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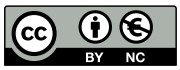

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Interconnected digital twins and the future of digital manufacturing: Insights from a Delphi study

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Abstract

Digital twins (DTs) are virtual representations of real-world entities like production assets, processes, or products. They are updated at a defined fidelity and frequency along the entire life cycle from development and engineering over the production or implementation of a product or process until its usage stage. Interconnected digital twins (IDTs) are DTs shared and connected across organizations with the objective to create holistic simulation and decision models of an entire physical system. In this paper, we investigate how IDTs shape future digital manufacturing scenarios and impact innovation management. We present the results of a real-time Delphi study, analyzing quantitative and qualitative estimates on a set of 24 projections, forecasting the future of digital manufacturing with a projection horizon towards 2030. Using this data and 22 additional use cases of IDTs in manufacturing companies, we present a baseline scenario where our Delphi panel reached a consensus, representing a likely future of digital manufacturing in 2030. By analyzing projections where our expert panels' evaluations vary widely, we identify key design decisions that may impact innovation management along the dimensions of variation, choice, and control in digital manufacturing. We explain how IDTs will impact external knowledge inflows, the emergence and governance of industrial data spaces, and the potential of data-driven and AI-enabled applications for prediction and regulation to drive better decision-making and continuous innovation.

KEYWORDS

digital manufacturing, digital twin, industry 4.0, platforms

1 | INTRODUCTION

The evolving fourth industrial revolution (Industry 4.0) is currently reshaping manufacturing industries with a broad deployment of new digital manufacturing technologies. By integrating information technology and sensors into mechanical systems, machines become able to collect and share data in ways not previously possible (Appio et al., 2021; Björkdahl, 2020). A core element of these cyber-physical systems are *digital twins* (DTs), that is, real-time representations of industrial assets and processes, synchronized at a specified frequency and fidelity along

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the life cycle (Digital Twin Consortium, 2020). In manufacturing, DTs access real time and historical data of products, machines, or entire facilities, and use this data in simulation models to enable more effective decision-making, optimize manufacturing systems, or develop new products and services (Fukawa & Rindfleisch, 2023; Tao et al., 2018). For instance, Bridgestone uses DTs to simulate the performance of its manufactured tires during usage by utilizing real-time data from actual vehicles, enabling the development of a new business model in the form of a price-per-kilometer service (Parrot et al., 2020).

Still, to date, DTs have been mostly isolated in functional silos and limited to specific phases of a product's lifecycle (i.e., DTs of an object's development, production, or usage stage). Firms such as Siemens extend this understanding by using DTs to interconnect and integrate data and analytics from different production resources into one data platform. The interconnection of DTs creates a single source database, which can be utilized to build shared data models for comprehensive real-time simulations across all phases of the product and factory lifecycles (Stark, 2022). The concept of *interconnected digital twins* (*IDTs*) refers to a network of virtual representations of physical objects or systems (twin of twins) to communicate and exchange data across lifecycles in real time and optimize performance and decision-making through simulation models on the system level (Redeker et al., 2021; Silva et al., 2022). IDTs serve as a central element in digital manufacturing by aggregating, integrating, and sharing data and models to enable advanced simulations throughout the product and production process lifecycle (Stark, 2022; West et al., 2021). While being accessible to multiple players within an industrial ecosystem, IDTs allow complementors to use them in combination with their data and models to develop complementary applications. Subsequently, as part of IDTs, simulation models become more comprehensive and meaningful for managing innovation activities (Redeker et al., 2021; Silva et al., 2022; Tao et al., 2018).

However, research lacks implication on how IDTs impact the amount and quality of external knowledge inflows into the innovation process while governing the resulting openness (Michael et al., 2022; West et al., 2021). IDTs build on the idea of open data exchange between all connected entities following a platform logic (Gawer, 2014; Xu et al., 2020) to create value and drive innovation jointly (Redeker et al., 2021; Silva et al., 2022). But, data openness implies that manufacturers surrender control over their data and its resource advantages (Alexy et al., 2018). Such a decision is challenging for most established firms and causes an inherent tradeoff between data openness and knowledge protection (e.g., Laursen & Salter, 2014; Moschko et al., 2023; Parker & van Alstyne, 2018; Stanko et al., 2017). Hence, exchanging data through IDTs among different actors poses new challenges and uncertainties (Fuller et al., 2020; Michael et al., 2022).

