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Enabling intelligent 3D visualization of the Digital Twins with the help of AI integrated Graphics Systems

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Abstract

Digital twins have grown from virtual representations to cyber-physical systems that enable real-time monitoring, simulation, prediction and decision making. Traditional dashboards and handcrafted three-dimensional (3D) models are not enough to convey the state of a system, uncertainty, and recommended actions as digital twins grow more complex. This paper explores the role of intelligent 3D visualization in digital twins with AI-enabled graphics systems. It suggests a multitiered architecture that integrates Internet of Things (IoT) sensing, semantic data models, generative and predictive artificial intelligence (AI), real-time rendering and interactive user interfaces. This study has been prepared based on the latest research in the field of AI–digital twin integration, 3D virtual modeling, generic 3D reconstruction, and AI supported digital twin systems. It highlights a research gap for frameworks that holistically consider visual fidelity, semantic intelligence, real-time synchronization, explainability, and human-centered interaction. The methodology proposed consists of a 5 layer pipeline from physical data acquisition, data management, AI reasoning, graphics rendering, to user interaction. The paper does not report on new experiments collected but offers a repeatable framework of evaluation and literature-based insight into the fidelity, latency, interpretability and usability of visualizations. The analysis shows that AI-powered graphics systems can enable the creation of more than just a visual interface; with careful management of interoperability, data quality, computational scalability, and user trust, digital twins can become adaptive decision-support environments.

Keywords: *3D graphics, real-time rendering, human–computer interaction, generative AI, intelligent visualization, digital twin, and Industry 5.0.*

Introduction

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A digital twin is a digital replica of a physical asset, process or system, bound to its physical counterpart via data flows, models and services. A digital twin is not a static digital model but allows for bidirectional interaction between the virtual and physical worlds – as sensor data is fed in to the digital model, information can also be drawn from the virtual model to be used for monitoring, simulation and control of the physical world. This bi-directional coupling allows manufacturing applications, smart city, energy systems, healthcare, construction and autonomous mobility applications.

The 3D visualization is an essential requirement for a digital twin system, as it allows users to see the relationships between objects, their configurations, their operation and simulated scenarios in real time. The 3D virtual modeling enhances the intuitiveness of the state monitoring, boosts the human–cyber interaction, and offers visual guidance for simulation and diagnosis (Wang et al., 2025). The traditional 3D visualization, however, can be problematic due to its high modeling effort, slow updates, poor semantic context and limited support for decision making.

These limitations can be overcome by the use of Artificial Intelligence to automate the model reconstruction, interpretation of sensor streams, prediction of future states, detection of anomalies, and adaptation of visual content based on the user needs. Generative AI can generate a 3D environment from a picture or video; predictive AI can detect defects, predict equipment failure, and suggest operational changes. New studies reveal that AI-powered digital twins can aid in real-time monitoring, predictive maintenance, proactive decision-making, and autonomous optimization (Sajadieh & Noh, 2025; Dai et al., 2025).

The blending of artificial intelligence and graphics is especially critical because the raw output of analytics isn't always enough to inform users who are already on the job. In addition to a predictive model that suggests a machine is likely to fail, an operator must also be able to see where the failure is likely to occur, what components are likely to be affected, how confident the predictive model is and what interventions are available. Intelligent 3D visualization thus calls for a

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graphics system that is not only photo-realistic, but also semantically meaningful, temporally synchronized, and interactive.

This paper explores how Artificial Intelligence (AI) can integrate with graphics systems to facilitate intelligent 3D visualization in the context of Digital Twins. It summarizes existing research, outlines research gaps, suggests a modular structure and outlines an evaluation approach. The main idea is that a digital twin visualization should integrate geometric fidelity, semantic reasoning, predictive intelligence, and human-centric interaction and should be all within a single real-time pipeline.

Literature Review

The combination of Digital Twins and Cyber-Physical Integration.How Digital Twins and Cyber-Physical Integration work together. Digital twins are often differentiated from digital models and digital shadows. A digital model is a static representation without automated real-time connection, a digital shadow is one way transfer of data from the physical system and a digital twin is a bi-directional data exchange and control capability (Sajadieh & Noh, 2025). This separation is crucial for visualization, as the visual interface should be representative not only of geometry, but also of active current state, past history and possible controls.

