Exploring Digital Twin platforms across industries: A multi-aspect SNA

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Abstract

Digital Twins have emerged as a transformative solution enabling organizations across sectors to digitally replicate physical assets and processes to extract operational insights. Implementing Digital Twin systems involves diverse stakeholders, ranging from providers to end-user developers and adopters. At the crux of Digital Twin implementation lies the need of Digital Twin platform – the foundational infrastructure on which solutions are built, integrations are executed, and data flows are managed. While substantial research targets advancing Digital Twin platforms' capabilities, investigations analyzing real-world implementations spanning industries remain scarce. This research profiles 19 platforms harnessing data aggregated from provider websites, white papers, press releases and user documentation to compile understanding on platform purpose, inbuilt security and interaction mechanisms, integration architectures, predominant use cases, real users' locations, and supported solutions. Social Network Analysis (SNA) conducted in Pajek detected valuable adoption patterns in the Digital Twin platforms market while community identification analysis linked predominant platform-capability combinations to industry and locational preferences, arming stakeholders to strategize road mapping. Results showed that Azure Cloud, IBM Cloud, and MindSphere were ranked highest in centrality among the platforms mapped. In parallel, to determine platform capability dimensions and their acceptance across geographies and use contexts, normalized centrality metrics were performed for other data types. Also, 58 solutions provided by platforms were classified into five categorical purpose groupings. The findings expand visibility into the dynamics of Digital Twin platforms and can be evolved by expanding sample diversity and blending functional, operational, and economic perspectives in future studies supporting stakeholders in implementation processes.

Keywords –

Digital Twin systems, Digital Twin Platforms, Social Network Analysis

1 Introduction

In the rapidly evolving landscape of digital transformation, organizations worldwide are increasingly turning to innovative solutions to enhance efficiency, streamline operations, and gain a competitive edge [1]. Among these, Digital Twins have emerged as a transformative force, revolutionizing the way industries approach data, simulation, and real-world processes. As the significance of digitalization continues to grow, the adoption of Digital Twins has become not only a strategic imperative but also a key driver in reshaping industries and fostering unparalleled advancements in technology [2]. Digital Twin provides the means to depict, emulate, forecast, optimize, and control physical space through real-time connectivity, mapping, analysis, and interaction with a specific fidelity and frequency [3]. This communication between the physical and virtual systems is enabled by explicitly defining the data produced by the system, augmenting it with information about system entities, and realizing "value adding services" on top of this data driven definition [4]. Core components of Digital Twin technology include high fidelity data collection via Internet of Things (IoT), sensors, predictive data analytics and process simulations to create the model, as well as visualization dashboards to provide services for users [5]. With the advantages of model, data, and service, Digital Twin offers superior solutions for enhancing quality, increasing efficiency, cutting costs, mitigating losses, ensuring safety, and conserving energy [6]. Therefore, Digital Twin enables maximum optimization of processes and value chains of the physical system. Moreover, the application of Digital Twin in diverse industries can effectively expedite their digitalization, networking, and intelligence development processes.

As the adoption of Digital Twin increases across sectors such as manufacturing, healthcare, automotive, construction, and urban development, dedicated software platforms have emerged to facilitate the Digital Twin development and scalability of Digital Twin [7]. A Digital Twin platform provides the core infrastructure to enable the creation, management, and utilization of Digital Twins across an organization's ecosystem while establishing the digital thread that connects the physical and virtual worlds [8]. According to [9], Digital twin platform ecosystem refers to collaborative environment involving Digital Twin platform providers, application developers, technology providers, system integrators, consultants, and user organizations for enabling digital transformation across industry verticals. The key capabilities of a Digital Twin platform include data ingestion and integration, simulation engine, visualization dashboards, analytics, reporting and notifications, collaboration tools, Application Programming Interfaces (APIs) and integration capabilities, security features, and scalability [10], [11]. Digital Twin platforms empower organizations to unlock key benefits, including predictive maintenance, improved asset performance, and accelerated innovation [12]. Prominent examples of Digital Twin platform include Microsoft Azure Digital 1Twins, GE's Predix, Siemens MindSphere, PTC's ThingWorx, Dassault Systemes' 3DEXPERIENCE, and Ansys Twin Builder. While these platforms are applicable across various industries, companies often opt for customized solutions based on Digital Twin platforms, avoiding a one-size-fits-all approach. Despite numerous investigations into developing Digital Twin platforms in recent years, there is a gap in gathering, categorizing, and analyzing the existing platforms provided by developer companies. An analysis of the implementation of existing Digital Twin platforms in different industries, along with their definitions, purposes, solutions, and other aspects is needed.