Companies also face uncertainties about the effects of IDTs on their business model, or how IDTs can become drivers for business model innovation (Stark, 2022; Xu et al., 2020). So far, it is uncertain how IDTs can overcome some of the limitations that humans face in innovation management, such as information searching, processing, and evaluation enabling data-driven decision-making while collaborating and cocreating across different domains and external stakeholders (Michael et al., 2022; West et al., 2021). With our study, we aim to contribute to a better understanding of how IDTs impact future digital manufacturing and innovation. The following question guided our research: "How do IDTs shape future digital manufacturing, what are the opportunities and challenges of IDTs, and what are the consequences for managing innovation?"

Our study uses a real-time Delphi study approach (Gnatzy et al., 2011; Gordon & Pease, 2006) to identify future scenarios for digital manufacturing enabled by IDTs with a projection horizon towards 2030. Based on

Practitioner points

- The paper presents the results of a Delphi study forecasting the future of digital manufacturing with a projection horizon towards 2030.
- Based on the assessments of 35 international experts from industry and academia, we derive a base scenario indicating that future digital manufacturing is likely to be (1) decentralized in the structure of its technical data exchange, (2) transparent to increase environmental sustainability, (3) automated through AI-assisted decision-making, and (4) outcome-oriented through subscription models enabled by real-time bidirectional data flows.
- A core technology of future digital manufacturing systems is interconnected digital twins (IDTs), understood as a network of virtual representations of physical objects or systems to communicate and exchange data across lifecycles in real time and optimize performance and decision-making through simulation models on the system level.
- A complementary analysis of 22 use cases derives a set of design choices that can help overcome the challenges posed by IDTs and capture the value promised by this new technology.

the assessments of 35 international experts from industry and academia on a set of 24 projections, we analyzed 1930 ratings about the likelihood of occurrence and the firm impact for these projections and 629 qualitative comments providing a rationale for their estimates. As a base scenario, our analysis indicates that future digital manufacturing is likely to be (1) decentralized in the structure of its technical data exchange, (2) transparent to increase environmental sustainability, (3) automated through AI-assisted decision-making, and (4) outcome-oriented through subscription models enabled by real-time bidirectional data flows. IDTs are a core enabler and consequence of the scenario. Complementing this base scenario, our analysis also identifies how specific design choices for IDTs yield consequences for managing innovation in future digital manufacturing. To investigate how these design choices impact innovation management, we further utilize insights from 22 use cases that complement our Delphi study. Overall, our study contributes to a better understanding of the impact of IDTs on the management of innovation for digital manufacturing and explores a set of design choices that can help to manage the challenges resulting from IDTs to capture the value this new technology promises.

2 | TECHNICAL AND THEORETICAL BACKGROUND

2.1 | Development of the DT concept

The engineering and IS literature have already covered the DT in some detail (Redeker et al., 2021; Tao et al., 2018). From this literature, we can distinguish three development levels of DTs: discrete, composite, and interconnected DTs, mirroring a changing understanding from their closed and silo-based local application towards system integration and finally the open and interconnected utilization of DTs in industrial ecosystems (Fukawa & Rindfleisch, 2023; Gartner, 2019; West et al., 2021). At the first level, discrete DTs are used to monitor and optimize the performance of individual products or equipment within a firm's value chain. At the second level, composite DTs integrate discrete DTs with other external data sources to simulate and predict the future behavior of an entire physical system. Composite DTs provide a complete digital footprint of an industrial asset, extending the traditional product lifecycle management concept from the design stage to its entire lifecycle (Gartner, 2019; Tao et al., 2018).

At a third development level, DTs are connected and shared across different actors and organizations. The simulation models underlying these *IDTs* become more meaningful when DTs of different actors are combined, but also when discrete or composite DTs are utilized by different actors from different perspectives (Michael et al., 2022; Redeker et al., 2021; Silva et al., 2022). IDTs enable the usage and commercialization of vast amounts of heterogeneous data across organizations in all stages of a product's life cycle from development and production to usage, service, and recycling. This triggers the development of new forms of digital platforms (Redeker et al., 2021). IDTs establish cross-company *data spaces* that link classic data silos across organizational boundaries (Otto, 2022; Silva et al., 2022). A data space describes the relationship between partners who adhere to a commonly agreed-level set of standards and guidelines about data storage and sharing within one or many industrial ecosystems (Braud et al., 2021; Otto, 2022). A central idea of the data space concept is that data is not stored centrally, but rather at the source. Thus, they are only transferred through semantic interoperability as necessary. Supported by artificial intelligence (AI) and machine learning, new insights can be created (Cappiello et al., 2020).