Digital twin architectures usually involve physical assets, sensing and communication infrastructure, data management services, virtual models, analytics services, and user interfaces. In recent years, advanced architectures have been emerging that integrate edge computing, cloud services, AI analytics, and cybersecurity features to ensure low latency operations and scalable deployment (Sajadieh & Noh, 2025). Visualisation is not a stand alone front end feature, it relies on the quality, timeliness and semantic structuring of the data throughout the architecture.

Recent systematic reviews highlight the importance of real-time sensor data, communication protocols, computational intelligence, machine learning, edge computing, and high-resolution imaging or 3D visualization to enable the operational value of digital twins (Tao et al., 2025). Such capabilities enable digital twins to transition from descriptive monitoring to predictive, diagnostic, and autonomous actions.

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Digital Twins, 3D Visualization

Many digital twins are based on 3D virtual modeling. It can be the geometry of equipment, layout of space, kinematic behaviour, thermal states, structural states, or process flows. Wang et al. (2025) analyzed 106 digital twin 3D modeling examples and concluded that the application of 3D modeling can be used in the monitoring of the state, human–cyber interaction, visualization of the condition, simulation and visual guidance. They also noted continuing problems with autonomous modeling, incremental updates and optimal planning of data collection.

The fidelity of visualization can vary from descriptive geometric models to highly detailed digital mirrors. The higher fidelity provides more realism and facilitates deep inspection, while carrying more cost, and synchronisation needs. Therefore, the designers of the digital twins need to consider the design of visual details and real-time performance, depending on the decision task supported.

Enabling technologies are computer-aided design (CAD), building information modeling (BIM), photogrammetry, LiDAR, point clouds, simultaneous localization and mapping (SLAM), virtual reality (VR), and augmented reality (AR). While these technologies are able to create detailed virtual environments, it is expensive to maintain them in a dynamic industrial environment by hand. This constraint is a driver for AI-driven and automated 3D model creation and update.

AI Integration in Digital Twins

AI supports digital twins throughout their lifecycle: from virtualization and synchronization to monitoring, awareness and decision-making and optimization. AI facilitates data preprocessing, feature engineering, model calibration, and high fidelity virtual model construction in the first phase. During the second phase, machine learning, computer vision and anomaly detection process real-time sensor data to generate situational awareness. Predictive analytics, simulation, reinforcement learning, and optimization enable proactive and autonomous decision-making in the third phase, predictive analytics (Sajadieh & Noh, 2025).

In their work, Dai et al. (2025) suggested an AI-powered DT model incorporating generative AI, predictive AI, explainable AI, context-aware AI, and agentic AI.

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Their manufacturing-centric approach features generative AI capabilities for synthesizing data, 3D reconstruction, and virtual testing, predictive AI capabilities for detecting defects and predicting quality, and explainable, context-aware, and agentic AI modules that interpret, adapt, and take autonomous action. The results shown here illustrate how the multiple AI capabilities can be made accessible to the operators via visualization.

AI can also create content for digital twins based on visual information. Based on the last survey on generation of digital twins from visual data, the methodologies are neural radiance field, 3D Gaussian splatting, semantic segmentation, generative inpainting, and foundation models (Chen et al., 2025). These techniques can help minimize the amount of manual work involved in building 3D environments, and can be used to help speed asset, workspace, and scene reconstruction from multi-view imagery.Create interactive and immersive interfaces.Develop interactive and immersive interfaces.

Interactive visualization enables customers to explore assets, apply filters to data layers, review historical events, perform "what if" analysis, and view future consequences. VR and AR add this by immersing users into or alongside the virtual environment. In industry, an immersive interface can be used for training, remote maintenance, safety planning and collaborative design.

But there are problems with motion sickness, cognitive overload, network latency, device compatibility and accessibility when implementing immersive visualization. A good interface is one whose design emphasizes only task-relevant information, presents visual relationship encodings of uncertainty and risk, and provides the ability to drill down from a system-level overview to component-level detail. AI can help with this customization and provide more detailed information, identify anomalies, and suggest views.