This paper aims to assist the evolving landscape of Digital Twin platforms and ecosystem partners dedicated to delivering asset-class or industry-specific Digital Twin solutions. This objective is accomplished by applying Social Network Analysis (SNA) techniques to model and interpret the relationships between various Digital Twin ecosystem participants on a global scale. Additionally, existing Digital Twin platforms are analyzed with respect to their functional and geographic concentration of interconnected providers and user communities.

2 Background

Digital Twins have gained traction in recent years across various industries, including manufacturing, aviation, healthcare, construction, and smart cities. Recent surveys on industry adoption levels indicate that manufacturing has taken an early lead in implementing Digital Twin prototypes and applications [13]. Although adoption levels vary across industries and applications, the common thread involves leveraging connected IoT devices, predictive analytics, and simulations through Digital Twin platforms. This is accomplished by utilizing core features such as physics-based equipment modeling, real-time data integration via IoT APIs, Artificial Intelligence (AI)-powered analytics, monitoring dashboards, and simulation tools [14]. Several studies have been conducted to develop Digital Twin platforms to address specific problems in different industries. In the manufacturing sector, [15] developed a Digital Twin for steel pipe weld quality control. A Digital Twin platform based on a microservices architecture and offering solutions for continuous deployment, data infrastructure and I4.0 business services was developed by [16]. [17] developed an AI-based injection molding machine Digital Twin able to prevent failures by recognizing machine deterioration patterns. [18] established a Digital Twin platform for the medical device assembly machine to diagnose the anomalies' root causes and predict the quality of the products with more confidence, higher speed, and less invasive methods.

While manufacturing leads in piloting Digital Twin platforms, momentum also exists in other sectors such as construction and smart cities. [19] developed a cyber-physical interconnection method for computational design and robotic construction in a wooden architectural realm. [20] employed Digital Twin within a human-robot collaborative system to assist in assembling complex-shaped architectures and tested it through a real system. [21] created a Digital Twin-enabled anomaly detection system for asset monitoring and with a data integration method based on extended Industry Foundation Classes (IFC) in daily Operation and Maintenance (O&M) management, which was successfully tested on a real case. [22] proposed a Digital Twin-enabled real-time synchronization system (DT-SYNC) aiming to facilitate Planning, Scheduling, and Execution (PSE) using real-time resource status and construction progress information obtained from high-fidelity Digital Twins. [23] introduced a digital-twin based multi-information intelligent early warning and safety management platform to address high safety risks during tunnel construction. [24] developed a blockchain-enabled Digital Twin collaboration platform for Modular Integrated Construction (MiC) fit-out operations for modular construction. [25] proposed a geospatial platform based on the universal game engine Unity3D, to manage large-scale individual mobility data for an Urban Digital Twin (UDT) platform. [26] proposed a Digital Twin platform to address challenges in incorporating Photovoltaic (PV) systems and wind energy sources into smart city power grids. [27] presented the design, implementation, and use cases of the Chattanooga Digital

Twin (CTwin) toward the vision for next-generation smart city applications for urban mobility management.. [28] presented an overview of different Digital Twin platforms that can be used in Electric Vehicle (EV) applications in smart cities.

Healthcare is also poised for Digital Twin adoption through "Digital Hospital" initiatives utilizing AI and simulation to optimize patient flow, resource allocation, and medical equipment maintenance [29]. [30] built a Digital Twin body through dynamic equations and pressure control mechanisms based on pressure reflexes. [31] built a Digital Twin coupled with blood flow and head vibration to develop diagnostic tools. Subramanian (2020) built a Digital Twin that integrated scientific information and clinical source information. [33] constructed a Digital Twin of lumbar spine based on AR, data analytics, motion capture system, Inverse Kinematic (IK) method and Finite Element Method (FEM). [34] developed a Digital Twin system for the vaccination process and tested it in a clinic. [35] built an emergency department Digital Twin simulation able to quantify the downstream impact of delayed or erroneous triage on patient outcomes. [36] developed a patient centric mathematical data model to formally define the semantic and scope of our proposed Healthcare Digital Twin (HDT) system based on Blockchain.On the other hand, there have been studies attempting to define the core infrastructure, tools, and capabilities of platforms to develop Digital Twins. As defined by[37], Digital Twin platforms aim to provide the technical foundation for virtual modeling, data orchestration, and digital thread management required in Digital Twin initiatives. Multiple conceptual reference models exist, detailing potential components of Digital Twin platforms covering aspects such as physical counterparts, virtual models, connectivity, intelligence, and visualization, among others. [5], [38].

