or Long Short-Term Memory (LSTM) provided sufficient accuracy and scalability for specific tasks, such as fault classification, technical degradation forecasting, or anomaly detection in streaming signals. Random Forest was effective with large feature sets and complex non-linear relationships, while LSTM models facilitated time-series prediction accounting for long-term dependencies between object states (Gao *et al.*, 2023).

A particular advantage was the ability to integrate with IoT infrastructure, allowing data processing in a near real-time mode without the need for intermediate storage on central servers. This enhanced the adaptability of systems to rapid changes in the technical state of assets, which is critically important in high-dynamic industrial environments (Hu *et al.*, 2021; Liu *et al.*, 2025). Additionally, algorithmic solutions employed by digital twins reduced reliance on traditional maintenance methods, shifting towards models based on the actual condition of equipment. Another efficiency factor was the availability of cloud-based model lifecycle management tools, such as Azure Machine Learning or Amazon SageMaker, which automated processes for training, validation, versioning, and deployment of analytical models. In combination with cloud infrastructure, these tools enabled centralised monitoring of model performance and continuous analytics improvement via AutoML mechanisms. Such platforms also facilitated the implementation of continuous integration/continuous deployment practices in industrial data processing, increasing the stability and reliability of digital twin systems in operational environments.

At the same time, several weaknesses were identified. A primary issue remained the dependence of model performance on the type of data and the specific task. Decision tree models, particularly Random Forest, exhibited decreased accuracy when faced with strong class imbalance, a common feature of real-world technical processes where failures occur far less frequently than normal operation (Liang *et al.*, 2022). Under such conditions, algorithms tended to focus on the dominant class, ignoring atypical or critical scenarios. Techniques such as synthetic minority oversampling or adaptive reweighting partially mitigated this issue but simultaneously increased model complexity and processing time. LSTM models, used for time series analysis, were resource-intensive. Their effective training required large volumes of historical data, powerful computational infrastructure, and long convergence times. In cloud environments, these requirements could lead to higher processing costs, increased prediction latency, or even the need to simplify model architecture at the expense of accuracy. Real-time LSTM applications often required data aggregation or down-sampling, limiting their suitability for highly dynamic assets.

Data drift – gradual changes in feature distributions or dependencies in sensor streams due to equipment wear, environmental changes, or system upgrades – posed a further threat. Model performance could degrade even if the formal structure of input data remained unchanged (Cai *et al.*, 2022). This necessitated mechanisms for continuous performance monitoring, periodic retraining, or dynamic parameter adaptation. However, such practices complicated the analytical component's operation, increased technical support requirements, and demanded clearly regulated quality-check procedures post-update. Analysis revealed opportunities to enhance algorithm efficiency, particularly in adaptability, scalability, and complex data stream processing. One promising approach was the use of ensemble systems that combined multiple model types to improve resilience to noisy or heterogeneous data. This method compensated for the limitations of individual algorithms through collective interaction, reducing overfitting risks and improving result accuracy.

Another promising direction was the implementation of stream analytics via specialised platforms such as Apache Flink, Apache Kafka Streams, or Azure Stream Analytics. These platforms enabled real-time sensor data processing without prior storage, improving system responsiveness to critical deviations. Extending these systems' functionality through integration with ML libraries allowed not only basic filtering and aggregation but also complex classification, clustering, and anomaly detection within the data stream. Additional opportunities included self-learning or adaptive models capable of automatically adjusting to changing operating conditions without manual retraining. Such models, based on online learning or evolutionary algorithms, could modify their structure or weights in response to data drift, operational mode changes, or new signal types (Lugaresi *et al.*, 2023). This preserved analytical relevance in dynamic environments and reduced the technical staff's workload. Adaptive strategies also increased model resilience to sudden changes, such as equipment upgrades or the introduction of new elements into the production process.

Nonetheless, threats affecting system stability, reliability, and security remained. Cybersecurity was a key concern: the openness of cloud interfaces, complex access structures, and multi-stage data processing created conditions for potential attacks (de Azambuja *et al.*, 2024). Threats included both unauthorised access to models and tampering with input or output data, both of which distorted analytics results. Particularly dangerous were data poisoning and model inversion attacks, where models trained on corrupted datasets could reveal confidential information. Inadequate environment segmentation or absence of multi-level authentication increased risks of compromising the entire digital twin system.

Challenges also arose in validating and verifying models operating on multi-source data streams. In cloud environments, sensor sources could differ in format, update frequency, latency, and accuracy, complicating consistency between input data and the digital representation of physical processes. Determining acceptable error margins was particularly difficult in critical sectors, where even minor deviations could lead to incorrect decisions (Plageras & Psannis, 2022). The opacity of complex models, especially neural networks, further complicated monitoring and ensured alignment with real-world asset states.

