AI-Augmented Digital Twins in Large Industrial Companies: From Use Cases to Industrialisation

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Abstract. Digital twins in manufacturing are often presented as a basis for intelligent and autonomous operations. However, we still have limited understanding of how AI helps them move from passive representations to practical decision-support tools. Based on interviews with eleven large manufacturers and software suppliers, we examine how digital twins and AI interact in manufacturing settings. We identify eighteen empirically grounded use cases and industrialisation constraints, grouped into six themes: real-time decision support, operator guidance, simulation-based optimisation, AI-assisted model generation, data governance, and deployment constraints. Many initiatives were still at the idea, pilot, or prototype stage, with respondents highlighting fragmented data governance and limited cloud connectivity as key barriers to deployment. Our findings suggest a two-way relationship: digital twins can provide operational context for AI, while AI can extend the analytical and predictive capabilities of digital twins. By outlining both opportunities and limitations, we support decision-makers in assessing the realistic role of AI-augmented digital twins in digital transformation initiatives.

Keywords: Digital twins · Artificial intelligence · Intelligent Manufacturing · Smart Production · AI Use Cases · Industrial systems

1 Introduction

AI predictions and recommendations need operational context to be useful in manufacturing decisions. For digital twins, this context depends on the connection between the virtual representation and the physical system. Digital twins are often distinguished from digital models and digital shadows by their level of data integration [1]. Digital models have no automated data exchange, digital shadows receive one-way data flows, and digital twins involve bidirectional data flow [1]. Such connections help digital twins organise physical logic, operational history, and process meaning [2]. This creates a basis for AI-supported prediction, recommendation, and optimisation in production decisions [3–6].

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We use the term AI-augmented digital twin for digital twin initiatives that use AI. These initiatives may support model generation, simulation optimisation, decision support, or operational recommendations. Such systems may use AI to detect anomalies, optimise processes adaptively, or support operational decision-making [5, 6]. Unlike analytics tools that operate on raw sensor streams, an AI-augmented digital twin uses a structured model of processes, machines, and products. This structure helps AI interpret operational states in context [2]. At the same time, AI can turn historical patterns into forward-looking operational guidance [5, 6]. This suggests a possible two-way relationship between AI and digital twins, but how this relationship appears in industrial practice remains unclear.

In industrial practice, however, many AI-augmented digital twin initiatives appear to remain distant from this vision. They often remain visualisation tools in controlled pilots rather than becoming part of daily operational decision-making [7]. Although the AI–digital twin intersection has been widely conceptualised [8–11], much of the literature remains theoretical. There is still limited empirical evidence on how manufacturing companies are advancing in practice. In particular, we know less about whether AI-augmented digital twins move beyond pilots. We also know less about which conditions support scaling and how AI affects this process [10, 11].

The purpose of this study is to examine how AI shapes digital twin use cases in manufacturing and to identify the conditions that determine whether AI-augmented digital twins scale beyond pilot stages into operational use. We address this purpose through an empirical multiple-case study based on semi-structured interviews with representatives from eleven large manufacturing companies and software suppliers across eight industries. The guiding research question is: How does AI shape digital twin use cases and their industrialisation in large industrial companies?

This study contributes to the literature in three ways. First, it provides an empirical base of eighteen first-order observations on AI-augmented digital twins, covering both use cases and industrialisation constraints, organised into six themes and three aggregate domains. Second, it sheds light on the industrialisation gap by identifying data governance and cloud connectivity as important conditions for operational deployment. Third, it proposes a conceptual model of AI–DT interaction, showing how the two technologies can support and extend each other in industrial settings. Therefore, these contributions may help decision-makers assess which AI-DT use cases their current data and infrastructure can realistically support.

2 Theoretical Background

The digital twin concept has evolved since its early description as a virtual representation of a physical product [3]. Later work extended the concept to product design, manufacturing, service integration, and big data [4]. Systematic reviews have mapped the emerging intersection of digital twins and AI [5, 11, 12]. Machine learning, deep learning, and reinforcement learning are often identified as central AI paradigms in digital twin architectures [5]. Layered taxonomies now distinguish data-level, model-level, and service-level AI augmentation [6]. However, many studies still focus on conceptual models or proofs of concept [7]. This motivates our focus on the industrialisation gap.