The German Railway (Deutsche Bahn) is currently exploring these virtual models of complex, interconnected entities (e.g., a composite DT of an entire drivetrain of a train that is shared with the trains' manufacturer, local operators of maintenance centers, and Deutsche Bahn's operation center). IDTs monitor operations of rail infrastructure to optimize the efficiency of its deployed resources. Thereby, they were able to improve the punctuality rate of trains while reducing maintenance and manufacturing costs of infrastructure assets. At the same time, Deutsche Bahn builds a data space (its Digital Mobility Twin Platform) to model multimodal means of transport by aggregating composite DTs from its own infrastructure, but also from complementors (like bus companies) and travelers to recommend the best mode of transport. The objectives of IDTs are better data-driven decision-making to achieve higher-level performance across organizations and innovate the underlying manufacturing of railway infrastructure (Deutsche Bahn, 2020).[1]

2.2 | IDTs, digital platform design, and innovation in manufacturing

IDTs demand that established firms develop a new understanding of value creation and value capture in digital manufacturing to capture their future opportunities

[1]In a further development, IDTs could become virtual representations of entire meta-organizations across corporate boundaries to simulate and steer cross-organizational collaboration and cocreation (West et al., 2021). This *DT of organizations* is primarily discussed in the context of smart cities as "DT of a city" (Gartner, 2019). However, this extended view is out of this article's focus on digital manufacturing systems.

(Silva et al., 2022; West et al., 2021). The sharing of knowledge, models, and data across all relevant domains within and between manufacturing firms and their users is commonly seen as a core element of the next generation of digital manufacturing. Different forms of digital platforms facilitate this exchange and knowledge sharing (Björkdahl, 2020; Jovanovic et al., 2021). These platforms act like an operating system that enables application programs to read data from and send control signals to various devices based on standardized internet technologies. IDTs become a new core element for these digital platforms (Hoffmann et al., 2019; Silva et al., 2022).

This development corresponds to the larger shift to digital, platform-based business models that we can observe in many sectors today (Redeker et al., 2021; Silva et al., 2022; Xu et al., 2020). Since the early 2000s, the industrial organization literature has begun to develop theories on platforms, also referred to as two-sided markets or multisided platforms (Cennamo, 2021; Otto & Jarke, 2019). Platforms connect multiple sides to enable transactions or foster innovation between different types of users who could not otherwise interact with each other. To do so, platforms coordinate the network of users (customers) and providers (complementors). Together, they build an ecosystem consisting of a central platform with multiple peripheral firms connected to it (Cennamo, 2021; Jovanovic et al., 2021). Hence, platforms are a new form of organization that increases the complementarity of assets to better create and commercialize innovation (Gawer, 2014; Parker & van Alstyne, 2018). The provision of a core technological architecture enables other companies to build their innovation capabilities and develop new products and services as complementary assets while the focal firms can innovate and extend the functionality and reach of the platform's core technology to end users (Cennamo, 2021; Jovanovic et al., 2021).

Following Gawer (2014), platforms are designed through the configuration of four attributes, *interfaces*, *accessible capabilities*, *organizational form*, and *governance*. The analysis of IDTs can be structured along with these four attributes (see Table 1). Utilizing DTs across organizational borders can yield new dimensions of industrial value creation and thus innovation through digital platforms when the right *interfaces* are designed, required *capabilities* are accessible, a specific *organizational* structure is established, and an adequate *governance* mode is in place that is accepted by all members of the platform ecosystem (Gawer, 2014; Silva et al., 2022; Xu et al., 2020).

The rise of IDTs creates challenges in traditional business-to-business relationships in vertically integrated, rigid supply chains characterized by asset-specific and process-specific investments, as typical for industrial

TABLE 1 Influence of digital twins structured around platform attributes of Gawer (2014).