While logical representations are instructive, surveys of commercial platforms reveal differing priorities and configurations of key elements such as digital shadow maintenance, analytics engines, simulation services and front-end apps [11]. In addition, studies have identified several common Digital Twin platform capabilities. [39] discussed key services required in Digital Twin enabled smart manufacturing, including sensing, data analysis, modeling, simulation, and visualization. [5] reviewed core concepts and technologies behind Digital Twins, including system integration, simulation, machine learning, visualization and deep learning. [40] summarized developmental components of Digital Twins into four parts: Digital Twin modeling and simulation, data fusion, interaction, and service. Required features for Digital Twins such as interconnection, simulation models, data collection, and visualization were discussed by [41]. [38] and [42] reviewed Digital Twin capabilities which are defined and summarized in Figure1. While substantial research activity exists around conceptual Digital Twin platforms, architectures, and capability frameworks, a gap persists in empirical documentation and evaluation of specific platforms developed and deployed across industries. For all the prototyping and technical specification efforts, a systematic investigation into platforms supporting operational Digital Twin initiatives remains lacking. This limitation not only hampers the benchmarking of the

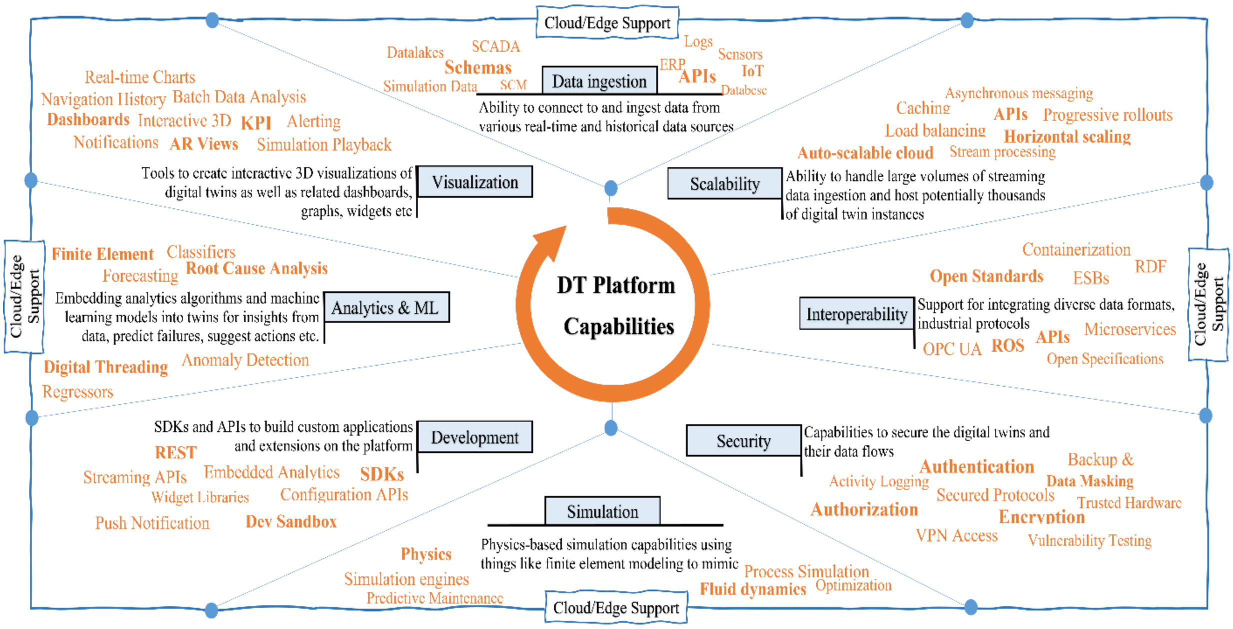

Figure 1 . Digital Twin platform capabilities

expansion of Digital Twin platforms adoption and deployment but also impedes the identification of obstacles and milestones crucial for guiding investment decisions. Asset owners, lacking evidence of platform viability and modernization pathways, face challenges in making informed trade-off decisions.

3 Data Overview

The Digital Twin platform dataset underpinning this research was compiled by drawing from secondary platform sources, press announcements, and providers' and users' websites. Structured information was captured for 18 unique Digital Twin platforms located in six different countries, covering details on the platform's launch year, core capabilities such as built-in security mechanisms and twin interaction methods, target use case, and roster of 58 solutions leveraging these platforms. Additionally, user community details were gathered related to leading industries and functional applications where available. Table 1 summarizes the findings and their definitions- the full data is available and will be provided upon request.