Thus, the effectiveness of cloud-deployed digital twin analytics depended on their ability to adapt to specific industrial requirements, maintain a balance between accuracy, interpretability, and computational complexity, and integrate with cloud-based model lifecycle management tools. Assessment showed that no single existing technology offered a universal solution, yet their combination – guided by modularity, adaptability, and automation – opened new prospects for industrial digital twin development.

Discussion

The study systematised architectural, sectoral, and algorithmic features of digital twin implementation in cloud environments for predicting technical failures. Patterns observed confirmed the absence of a universal deployment model; architecture, analytical methods, and integration tools depended heavily on the industrial context. Interaction between IoT, cloud computing, and AI models was particularly relevant, forming the backbone of next-generation intelligent analytics systems. This aligns with R.S. Kenett & J. Bortman (2022), who viewed digital twins not as isolated components but as part of an integrated quality and reliability management ecosystem, focused on context-dependent analytics. The effectiveness of digital twins depends not only on model accuracy but also on their integration with production logic, representation of current asset states, and dynamic response to internal and external disturbances.

Industry scenario analysis corroborated R. Gonzá lez-Herbón *et al.* (2024), emphasising that digital twin structures must adapt to the physical object type, sensor load, and decision-making cycles. In highly automated sectors, digital twins must cover both monitoring and active process management. Three primary architectural approaches were identified, each relevant predominantly to a specific task type, highlighting that no architecture can claim universality without losing adaptability or efficiency. Among analytical methods, those balancing prediction accuracy, response time, and computational cost were most effective. This aligns with S. Attaran *et al.* (2024), who emphasised that intelligent flexibility and cloud scalability determine digital twin performance in Industry 4.0. The ability to scale, adapt to rapidly growing data streams, and leverage AI components was key to successful digital enterprise implementation. Systems using stream processing of IoT data responded best to failures and anomalies.

Detailed analysis of digital twin architectures confirmed findings by C. Stergiou & K. Psannis (2022) on the critical role of cloud environments in managing large data volumes. Their three-tier model was considered optimal for heterogeneous data streams in distributed systems. Results showed practical efficiency: the edge tier allowed rapid signal filtering and preprocessing, while the cloud aggregated, stored, and analysed data. This reduced communication load and improved resilience to latency and data loss. Coordination complexity and the need for model standardisation aligned with the authors' discussion of configuration management challenges in heterogeneous environments.

Trust in digital twin analytics remained a critical factor (Kamble *et al.*, 2022). Lack of transparent validation, audit complexity, and opacity of deep models, including LSTMs or autoencoders, constrained their adoption in critical industrial contexts. When models required not only accurate predictions but also explainable decisions, AI opacity was a barrier. Data drift requiring frequent retraining posed additional challenges, often infeasible in real time without halting critical functions, reducing operator trust and adaptive management applicability. Integration of deep learning improved recognition of complex patterns and degradation forecasting (Lee *et al.*, 2020), but required careful control of infrastructure. This study confirmed that LSTM-based architectures' performance depended on stable access to cloud resources capable of scalable training. Network bandwidth fluctuations or absence of adaptive scaling led to decreased efficiency or delayed responses, negating high accuracy advantages. Similar conclusions were reached by

T. Savchuk & A. Kozachuk (2015), who proposed an automated decision-making algorithm for cloud application scaling based on reactive rules and an efficiency evaluation function. Their approach emphasised the need to balance infrastructure cost and user retention under variable loads, which directly supports the premise that adaptive scaling mechanisms are essential for maintaining digital twin responsiveness in dynamic industrial environments.

Analytical methods for unsupervised anomaly detection were significant, as noted by A. Ucar *et al.* (2024), who highlighted autoencoders' potential in predictive maintenance. This study confirmed their effectiveness in distributed IoT systems with limited labelled data, though their sensitivity to operational variability and input changes posed challenges for long-term cloud-based performance. Comparing architectures with predictive efficiency allowed analytical generalisations regarding digital twin suitability in various industries. D. Zhong *et al*. (2023) found digital twins most effective in predictable or repetitive scenarios, allowing standardisation of behaviour and creation of normal operation templates. This aligns with findings in energy and mechanical engineering sectors, where digital models were more stable and less sensitive to update frequency. Dynamic environments required complex simulations and high update rates (Alshathri *et al*., 2023).