Platform attributes	Influence of interconnected digital twins (IDTs)	Core references
Interfaces	Interfaces address both human-machine interfaces (HMI) and machine-to-machine interfaces (APIs), which are core enablers for IDTs. Externally, the openness of an API is a key design factor of digital manufacturing platforms. Internally, HMI captures layers between a human operator and a manufacturing system from a cognitive and spatial dimension.	Damjanovic-Behrendt & Behrendt, 2019; Michael et al., 2022; Piller & Nitsch, 2022; Stark, 2022; Xia et al., 2021
Accessible capabilities	Capabilities refer to the organizational ability to access new skills and external knowledge. IDTs offer opportunities in collaborative work environments and offer increased efficiency, innovativeness, and sustainability in industrial production.	Michael et al., 2022; Redeker et al., 2021; Silva et al., 2022; West et al., 2021
Organization	Organization embodies the effect of introducing IDTs with their automation possibilities (e.g., through artificial intelligence) on work organization, hierarchies, and human-machine interactions in digital manufacturing.	Brauner et al., 2020; Dellermann et al., 2019; Fuller et al., 2020; Piller et al., 2022; Xia et al., 2021
Governance	Governance refers to the impact of IDTs on the governance structures of manufacturing ecosystems. A particular focus is on collaborative value creation (innovation) and capture (commercialization), that is, how different participants of data spaces can profit from their contributions, and inquiring about the rules and regulations for data exchange via IDTs across organizational boundaries.	Cappiello et al., 2020; Otto, 2022; Silva et al., 2022; Xu et al., 2020

manufacturing firms today (Fuller et al., 2020; Michael et al., 2022). IDTs establish a different logic of value creation and innovation by connecting multiple sides of the market, including competing actors. While some firms might profit from such collaboration in terms of increased innovativeness, the competitive advantage of others may shift from the machine (hardware/product) to the data (virtual/service) layer. This shift creates uncertainty about the future outcome and impact of DT technology and could negatively affect firms without continued data access (Michael et al., 2022; Redeker et al., 2021; West et al., 2021).

Our research objective is to show how the implementation of IDTs will shape future digital manufacturing and its consequences for innovation management. Given the high degree of environmental and technological uncertainty resulting from system changes imposed by IDTs, we want to derive reliable scenarios that predict these consequences. The Delphi method has been established in the technology management literature as a systematic and holistic approach to develop different scenarios for such research questions (Schoemaker, 1995).

3 | RESEARCH METHOD

We employ various methods to analyze the implications of IDTs on innovation management. Our real-time Delphi study included projection development workshops, a survey with academic and industry experts, and the development of a consent and dissent scenario. Complementing the Delphi, we analyze a large sample of industrial use cases of DT technologies to gain insights into pioneering applications of IDTs in digital manufacturing today and to better illustrate the different future scenarios. Table 2 provides an overview of our methods, indicating our approaches (*how*), the participants involved (*who*), the outcome, and the intended purpose of each step.

3.1 | Real-time Delphi

Technological forecasting methods are an established methodology in technology management (Beiderbeck et al., 2021; Linstone & Turoff, 2002). Following common practice, we drew on expert assessments to reflect the diverse set of disciplines involved in the design, development, and deployment of DT technologies and used the Delphi method as a proven technique to structure complex opinions from experts (Beiderbeck et al., 2021). Building on the idea of "judgmental forecasting" (von der Gracht & Darkow, 2010), Delphi studies are constructed in an interactive multi-round format, conducted anonymously, and in written form. The main part consists of the evaluations of statements about the future, so-called projections. We chose a *real-time Delphi* approach, originally developed by Gordon and Pease (2006) and improved by Gnatzy et al. (2011). It uses an online interface to make the process more interactive and collaborative by providing instant feedback to participating experts. Studies have shown the efficacy of real-time Delphi approaches to be equal to the conventional method relying on sequential offline rounds while providing more qualitative insights (e.g., Markmann et al., 2013). An exemplary real-time Delphi in the context of an emerging digital manufacturing technology, additive manufacturing (3D printing), is Jiang et al. (2017). To ensure the reliability and validity of the results, a strict adherence to a clear process is important (Hasson & Keeney, 2011; von der Gracht & Darkow, 2010). Specifically, our real-time Delphi study follows four building blocks:

3.1.1 | Projection development

First, we developed a set of projections on the implications of IDTs structured around the platform logic. We organized two formulation workshops to develop statements on how IDTs could impact future digital manufacturing. These statements build the foundation for the actual survey among our expert panel. Common time horizons for these projections range from 8 to 10 years (von der Gracht & Darkow, 2010), which is why we chose 2030 for our scenarios. As an analytical frame and to anchor our study in existing theories (Beiderbeck et al., 2021), we used the previously introduced platform framework by Gawer (2014) (see Table 1). The workshops were conducted in person at our university, each lasting 4 h. During these formulation sessions, 27 experts from engineering, computer science, social sciences, and management to get a broad range of perspectives covering all aspects of DTs and our analytical framework. These experts did not participate in the survey later. As a result of the first workshop, we identified an initial set of 76 projections across all four attributes. By clustering similar projections to rule out redundancy, we could reduce the number to 45. We performed dedicated desk research to validate the projections (Schmalz et al., 2021). We then circled the reduced setback to the workshop participants to analyze dependencies and to guarantee that all dimensions of our framework were covered. During this second session, we could reduce the number to our final set of 24 projections (stated in Table 4). To ensure methodological rigor, we checked the projections for short, unequivocal, and precise wording to avoid any ambiguity (Linstone & Turoff, 2002) and iteratively shaped the wording (Markmann et al., 2021). Subsequently, we

TABLE 2 Summary of research methods.

Method	How	Who	Output	Purpose
(1) Real-time Delphi				
Projection development	Formulation workshops Desk research Pretest	Workshops: 27 experts from engineering, computer science, social sciences, and management at the university Author Team Pretest: 13 external experts from industry and academia	24 projections structured by Gawer's (2014) platform framework	Identifying IDTs' impact factors on future digital manufacturing anchored in existing theory
Survey	Expert panel Multi-round survey through a real-time online tool	A panel of 35 experts in digital manufacturing (refer to Table 3)	1930 quantitative estimations 629 qualitative comments	Forecasting the impact of IDTs on digital manufacturing
Consent scenario	Analysis of descriptive statistics (quantitative analysis)	Author Team	Base scenario structured by Gawer's (2014) platform framework	Identifying consensus among experts about the impact of IDTs on future digital manufacturing
Dissent scenario	Deductive and inductive coding (qualitative analysis, refer to Appendix B)	15 researchers from engineering, computer science, social science, and management at the university (subset of formulation group)	Data structure of first- and second-order codes that inform the design choices for positioning IDTs in digital manufacturing structured by Gawer's (2014) platform framework (refer to Figure 2)	Determining uncertainties and risks for innovation; Analyzing opportunities and challenges resulting from IDTs; Deriving reliable scenarios and a set of design choices for IDTs and implications for innovation management
(2) Case studies				
	Identification through experts, literature review, internet research Selection through snowball and theoretical sampling	Author Team	22 case studies of DTs in real-world manufacturing settings (refer to Appendix A)	Getting insights into pioneering applications of IDTs; Providing examples for scenarios bridging the gap between status quo and future projections

conducted a pretest with 13 experts from both industry and academia to ensure content reliability as well as face validity (Beiderbeck et al., 2021). After a final editing round, we settled on a set of 24 projections.

3.1.2 | Survey

Second, we identified, selected, and recruited a set of experts in the field of digital manufacturing to serve as our panel for the study (Gordon & Pease, 2006). It is necessary to predefine criteria for expert selection, ensuring the right size of the panel, level of expertise, level of heterogeneity, level of interest, and access to the panel (Beiderbeck et al., 2021). Selection criteria included technical expertise, publications in the field of the domain, or their professional experience. Put differently, the experts did not only need knowledge about but should also be in a position to influence the future. We identified the experts by drawing on our network as well as professional platforms like LinkedIn. Using a pyramiding approach, we asked the initially identified experts to

refer people who know more about digital manufacturing than they do to gather the most relevant and knowledgeable set of experts. Our final panel includes 35 experts (see Table 3), which is in line with methodological recommendations and previous Delphi studies (e.g., Beiderbeck et al., 2021; von der Gracht & Darkow, 2010). Linstone (1981) suggests incorporating multiple perspectives—in terms of both subject matter

TABLE 3 Expert panel.