The dataset provides reasonable coverage across industry segments investing in Digital Twin, with over 40 industry segments identified including manufacturing, energy, healthcare, automotive, and construction. These major segments are located in 19 different countries. It is important to note that the depth of details on solutions varies considerably based on how much detail each provider or user provides for the solution they are using.

Table 1. Dataset summary

Data Attributes	Definition
Platform provider	Owner name and headquarter location
Launch year	Year when platform first released
Platform purpose	Primary functions and digital twin focus areas
Platform integration method	Integration classification
Twin interaction methods	IoT connectivity and data ingestion protocols
Security mechanisms	Data and processes security protocols and mechanisms
Platform users	Industries that the platform can be deployed
Current users' location	Countries that are using each platform
Digital Twin platform's Solutions	Names and descriptions of developed solutions
Solution focus	Solutions' purposes

4 Analysis and Discussion

Social Network Analysis (SNA) was employed to analyze the dataset using Pajek software. In this analysis, Digital Twin platforms, users' industry, security mechanism, twin interaction method, and users' location are modeled as nodes with edges defined based on stated collaborations, integrations, and deployments. Both visual and quantitative SNA techniques are applied to identify key patterns.

SNA yielded several insightful observations regarding the current state and trajectory of the Digital Twin ecosystem. As depicted in Figure 2 and indicated by Degree of Centrality (DoC) rankings, a select few platforms have emerged as most influential in shaping today's deployments. Azure Cloud (DoC: 18), IBM Cloud (DoC: 18), MindSphere (DoC: 17), and Vuforia (DoC: 17) are identified as the top platforms, experiencing significant most adoption across various industry verticals. The dominance of these mainstream platforms aligns with the finding that cloud-based (DoC: 8) and hybrid (DoC: 6) integration methods now prevail in how Digital Twin solutions leverage platforms.

Additionally, the SNA results identified key security and twin interaction mechanisms that are central to Digital Twin platforms. Authorization (DoC: 18), authentication (DoC: 14), and encryption (DoC: 10) emerged as the most common security mechanisms, while service APIs (DoC: 15), bidirectional synchronization (DoC: 13), and interface simulation (DoC: 13) lead in enabling integration and communication with physical assets. The widespread use of these platform-enabled capabilities emphasizes their significance in ensuring the usability and security of Digital Twin platforms. However, the network topology also revealed gaps in the adoption of these leading practices, particularly among Asian user organizations. Providing more implementation guidance and sharing best practice could accelerate the assimilation of platform services in these regions.

Moreover, examining the industry and geographic distribution of Digital Twin platform adoption adds value by identifying demand patterns. Manufacturing (DoC: 10), automotive (DoC: 8), energy (DoC: 7), and construction (DoC: 5) industries emerged as leading segments actively leveraging Digital Twin platforms. Furthermore, and as depicted in figure 3, the community detection analysis provides particularly useful insights into industry and location combinations that tend to utilize specific platform and mechanism combinations. For instance, MindSphere platform with Authorization and secured protocols, paired with Hybrid integration method, see adoption in construction and agriculture use cases across USA and Germany. These patterns suggest that specific platform configurations meet the needs of these industries and locations.