As digital twins have added AI-based prediction, anomaly detection, and optimisation, the literature points to three functions. First, the digital twin as a reflective or mirrored model is sustained by continuous data flows between physical and virtual entities [2]. Second, the digital twin as an inference engine builds on this by using machine learning to automatically recalibrate the model and generate predictions or anomaly signals [8, 11]. Third, a digital twin can support scenario exploration by using AI to identify suitable production settings within defined limits [13]. This distinction helps explain how the literature understands the evolution of digital twins.

As digital twins take on more active roles, such as generating recommendations or triggering adjustments, human–AI complementarity has attracted increasing attention [14–16]. A key challenge is the tension between automating tasks and supporting human decision-making. Prior work argues that systems should be designed for complementarity rather than substitution [14]. Prior work on AI implementation suggests that many successful applications augment rather than replace human capabilities [15]. This preserves operator accountability while reducing cognitive load. Task-level conditions also shape when AI-based augmentation adds value [16]. Accordingly, this work suggests that the organisational setting strongly shapes how an AI-augmented digital twin is implemented and used [17].

Digital twin simulations are increasingly explored for AI training, including reinforcement learning for production scheduling [18] and agent-based policy learning before physical deployment [12], while AI-assisted model development may reduce modelling effort [19]. Yet industrialisation depends on data and organisational readiness: data-driven decision-making requires complementary capabilities [20], and heterogeneous data provenance, change management, and production misalignment continue to constrain scaling from pilots to operational use [1, 10, 21]. The specific challenges of industrialising AI-augmented digital twins remain underexplored.

3 Research Method

3.1 Research Design

A multiple-case study design was selected because the research question concerns how digital twins evolve through AI integration. This phenomenon requires interpretive depth rather than statistical measurement. Semi-structured interviews allowed informants to describe their work in their own terms. They also enabled comparison across cases [22]. We follow a multiple case logic [23], aiming for analytical rather than statistical generalisability [24].

3.2 Sampling and Data Collection

We selected cases through purposive sampling [25], targeting organisations actively engaged with digital twin technology. Each organisation had to meet three criteria. It had to operate at industrial scale, have at least one digital twin project beyond planning, and include a respondent involved in digital twins, AI, simulation, or manufacturing digitalisation. Eleven organisations participated across eight sectors (Table 1). Nine of the cases are from manufacturing companies; two are software suppliers included to capture both the user and the technology provider perspective on industrialisation and cross-industry patterns.

Table 1. Sample overview

Firm	Industry	Employees	Respondent Role
A	Automotive	>10,000	Head of Digital Twin
B	Automotive	>10,000	AI Lead, Manufacturing
C	Aerospace	>10,000	Digitalisation Manager, DT Lead
D	Heavy Industry	>10,000	Director of Digitalisation; Automation and Simulation Manager
E	Electronics	5,000–10,000	AI Lead; Engineering Manager
F	Energy Intensive Manufacturing	1,000–5,000	Technology Specialist, Flow Simulation
G	Pharma/Medical	>10,000	Digital Manufacturing Lead
H	Batteries	1,000–5,000	Simulation Specialist
I	Software Supplier	1,000–5,000	Product Manager, DT
J	Software Supplier	5,000–10,000	Product Developer, DT
K	Industrial Equipment	>10,000	MES Product Owner, Product Information Specialist

We conducted semi-structured interviews between early 2025 and early 2026. The interview protocol was developed by drawing from approaches in operations management and digital twin research [22] and covered five domains: (1) current digital twin development and scope, (2) AI applications within or alongside the digital twin, (3) data infrastructure and governance maturity, (4) barriers and enablers for scaling beyond pilot, and (5) anticipated developments. Interviews ranged from 45 to 90 min, were

audio-recorded with participant consent, and transcribed verbatim. Preliminary findings were discussed in a workshop with industry participants to validate the interpretation. Because the study relies on expert interviews, the findings may reflect respondent interpretation; this was mitigated by asking for concrete examples and by comparing patterns across cases.

3.3 Analysis

We analysed transcripts using thematic analysis following Braun and Clarke [26], which is well suited to identifying patterns across qualitative datasets when the research aims to capture experiential meaning. The analysis proceeded through five phases: familiarisation with the data, generation of initial codes, development of candidate themes, review and refinement, and final definition. The resulting structure (Fig. 1) includes eighteen first-order codes organised under six themes and three aggregate dimensions. The coding was conducted by the first author and iteratively refined through repeated comparison with the interview transcripts. Codes were developed from concrete statements about AI-augmented digital twin use cases, enabling conditions, and industrialisation constraints, and were then grouped into themes and aggregate domains. The interpretation was discussed in a workshop with industry participants as a form of validation. As a qualitative multi-case study, the analysis supports analytical rather than statistical generalisation.