No.	Affiliation	Country	Field	Competency
1	Academia	Europe	Information Systems	Professor for Computational Analysis of Technical Systems
2	Industry	Europe	Aerospace	Digital Transformation Manager
3	Industry	Europe	Automotive	Data Scientist
4	Industry	Europe	Consulting	Consultant in Industrial Complexity Management
5	Industry	Europe	Conglomerate	R&D Strategy Consultant
6	Academia	North America	Engineering	Professor for Manufacturing Systems
7	Industry	Europe	Industrial Equipment	Expert Manufacturing Excellence
8	Industry	Europe	Industrial Equipment	Executive Vice President
9	Academia	North America	Engineering	Professor of Mechanical and Aerospace Engineering
10	Academia	Europe	Engineering	Professor of Prognostics and Health Management
11	Academia	Europe	Engineering	Senior Researcher for Applied Industrial Engineering and Ergonomics
12	Industry	Europe	Conglomerate	Expert Additive Manufacturing
13	Industry	Europe	Aerospace	Director of Production
14	Industry	Europe	Consulting	Managing Director and Partner, Global Leader Manufacturing
15	Academia	Europe	Engineering	Professor of Production Systems
16	Industry	Asia	Electronics	Vice Chairman and Board Member
17	Industry	Europe	Industrial Software	Managing Director
18	Academia	North America	Engineering	Professor of Manufacturing Engineering
19	Academia	Europe	Economics	Professor of Economics and Entrepreneurship
20	Industry	Europe	Automotive	Industrial Engineer
21	Industry	Europe	Chemicals	Innovation Manager
22	Industry	Asia	Conglomerate	Senior Chief Researcher
23	Academia	Europe	Information Systems	Professor of Software- and Systems Engineering
24	Industry	Europe	Industrial Equipment	Head of Product Marketing
25	Academia	Europe	Information Systems	Professor of Business Informatics and Data Science
26	Industry	Europe	Industrial Software	Chief Technology Officer
27	Industry	Europe	Automotive	Director of Manufacturing
28	Industry	Europe	Industrial Equipment	Managing Director
29	Industry	Europe	Industrial Equipment	R&D Manager Laser Technology
30	Industry	Europe	Textile manufacturer	Head of Finance
31	Academia	Europe	Engineering	Professor of Production Planning and Control
32	Industry	Europe	Aerospace	Founder and Technical Director for Lightweight Construction Parts
33	Industry	Europe	Materials	Chief Technology Officer
34	Industry	Europe	Automotive	Head of Operations Production Support
35	Academia	North America	Economics	Professor of Management

expertise and regional contexts—emphasizing the relevance of different viewpoints. Thus, we aimed to compose a heterogeneous panel, including experts from industry (23) and academia (12), representing a broad range of nationalities (8). In future-related settings that involve technical and economic complexity, a higher level of heterogeneity can mitigate cognitive bias (Bokrantz et al., 2017). Previous studies have also shown that heterogeneous panels produce more accurate assessments as they reduce polarization of preferences (Yaniv, 2011).

For the actual survey, we used an internet-based software tool by Gnatzy et al. (2011). The experts were exposed to one projection at a time and asked to assess its estimated probability of occurrence (in percentage) and firm impact on a 5-point Likert scale (1 = very low; 5 = very high) for the year 2030. To support a more nuanced analysis, we asked the experts to provide qualitative arguments to explain their estimates. In total, we collected 1930 quantitative estimations and 629 comments. After each response, the experts were displayed the intermediate results (mean, interquartile range [IQR], and standard deviation) and the anonymized comments from the other participants. Then, experts were asked to revise their estimates and to engage in the discussion. Direct feedback and the possibility to see and react to the qualitative arguments from other experts—while ensuring anonymity—have proved to increase the accuracy of the results (Aengenheyster et al., 2017; Gnatzy et al., 2011).

3.1.3 | Consent scenario

We used the Delphi results of the survey to develop future scenarios. For that, we first calculated descriptive statistics, including mean and standard deviations for the probability of occurrence and firm impact. To identify consensus, we used IQRs as a robust statistical measure (Beiderbeck et al., 2021). Following previous studies, a consensus was reached if the IQR of the estimated probability of occurrence did not exceed 2.0 for the projection (Jiang et al., 2017; von der Gracht & Darkow, 2010). These projections comprise our base scenario.

3.1.4 | Dissent scenario

While Delphi studies aim to structure expert assessments to achieve consensus, it is common practice to look at extremes or varying degrees of consensus to build scenarios (Markmann et al., 2013). Such a dissent analysis can provide additional insights (Beiderbeck et al., 2021). Given that the realization of IDTs leads to challenges, in particular for the platform logic of digital manufacturing, we decided to include not only projections with high probability and high impact, but also selected projections that did not reach consensus, but can be classified as "black swan projections" (Jiang et al., 2017), that is, projections with low probability, but medium to high impact in case they would occur, as well as projections with extreme uncertainty. This second step included clustering some of the projections to higher aggregate themes (von der Gracht & Darkow, 2010).