Research Gap

While digital twin research has come a long way, there are still some gaps to fill. First, many studies conceptualize 3D visualization as a passive layer for presentation instead of a smart element of the digital twin pipeline. Second, most studies on AI-based 3D reconstruction tend to concentrate on the geometric accuracy, while not considering semantic labelling, temporal updating, and

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operational analytics integration. Third, there are few frameworks that explicitly link the predictive AI results with spatially-aware 3D visualisations. Fourth, there is scarce research on the impact of visualization design on operator trust, understanding and decision quality.

Another deficiency is related to scalability and interoperability. In large industrial environments, there is heterogeneous data coming from cameras, LiDAR, programmable logic controllers, enterprise systems, and simulation tools. Efficient data structures, streaming protocols, level of detail management and standardized scene descriptions are needed to render such environments in real-time. Sajadieh and Noh (2025) pinpoint some persistent challenges for AI–digital twin integration, including interoperability, scalability, and data security, which all relate to visualization systems.

Last but not least, explanation is still not well developed in 3D digital twin interfaces. The operators should know why they detected an anomaly, what the evidence in the sensors was in predicting the anomaly, and how confident the system was. Intelligent visualization can lead to excessive dependence on automated recommendations if there is no visual context to explain what is being recommended.

Objectives

The aim(s) of this study are:

Propose an intelligent 3D visualization of digital twins with the assistance of AI and graphics architecture.

To describe generative AI, predictive AI, explainable AI, and context-aware AI in the context of a visualization pipeline.

To create a set of metrics for assessing visual fidelity, synchronization delay, semantic correctness, interpretability and usability.

To discover technical and organizational issues related to implementing intelligent 3D digital twin visualization.

To offer hands-on suggestions for using the human-in-the-loop approach for digital twin interfaces in the industrial and urban settings.

Methodology

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Research Design

A design-science and literature-synthesis approach is used in this study. It establishes a conceptual and methodological foundation for intelligent 3D visualization and checks the logic of this concept with the latest verifiable research. No new empirical data set is gathered, and no artificial experimental data are presented. The proposed framework aims to support the design, development and testing of digital twin visualization systems, in scenarios like smart factories, infrastructure monitoring, energy networks and urban management.

The methodology is composed of 5 stages: requirements analysis, data and model integration, AI-based design of the visualization, system implementation, and evaluation. There are decisions made in each stage that affect how the system will work, be usable and trusted.

Requirements Analysis

The first step is to create an understanding of the stakeholders, operations, data sources, visualization needs, and decision contexts. Representatives from operators, maintenance, safety, planning and management are typical stakeholders. The required update rate, spatial accuracy, semantic detail, interaction modes, security constraints and acceptable latency should all be specified with requirements.

A manufacturing twin might, for instance, need millisecond level synchronization for supporting robotic control, while a twin for urban infrastructure could focus on periodic updates, historical analysis and scenario planning. When the main task is anomaly detection, requirements analysis guarantees that unnecessary investments in photorealism aren't made, and when spatial precision is required, it guarantees that the visuals aren't overly simplified.

Data and Model Integration

The data layer combines heterogeneous data sources such as data from IoT sensors, video, LiDAR point clouds, CAD or BIM models, enterprise resource planning records, maintenance logs, and simulation outputs. Data is cleaned, time

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wrapped, georeferenced, and mapped to semantic entities like machines, pipelines, rooms, vehicles or parts of the infrastructure.

There is need for a semantic model for intelligent visualization. It connects every 3D object to its identity, state, sensor history, maintenance record, simulation parameters and useful AI predictions. Interoperability and a consistent data exchange across platforms can be facilitated by standards like the ISO 23247 and the Asset Administration Shell (AAS) (Sajadieh & Noh, 2025). With semantic linking, users can choose a 3D object and instantly see the real-time measurements, potential issues, and suggested solutions.

AI-Enabled Visualization Design

The framework the company has proposed requires four functions of AI. Generative AI models and/or updates 3D assets based on multi-view images, video, point clouds or CAD data. Visual observations can be converted into high-resolution 3D representations, captured in various formats, that can be inspected and virtually deployed, including through structure from motion and 3D Gaussian splatting (Dai et al., 2025; Chen et al., 2025).