4 Empirical Findings

4.1 Themes of AI-Augmented Digital Twin Capabilities

Figure 1 summarises the eighteen first-order observations, grouped into six themes and three aggregate domains. Across the cases, AI affected digital twin use by supporting operational decisions, accelerating model creation and simulation, and exposing the data and deployment conditions needed for industrialisation.

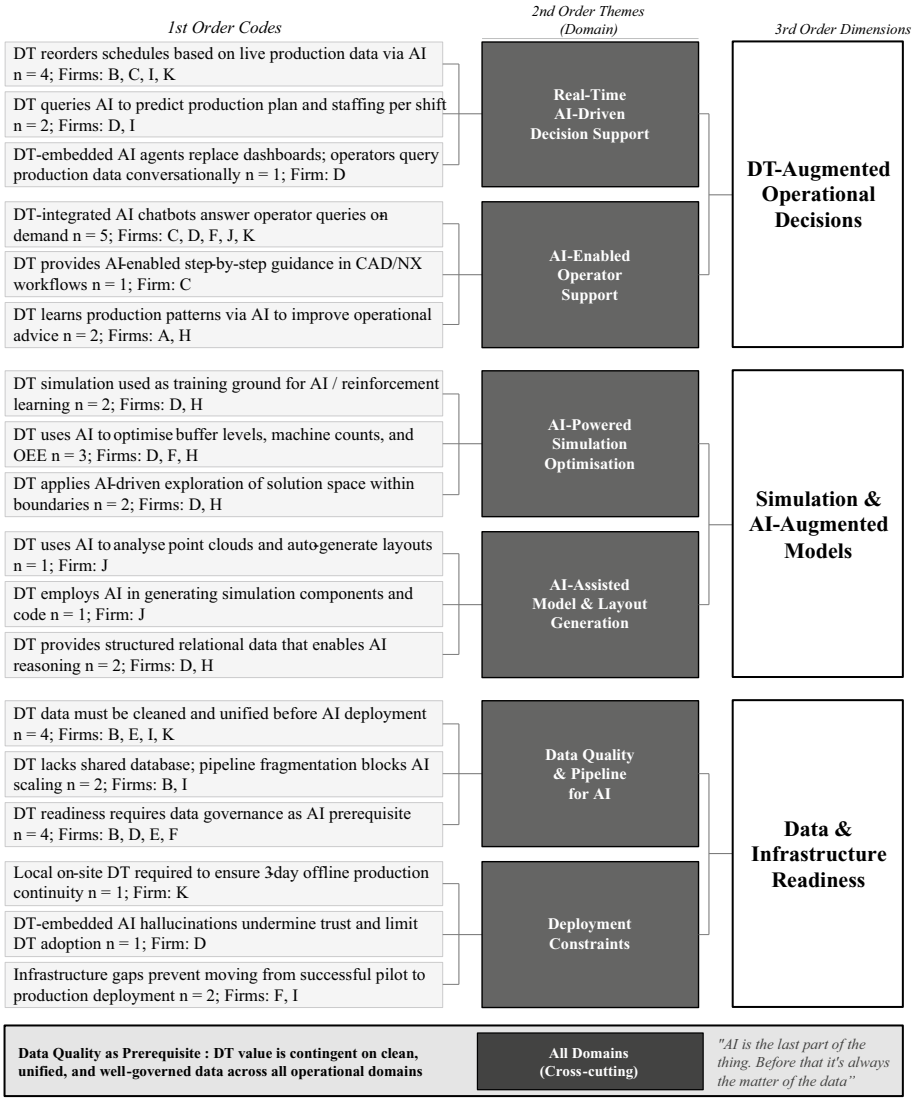

Fig. 1. Functional taxonomy of AI-augmented digital twin use cases and industrialisation constraints. Note: n indicates the number of distinct firms in which the first-order code was observed. Firm letters correspond to the anonymized firms in Table 1.

4.2 Real-Time Decision Support

> "The real benefit is when you really act on the data in real time. If the digital twin should be successful, we should have it connected to the AI." (Respondent Firm B)

Respondents saw real-time decision support as one way for AI to extend digital twins in production. They saw the digital twin not only as a monitoring layer, but also as

a support system for production decisions. Participants discussed examples such as schedule adjustments based on live data, staffing predictions when only part of the production plan is available, and conversational interfaces for querying production data. These examples suggest a shift from using the digital twin mainly for analysis toward using it as real-time decision support. At the same time, respondents also noted that this type of use case depends heavily on data availability, system integration, and reliable infrastructure.