The analysis of the qualitative comments involved a combination of inductive and deductive coding (e.g., Goduscheit & Faullant, 2018; Michelfelder & Kratzer, 2013). The inductive part employed open coding (Saldaña, 2021). Following Gioia et al. (2013), this first-order analysis stayed close to the experts' statements representing their different arguments and evaluations. In a second-order analysis, we used axial coding (Strauss & Corbin, 1990) to cluster these codes into higher themes. This deductive part linked the codes to our theoretical framework by Gawer (2014). The coding was done with 15 researchers from different disciplines who coded all themes. Initially, each researcher coded individually. After each step of coding, we compared the outcomes and discussed the differences. Through refinements in a live session, we iteratively adjusted the coding, referring back to our theoretical framework, until we achieved intercoder agreement. Combined, the first-order and second-order analyses served as the basis of our data structure (Cloutier & Ravasi, 2021). Appendix B (Table B1) presents the coding scheme used in this research stage and the results from this analysis. The data structure informs the design choices for positioning IDTs in digital manufacturing and its implications for managing innovation.

3.2 | Use case analysis

While the Delphi study focused on the impact of IDTs and platforms on *future* digital manufacturing, we conducted an additional use case analysis to assess the impact of DTs on levels one and two (discrete and composite DTs), but also to get early evidence on pilot applications of IDTs. Using a snowball sampling method (Noy, 2008), we identified use cases based on the consultation of our Delphi experts, extensive literature review, and internet research. The final selection of relevant use cases was guided by theoretical sampling along with the four platform attributes (Eisenhardt & Graebner, 2007). Further, all use cases should present DTs in real-world manufacturing settings. Purely conceptual examples, cases limited to research contexts, or cases outside manufacturing were disregarded. For providers of generic

DT software, such as Amazon TwinMaker or Siemens Intosite, we chose specific customer use cases that illustrate the functionality of the respective DT (software). We further search for use cases that provide insights into the data spaces that emerge as a result of IDTs, like Catena-X or DataConnect. As a result, we compiled 22 use cases across different manufacturing industries. For each case, we collected data from several sources, including interviews, internal firm documents, company websites, press releases, and literature research (see Appendix A, Table A1 for an overview of the use cases and sources). With this collection, we are able to provide examples for each Delphi scenario, but also to illustrate the gap between the status quo and the future projections. In addition, it supports the triangulation of our Delphi results and the illustration of our findings.

4 | RESULTS

4.1 | Descriptive statistics of the Delphi survey

Table 4 shows the set of projections along the four platform attributes of Gawer (2014) and the quantitative results of our Delphi study. Figure 1 shows the average estimates for the probability of occurrence and firm impact for all 24 projections. Most of the projections have an estimated impact >3.0, indicating a high relevance and fit for the study. We achieved consensus (IQR ≤2.0) for 4 out of 24 projections (16.6%), namely Projection P1 (subscription models), P11 (workforce reduction), P15 (environmental sustainability), and P24 (decentralization). All those projections have an estimated probability of occurrence ≥50%, as expected from other Delphi studies (e.g., Ogden et al., 2005). The relatively low consensus rate is common in technology-related Delphi studies (e.g., Jiang et al., 2017; Keller, 2014). At the same time, it indicates that the impact of IDTs is still very controversial, especially when incorporating experts from different fields. In addition, DT technology integrates a variety of different sub-technologies, making consensus less likely. From the descriptive analysis, we further structured our Delphi study results into two parts, each using the platform attributes of Gawer (2014) as our analytical theory frame to analyze how IDTs shape future digital manufacturing. First, we explain the consent projections that build a base scenario about the impact of IDTs on future digital manufacturing. Second, we explain the dissent projections that create opposing design choices for positioning IDTs in future digital manufacturing, which we use in the final chapter to discuss the consequences for future innovation management.

4.2 | Base scenario: Impact of IDTs on future digital manufacturing

As usual for Delphi studies, the base scenario builds on the projections that reached consensus (P1, P11, P15, and P24). The platform attributes adapted from Gawer (2014) served as our theoretical lens to structure the impact of IDTs on future digital manufacturing when drafting this scenario.