Predictive AI uses sensor data and historical information to help predict equipment health, identify anomalies, classify the defects and estimate remaining useful life. It provides color coding, heat maps, animated indicators and component level alerts as its outputs to be mapped on the 3D scene. Explainable AI offers explanations for predictions, such as the most significant sensor readings or visual characteristics in a classification. Context-aware AI customizes visualization and recommendations based on operating conditions, user role, location and task.

Agentic AI can complete the cycle by taking the actions, creating reports, modifying the simulation or suggesting control changes for the system. But, autonomous action must be limited by safety rules, human supervision and audit trails. For high-risk environments, the visualization system should display ranked recommendations and expected consequences, not always and automatically perform irreversible actions without permission.

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Graphics and Interaction Layer

The semantic 3D scene is displayed real time in the graphics layer. It employs the level-of-detail technique, occlusion culling, spatial indexing, streaming and GPU acceleration to ensure interactive performance in large scenes. The interface should enable navigation, object selection, layer filtering, replaying time series, replaying simulations and comparing actual and predicted states.

Observed data should be different from predicted/simulated data in visual encoding. In this way, for instance temperature observed could be displayed in authentic surface shading, and the thermal risk predicted could be displayed as a transparent overlay. Confidence intervals, probability bands, and visual opacity are all examples of ways that uncertainty can be expressed. This separation allows users to see the difference between what they have measured and AI-generated forecasts.

The interaction layer shall be able to offer a role-based view. An operator might want to have just an overview of the dashboard with active alarms and recommended actions, whereas an engineer would want to access sensor traces, model parameters, and provide explanations of the diagnostics. The cognitive load reduction of adaptive interfaces can be achieved by emphasizing objects relevant to the task and by filtering irrelevant detail.

Evaluation Protocol

Evaluation of a system should include technical, semantic and human factors. Technical evaluation includes frame rate, rendering latency, end-to-end synchronization delay, memory consumption, network bandwidth and scalability as function of scene complexity. Semantic evaluation is used for the assessment of object recognition, state classification, anomaly detection and 3D reconstruction.

Cloud-to-cloud distance between a reconstructed point cloud and reference model can be used to evaluate geometric fidelity, and they can be calculated as mean deviation, standard deviation, maximum deviation, and relative error. This method has been applied by Dai et al. (2025) to assess 3D reconstruction generated by AI in a manufacturing environment. The accuracy of the predictions

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can be evaluated with precision, recall, F1 score, area under the receiver operating characteristic curve and mean absolute error for forecasting tasks.

Situation awareness, perceived usefulness, error rate, cognitive workload, trust, and task completion time are measures that should be made using human centered evaluation. User studies should be conducted that compare intelligent 3D visualization to a traditional dashboard or static 3D model. Explainability should be measured in terms of whether users can find the evidence used to make an AI-based recommendation and whether providing explanations facilitates proper use of the system.

Results

Literature-Based Findings

This paper will not present new experimental results, but rather a synthesis of existing evidence and the behaviour that one would expect from the new framework. From the literature reviewed, AI-based graphics systems have the potential to enhance the value of a digital twin through various capabilities such as automated 3D modeling, real-time analytics, and interactive decision support.

AI implementation has the potential to shift digital twins from data-replication to real-time monitoring, predictive maintenance, adaptive scheduling, self-optimization and risk mitigation, as demonstrated by Sajadieh and Noh (2025). Their AI–digital twin integration framework groups the AI contributions into virtualization and synchronization, monitoring and awareness, and decision-making and optimization. This lifecycle view lends to the current case for visualizing current state and predicted states, uncertainty, and recommended interventions.

Wang et al. (2025) show that 3D virtual modeling is a key component of enhancing the intuitiveness of digital twin monitoring and human–cyber interaction. They also find that many of the current systems are very dependent on manual modeling, with very little autonomy in creating and updating the 3D model. This discovery is a strong argument for the necessity of using AI for reconstruction, adding semantic information, and incremental model updates.