4.3 Operator Support

> "The new AI assistance is like 'oh you forgot this step' or 'you need to do this first'… especially in the more complex systems it can be quite helpful." (Respondent Firm C)

Respondents also described AI-supported guidance as a possible extension of digital twin use. Examples included chatbots trained on help files, context-aware prompts in engineering software, and assistants that remind users about missing procedural steps. These applications were framed less as replacements for operator or engineering expertise and more as support for users working with complex systems. Participants suggested that this type of support could make digital twin tools easier to use, especially for tasks that are performed infrequently or require knowledge across several systems. Compared with real-time decision support, this was described as a more accessible entry point for AI use, although the examples were still mainly exploratory.

4.4 Simulation-Integrated Optimisation

> "The exploration of the solution space within different boundaries, if you want to reduce cost, then AI together with simulation will be very powerful." (Respondent Firm H)

The interviews show that simulation-based digital twins can help firms test production scenarios before changing the real system. Respondents mentioned machine settings, buffer levels, and scheduling rules as examples. AI and optimisation methods can compare many alternatives faster than manual analysis. At the same time, respondents stressed that experts still need to define the limits, targets, and acceptable outcomes. AI then helps search for useful options within those limits. However, this domain requires integrated production data. The quality of simulation-based exploration depends on the quality of the underlying data infrastructure.

4.5 AI-Assisted Model Generation

> "You could make a point cloud, drag and drop it, and let AI analyse what is in the point cloud and just replace it with simulation components. So you just get your layout for free." (Respondent Firm I)

In this theme, respondents described how AI could reduce the effort needed to build or update digital twin models. One example was the use of point-cloud data to identify physical objects and replace them with simulation components. Participants also mentioned possible future uses of AI for generating simulation logic or model structures. These examples suggest that AI may support parts of the model-building process, especially when the input data are available in structured or semi-structured form. Respondents generally viewed this domain as less dependent on continuous real-time connectivity than real-time decision support, since model generation can often be based on offline datasets or point-cloud scans.

4.6 Data Governance

> "AI is the last part. Before that it's always the matter of the data, how much data is clean and prepared." (Respondent Firm E)

Data governance shows as a condition that shaped whether AI-augmented digital twin use cases could move beyond pilots. Several respondents described pilots that worked in controlled settings but became difficult to scale. The difficulty increased when data had to be collected across systems, departments, or sources. The main challenge was rarely described as the AI model itself. Instead, respondents pointed to data quality, fragmented pipelines, unclear ownership, and limited integration across systems. The interviews suggest that data collection, integration, and governance need to be established before AI can be meaningfully embedded in digital twin applications. In some cases, respondents noted that organisations focused on AI before the underlying data infrastructure was ready.

4.7 Deployment Constraints

> "A lot of the AI functionality requires a connection to the cloud. We have a rule: we need to be possible to run production for at least three days without any Internet connection." (Respondent Firm K)

Respondents described three deployment constraints that can limit the transition from pilot to operational use. The first was connectivity dependency. Some AI applications assume cloud access, while some production environments must continue to run without internet connectivity. The second was reliability and trust. Respondents noted that unreliable AI outputs, including hallucinated or incorrect responses, could reduce confidence in AI-supported recommendations. The third was infrastructure immaturity. Several respondents described missing deployment pipelines, unclear ownership, or limited operational support as barriers to scaling AI-augmented digital twins beyond pilots.

5 Discussion

This section synthesises the empirical findings into a conceptual model that explains how AI reshapes the role of digital twins in industrial contexts. While Fig. 1 presents the empirical coding structure, Fig. 2 brings these elements together into three domains,

namely creation and maintenance, scenario exploration, and real-time inference. Rather than representing separate applications, these domains illustrate how AI interacts with the digital twin by contributing to its construction, by enabling the exploration of possible system states, and by supporting decisions based on its real-time condition. The model also suggests that the challenge of industrialisation lies not in any single domain, but in the extent to which these activities can be supported by mature data practices and appropriate architectural choices, as many firms expect AI capabilities to run at the edge in order to keep data within production systems while still enabling operational use.