Stream analytics approaches in this study align with Y. You *et al.* (2022), emphasising continuous sensor signal processing for timely anomaly detection. In short-lived or unexpected disturbances, periodic data collection may be insufficient. Integrating real-time stream analytics is crucial for effective digital twin response to technical state changes. Dynamic balancing between edge, fog, and cloud tiers was observed, consistent with Y. Wang *et al.* (2023) cooperative computing model, automating resource coordination based on network status, system load, and signal priority. This is suitable for complex industrial scenarios with uneven loads and unpredictable disturbances.

Overall, results align with contemporary scientific trends in digital twins and clarify important aspects of cloud implementation. Combining IoT sensors, stream analytics, flexible AI algorithms, and adaptive architectures creates potential for new tools supporting industrial system technical states. These findings highlighted the shift toward predictive and self-optimising infrastructures, where digital twins not only reflect real-time operational data but also enable proactive decision-making. Such an approach enhances system reliability, reduces maintenance costs, and fosters sustainable industrial innovation.

Conclusions

The study systematised key architectural approaches for cloud-based digital twins and generalised their structure through a four-tier model. In most technical scenarios, system effectiveness depended on the analytical tier's ability to interact with real-time data, maintain low processing latency, and adapt simulation parameters to dynamic operating conditions. Literature analysis showed that interaction between edge and cloud components is critical for both responsiveness and long-term predictive capability. Functional decomposition into sensor, logical, analytical, and interface tiers is a universal framework applied across industries. Comparative analysis indicated that distributed analytics, with part of data processing at the edge, provided greater resilience to network failures and reduced cloud infrastructure load. Centralised components remained necessary for adaptive long-term forecasting based on historical data. Cloud interaction failures created risks of critical latency, particularly with high-frequency data updates, limiting real-time digital twin applicability without local buffering.

Current approaches showed ambiguity in function allocation across architectural tiers. Analytical tasks were sometimes offloaded to the logical tier or duplicated at edge and cloud levels, indicating a lack of unified functional decomposition principles. In-depth analysis of the analytical component clarified technical and methodological features of commonly used algorithms, considering advantages and limitations in cloud environments. Algorithm effectiveness depended on input data type, IoT infrastructure configuration, and resource constraints. Low model interpretability, high computational costs, and sensitivity to data drift remained barriers to large-scale deployment. However, identified opportunities offered paths to improve digital twin reliability, scalability, and flexibility in industrial environments. Future research should leverage empirical data to verify identified digital twin architectures in real industrial settings. Particular attention is required for testing cloud synchronisation mechanisms and scalability of analytical modules under dynamic changes in asset technical conditions.

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Conflict of Interest

None.

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Хмарні цифрові двійники: як симуляції можуть передбачати збої в промисловості

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Анотація. Актуальність дослідження зумовлена зростанням складності промислових систем і необхідністю обробки великих потоків даних у реальному часі для забезпечення надійного моніторингу, прогнозування технічних збоїв і підтримки прийняття рішень. Метою роботи було ідентифікувати типові архітектурні конфігурації цифрових двійників у хмарному середовищі та визначити, як розподіл аналітичних функцій між архітектурними рівнями впливає на ефективність таких систем у виробничих умовах. Методологія дослідження ґрунтувалася на критичному аналізі міждисциплінарних джерел із застосуванням контент-аналізу, порівняльного аналізу та SWOT-аналізу, що дозволило здійснити тематичне структурування матеріалу за архітектурними, алгоритмічними та організаційно-нормативними параметрами. У результаті встановлено, що багаторівнева модель цифрового двійника є універсальною основою для опису архітектур у машинобудуванні, енергетиці й автоматизованому виробництві. Гібридні рішення з перенесенням частини аналітики на edge-рівень забезпечували підвищену стійкість до мережевих збоїв і кращу адаптацію до змін технічного стану об'єктів. Виявлено, що ефективність систем залежала не лише від топології обчислювальних задач, а й від здатності аналітичних моделей обробляти потокові дані, зберігати точність при дрейфі даних і залишатися інтерпретованими в умовах критичних рішень. Показано, що ключовими бар'єрами реалізації залишалися фрагментарність підходів до функціональної декомпозиції, відсутність єдиних стандартів та чутливість до нестабільної взаємодії між компонентами. На основі міжгалузевого зіставлення сформовано типологію архітектур цифрових двійників, що враховує характер розподілу аналітики та її інтеграцію з хмарною інфраструктурою. Отримані результати становлять концептуальну основу для подальших емпіричних досліджень, спрямованих на практичну верифікацію стабільності, адаптивності й масштабованості цифрових двійників у виробничих умовах

Ключові слова: потокова обробка даних; симуляційне прогнозування; виробничі IoT-системи; прогнозна аналітика; гібридна інфраструктура