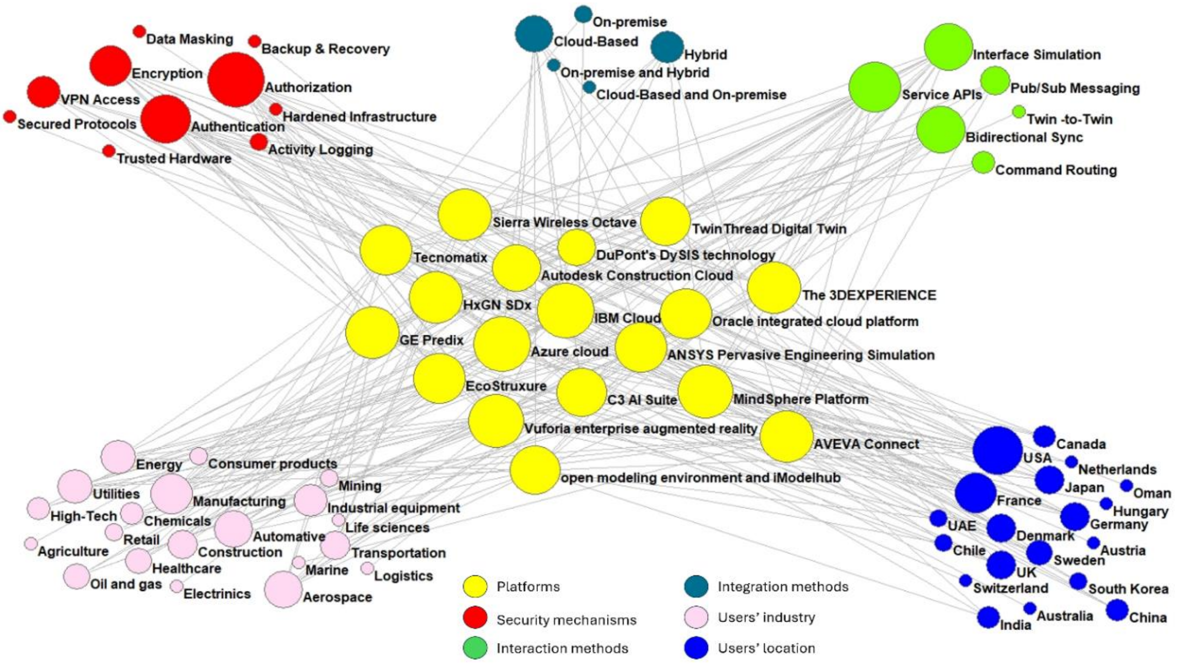

Figure 2. SNA results

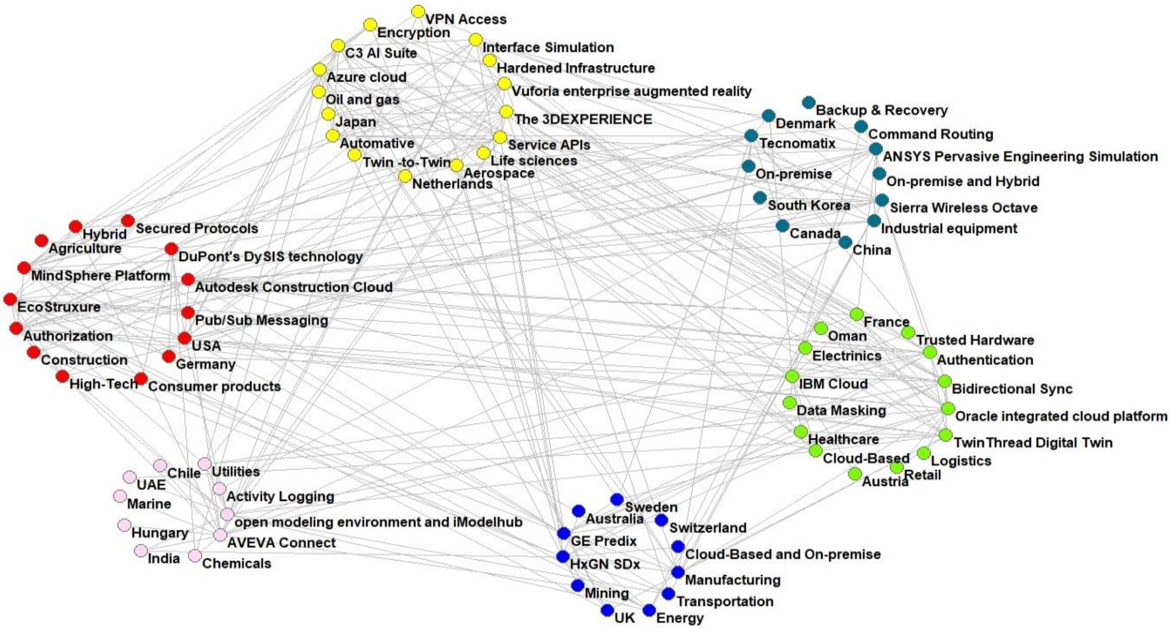

Figure 3. Community identification analysis

Finally, the temporal social network analysis indicated that the development and implementation of Digital Twin platforms have entered a phase of rapid growth and acceleration over the past three years. The increasing rate of participation across both supply and demand sides of the market signals the crossing of a tipping point. Digital Twin providers are developing various solutions with specific purposes, moving beyond isolated proofs of concept into scaling adoption across industries. The analysis of the range of solutions associated with major Digital Twin platforms revealed that the purpose of these solutions largely falls into five key categories: 1) detailed virtual modeling, 2) simulation and predictive analysis, 3) connectivity and data integration, 4) immersive interaction, and 5) lifecycle and change management. For example, solutions like CATIA, Creo, NX, OpenBuildings, and Unified Engineering provide sophisticated CAD and engineering environments to model highly accurate Digital Twin representations. Complementary simulation tools like SIMULIA, Discovery Live, Plant Simulation, and Twin Builder enable predicting real-world performance through digital prototypes. Solutions including IoT Hub, Watson IoT, and C3 IoT focus specifically on ingesting and managing streams of data from physical assets. Augmented and virtual reality solutions provide new ways of immersive interacting with Digital Twins on-site or remotely. Furthermore, solutions like Windchill, Teamcenter, and iModelhub help manage Digital Twin data and relationships throughout ongoing change.

While most platforms provide an integrated set of solutions spanning the five main areas, the analysis reveals some differentiation and specialization as well. For example, the ANSYS Digital Twin platform emphasizes simulation-centric solutions for digital mission engineering across complex systems. Autodesk brings generative design paired with construction site data flows. Azure offers cloud-native capabilities for scalable Digital Twin data and lifecycle management. Also, augmented reality leaders like Vuforia integrate immersive Digital Twin experiences as a key solution area. Observing these patterns provides perspective on the expanding functionality Digital Twin platforms now offer as enablers, spanning detailed modeling to operational connectivity to simulation-driven insights and beyond. Additionally, while Digital Twin platforms host an expanding roster of twin-enabled solutions, the depth of solution details wildly varies. Identifying use case patterns to determine which solutions best match the purpose will accelerate the large-scale adoption and implementation.

5 Conclusion

Numerous Digital Twin platforms, each designed for specific purposes, have been developed by providers globally. The comprehensive information gathered on these platforms and analyzed through SNA offers valuable insights into the current status, intentions, capabilities, and associated solutions of these platforms summarized as below:

- **Platforms:** SNA's analysis revealed that among these robust platforms, Azure Cloud, IBM Cloud, and MindSphere exhibit the highest centrality.