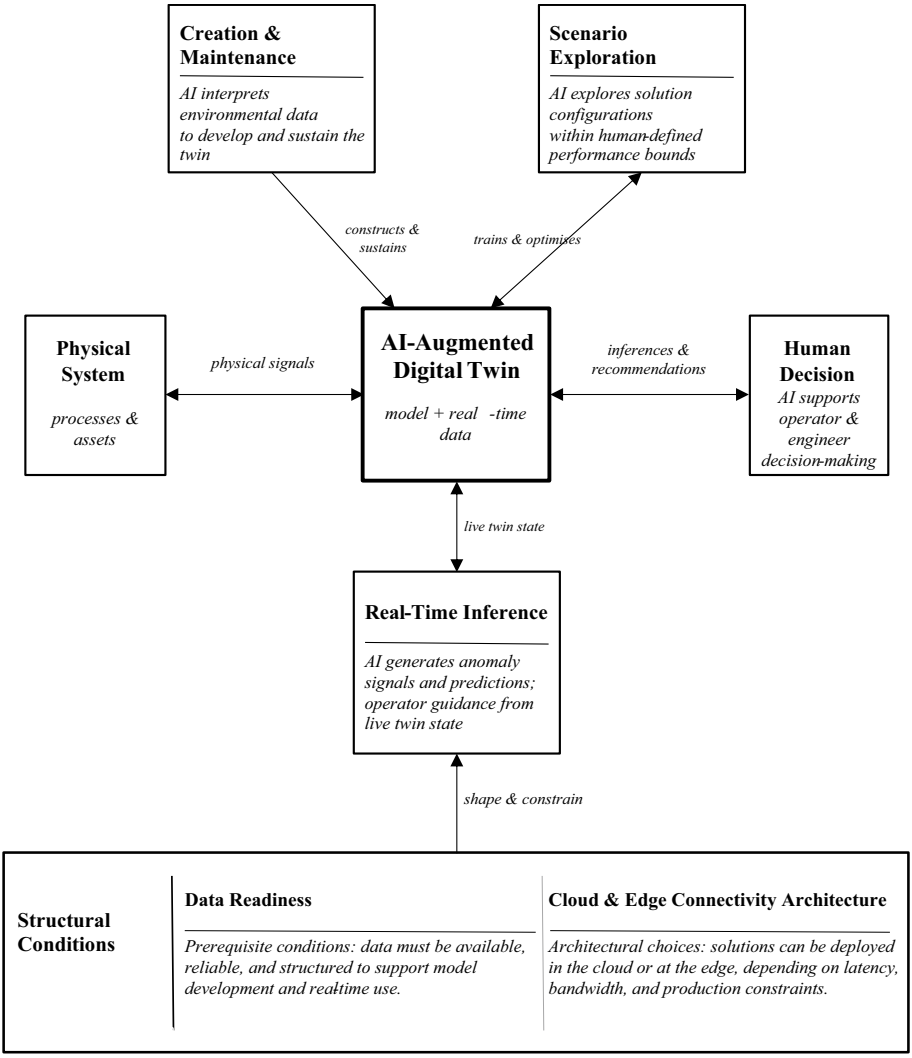

Fig. 2. Conceptual model of AI augmented digital twins

5.1 Three Application Domains of AI-Augmented Digital Twins

The first domain, creation and maintenance, concerns the digital twin's role in its own development. In this domain, AI can support layout generation, model recalibration, and simulation logic. This extends digital twin-driven smart manufacturing reference models [27] and builds on the distinction between digital models, digital shadows, and digital twins as levels of data-flow integration [1]. Our findings suggest that AI may extend digital twin development beyond passive synchronisation by supporting model generation, recalibration, and updating activities. This creates a basis for examining AI and digital twins as mutually dependent technologies in industrial settings.

The second domain, scenario exploration, describes how digital twin models can be used as environments for AI-supported experimentation. In this domain, respondents described a human role focused less on manually evaluating alternatives and more on defining the constraints within which AI or optimisation methods operate, consistent with the augmentation logic described by Raisch and Krakowski [14].

The third domain, real-time inference, includes real-time decision support and operator guidance. It appears to be the most operationally demanding domain because the digital twin must generate predictions, anomaly signals, guidance, and recommendations in real time. Respondents did not describe autonomous production decisions as established practice. Instead, the AI-augmented digital twin recommends while the operator decides. This aligns with Bughin et al. [28], who argue that firms can retain human decision authority while automating analytical tasks. Trust also plays a central role because decision-makers must judge when AI recommendations are reliable.