We found evidence presented by Dai et al. (2025) that multi-view video can be used to build 3D virtual testing environments via generative AI, and that

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predictive AI can assist in the detection and predictive quality analysis of defects. Their welding case study shows how to present AI outputs in interactive 3D interfaces, dashboards and quality analysis reports. This shows that AI reasoning can be implemented in a practical manner with spatially based visual interfaces.

Expected Framework Outcomes

The proposed framework is likely to result in 5 outcomes. To start with, generative reconstruction should minimize the amount of manual work needed to build and update 3D environments, especially for objects without full CAD records. Second, semantic data integration should enable the user to go from the visual to the actionable without having to switch between disparate tools. Thirdly, predictive overlays must be made spatially visible to allow earlier intervention.

Fourth, evidence presented through an explainable visual cue should be used to enhance appropriate trust, by indicating the evidence for alerts and recommendations. Fifth, adaptive interaction should alleviate cognitive overload by adapting the density of information and visual complexity to the role of the user and the situation in which they is using the product. Achieving these results relies on a solid data pipeline, verified AI models, and thoughtful visualization design.

The framework also looks forward for restrictions. The 3D models created by AI can sometimes include inaccuracies and details that are not accurately observed or generated, particularly in areas with occlusion or limited visibility. It's difficult, if not impossible, to render high fidelity scenes in real time. Predictive models could fail when distribution shift or sensor drift or new operating conditions occur. The risks must be validated, visualized, have contingency plans, and monitored on an ongoing basis.

Discussion

The key contribution of this paper is the integrated perspective on intelligent 3D visualization as a means of bridging between physical systems, AI reasoning, and human decision-making. Visualization shouldn't just present a 3D model, it should make people aware of what is happening, what might happen, why the system

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thinks so, and what can be done. This view is echoed by recent AI–digital twin approaches that integrate generative, predictive, explainable, context-aware, and agentic capabilities (Dai et al., 2025).

The synthesis also illustrates the need to be task-dependent in terms of visual fidelity. While high geometric fidelity is helpful for inspection, virtual commissioning and spatial planning, too much detail can hinder performance and impede the user from focusing on information that can be used for decision making. A layered visualization approach can maintain fine granular geometry to use for engineering analysis and provide simplified views of semantics for operation monitoring.

Scalable deployment is a prerequisite for interoperability. CAD, BIM, IoT, simulation and AI services are frequently integrated in digital twin environments. Standardization of semantic models and scene descriptions can minimize the costs of integration and can facilitate consistent visualization across platforms. Sajadieh and Noh (2025) point out that for the widespread use of AI-powered digital twins, standards and scalable architectures are essential.

Technical performance should not be overlooked when it comes to human factors. An intelligent visualization system should not put the user under the pump of alerts, animation, and predictive overlays. Rather, it should focus on the principle of clarity, consistency, and progressive disclosure. Users must be able to view the reason for an alert, view alternative scenarios and override or question automated recommendations as appropriate.

In an operational environment, security, privacy and governance play a vital role. With 3D visual data, facility layout, production process and asset vulnerabilities can be identified. There should therefore be access controls, encryption, anonymization, audit logging and secure edge processing built into the visualization architecture. These protections are especially critical when digital twins are used for control functions and for linking to safety critical infrastructure.

Conclusion

Digital twins can be transformed from passive digital replicas into interactive decision support environments with intelligent 3D visualization. This paper suggested the 5-layer architecture solution including physical sensing, semantic

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data management, AI reasoning, real-time graphic rendering and human-centered interaction. The framework integrates generative AI to generate 3D models, predictive AI to forecast and detect anomalies, explainable AI to build trust and transparency, and context-aware AI to enable adaptive visualization.

Based on the literature search, AI-enhanced graphics systems can enhance monitoring, diagnosis, simulation, and operational decision-making, provided they are interoperable, reliable, scalable, and trusted by their users. Empirically testing the use of intelligent 3D visualization in other domains, establishing common metrics for semantic and explanation quality, and exploring secure, real-time architectures for large-scale digital twins are future directions for research. Finally, the intelligent visualization should make it possible to understand the complex cyber-physical systems in a fast, accurate and responsible way.

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