- **Platform users' industry:** When examining user industries across all platforms, Manufacturing emerged as the most prominent, followed by Automotive, Aerospace, and Marine, with Logistics and Agriculture being the least common industries.
- **Platform users' location:** In terms of geographic distribution of users, the USA takes the lead, followed by European countries, while Asian countries having the least widespread adoption.
- **Security mechanisms:** According to the SNA, Authentication, Authorization and Encryption represented the most widely implemented security mechanisms, whereas Data Masking, Secured Protocol, and Trusted Hardware ranked as less common.
- **Twin interaction methods:** As a crucial capability of Digital Twin platforms, Service APIs were the predominant method of twin interaction, whereas Twin-to-Twin approaches ranked as the least used.
- **Integration methods:** Regarding integration methods, Cloud-Based platforms were deemed the most probable, with combinations of On-Premise with Hybrid, as well as On-Premise with Cloud-Based, ranking as the least probable.

Additionally, within such analyses, the identification of communities in the established relationship network can offer valuable insights. Community detection revealed groupings that include at least one node of each type: platforms, security mechanisms, interaction techniques, integration approaches, probable industry adopters and locational distribution. Mapping these associations highlights the most relevant combinations of platform capabilities for specific industry applications and geographies. This community perspective informs strategic decisions in selecting appropriate platforms capabilities for given use case requirements. Moreover, individual platforms offer differentiated solutions that serve distinct purposes, grouped into five categories: detailed virtual modeling, simulation and predictive analytics, physical-to-digital connectivity and data integration, immersive interaction modes, and lifecycle and change management. This research also confirms accelerated growth and maturation within the Digital Twin platform landscape over the past three years.

Despite limitations such as potential geographical bias toward platform providers and constraints related to documentation availability, the current analysis expands visibility into the dynamics of the Digital Twin platform ecosystem. Moving forward, several facets warrant deeper investigation in future research. For instance, expanding sample diversity and analyzing fringe use cases in terms of industry vertical and regional adoption to spotlight capability gaps restricting implementation. Longitudinal monitoring of advancing functionality across simulation fidelity, automation sophistication and cloud orchestration flexibility would reveal comparative platform suitability rates. Finally, incorporating financial partnership ties and usage data can provide tangible indicators of real-world sustainability alongside technical capability. By blending functional, operational, and economic perspectives, evolving social network modeling and simulation techniques will empower stakeholders to chart technology maturation, predict partnership risks, and plan implementation timelines as industrial Digital Twins progress toward mainstream viability.

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