5.2 Structural Conditions and AI–DT Interaction

Data readiness was a recurring condition across the three domains. Digital twins may use data from sensors, ERP systems, manual records, and simulation outputs. In practice, these data are often stored in different systems and owned by different departments. This makes data integration both a technical and organisational challenge. The interviews show that AI-augmented digital twins could only scale beyond pilots when firms had established stable data pipelines and clear data ownership. When these conditions were missing, prototypes could work in controlled settings but failed to become part of repeated operational use because data had to be manually extracted, cleaned, or reconciled across systems. Cloud architecture adds another constraint. Some AI applications assume continuous cloud access, while some production environments must continue operating without internet connectivity for extended periods. Qi and Tao [29] propose edge-fog-cloud architectures as one possible response to this challenge. However, respondents did not describe such architectures as established practice in the studied firms. This points to a gap between architectural concepts in the literature and current industrial implementation.

The findings also point to a two-way relationship between AI and digital twins. The digital twin can make AI more useful by providing structured representations, process logic, and operational history that raw sensor data alone may not offer. In turn, AI expands what the digital twin can do, from model development to scenario exploration and real-time inference. This suggests that the digital twin is not only a passive setting for AI, but a structured system that can both support and be extended by AI.

5.3 Industrialisation Gap

We define the industrialisation gap as the distance between a demonstrated AI-DT prototype and repeated operational use in daily production, planning, or engineering decisions. A use case was treated as operational only when respondents described recurring use by practitioners beyond a limited pilot, test environment, or one-off demonstration. In the interviews, early-stage initiatives were described as ideas, feasibility tests, or limited prototypes with restricted users, data scope, or site coverage.

The findings suggest that the three domains require different levels of readiness. Creation and maintenance can function with limited data connectivity, as AI-assisted model generation can operate on point-cloud scans and offline datasets. Scenario exploration requires more integrated data, but it can often tolerate batch processing. Real-time inference, by contrast, depends on governed data pipelines and low-latency connectivity that were not yet widely established across the cases. Errandonea et al. [30] observed a similar pattern in maintenance-oriented digital twins, where advanced predictive functions presupposed data infrastructure that many organisations had not yet established. Across our cases, real-time AI-augmented digital twin initiatives that were tested in a lab or limited production area often struggled to move into repeated operational use when data governance and connectivity constraints remained unresolved. The implication is that organisations may benefit from matching AI-augmented digital twin use cases to their current readiness. For managers, this means starting with offline model generation, moving next to batch-based scenario exploration, and pursuing real-time inference only when governed data pipelines and robust connectivity are in place.

6 Conclusions

This study examined how AI-augmented digital twins are developing in large industrial companies and why many initiatives remain difficult to scale. While prior work has described the technical potential of AI and digital twins, this paper provides empirical evidence on use cases, industrialisation constraints, and barriers to operational deployment.

This study contributes to the literature in three ways. First, it identifies eighteen first-order observations on AI-augmented digital twins, covering both use cases and industrialisation constraints, and organises them into six themes and three domains. Second, it shows that many initiatives in the studied cases remained at concept or pilot stage because fragmented data governance and connectivity constraints limited operational deployment. Third, it develops a more practice-based understanding of AI-augmented digital twins by showing that their value depends not only on technical functionality, but also on the organisational and infrastructural conditions required for repeated operational use. In our cases, the main challenge was not a lack of promising use cases, but the readiness needed to put them into operation.

Researchers and practitioners can use the findings as a starting point to assess the potential and limits of AI-augmented digital twins in digital transformation roadmaps. The use case taxonomy can serve as a diagnostic tool for organisations seeking to understand which AI capabilities their digital twin infrastructure can realistically support. The industrialisation gap analysis can also help prioritise investment in data governance

and connectivity as prerequisites for operational use. The findings further suggest that technical readiness alone is not sufficient. As AI-augmented digital twins move closer to operational decision support, organisations also need to consider how users evaluate, trust, and act on AI-supported recommendations.

The study has limitations that open directions for future research. The sample focuses on large firms and software suppliers, so future studies could examine whether the same patterns apply in small and medium-sized firms. The data are interview-based and may reflect respondent interpretation; longitudinal studies could therefore follow AI–DT pilots as they move, or fail to move, into operational use. Further work should also examine governance models for data ownership, model validation, and accountability for AI-generated recommendations. These efforts can support future work on moving AI-augmented digital twins from isolated pilots toward trusted, governed, and scalable decision-support systems.

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