The *interface attribute* describes how DTs interact with other DTs, complementary assets, and users. Here, the projection of decentralization (P24) reached a consensus among experts. Decentral production systems are driven by the desire to produce more locally to become more resilient against global supply chain disruptions, to be able to serve customers faster, and to reduce the environmental footprint. "Current trends towards deglobalization and greater self-sufficiency, together with rising geo-political trade conflicts are all likely to make more local production quite likely" (Expert 19, academia). IDTs are a strong enabler for this setup. First, they allow a network of local plants to still achieve economics of learning and generate visibility about best practices (resulting, e.g., from local continuous improvement activities) as in a large centralized manufacturing setup. Software companies like SWIM.AI already help to build locally connected DTs that combine local data processing, data analytics, edge computing, and machine learning to provide real-time insights to optimize production processes (Case no. 6). However, decentralized production setups require an aggregate level to manage the production network in a connected way. Such an aggregation of local twins to "twin of twins" or "system of system twins" is a typical task of a platform architecture that becomes crucial for realizing a decentralized setup without losing the efficiencies of a local manufacturing system. In the future, manufacturing firms could use these production networks to share even manufacturing capabilities and resources on the platform. Hence, IDTs build the basis to enable shared and virtualized production capacity across different production systems.

For the *accessible capabilities attribute*, which describes the ability of organizations and innovating agents to access external knowledge and competence, we identified environmental sustainability (P15) as a consensus. Our panel experts stated that shared simulation models enable effective virtual prototyping, fewer defections, optimized inventory, and better forecasting of required outputs. Hence, the consumption of resources and energy can be significantly reduced through IDTs. Further, the recycling and reuse of products are supported by information about the exact usage profiles of each product or asset.

TABLE 4 Delphi projections for 2030.

Attribute	No.	Projection	Description	Probability of occurrence			Firm impact
				IQR	Mean	SD	
Governance	1	Subscription models	In 2030, subscription models for production machines will be the new industry standard, fulfilling an assured performance level based on real-time usage data in return for a periodic payment.	2.0*	57.79	19.22	3.32
	2	Central data platform	In 2030, one central platform provider will serve as the operating system for the Industrial Internet of Things enabling to make use of data by integrating machine manufacturers and complementary service providers and capturing the greatest share of the value created.	4.0	30.15	18.93	3.09
	3	Data mediator	In 2030, platform orchestrators or dedicated third-party providers will mediate data sharing between all actors involved in a production network.	4.1	52.34	24.65	3.09
	4	Industrial GDPR	In 2030, industrial data protection regulations (like a special GDPR—General Data Protection Regulation for Business-to-Business) will govern the application of data-based digital services.	2.5	60.16	22.52	3.52
Organization	5	Autonomous robots	In 2030, collaborative robots that move autonomously on the shop floor and interact directly with humans will have replaced most conventional robots that only interact in protected cells.	3.5	40.81	25.72	3.06
	6	Hybrid intelligence	In 2030, strategic production decisions will be executed in close interaction between humans and AI-based algorithms ("hybrid intelligence").	3.0	65.13	23.66	3.71
	7	AI-Assistant	In 2030, operative production decisions will no longer lie with people, as they will be made by AI-based decision-making agents.	3.5	49.68	22.61	3.48
	8	New leadership	In 2030, AI-based decision systems will have changed our current understanding of management completely, increasingly eliminating hierarchies and leadership based on human interactions.	3.0	34.19	20.25	3.10
	9	Employee twin	In 2030, a full digital twin of each production worker and all of her/his operations will be available, becoming a valuable tool for production planning and optimization by reflecting the workload, stress, but also the need for training for each worker in real-time.	3.8	44.19	23.80	3.13
	10	Employees' rights	In 2030, adequate anonymization procedures for the protection of employees' personal rights will have been introduced for firms that collect data on personal performance and work patterns in form of digital twins of their employees.	5.0	57.07	26.01	2.93
	11	Workforce reduction	In 2030, AI-based software and robots will have reduced a firm's workforce significantly.	2.0*	51.55	18.85	3.62

TABLE 4 (Continued)

Attribute	No.	Projection	Description	Probability of occurrence			Firm impact
				IQR	Mean	SD	
	12	Production costs	In 2030, production costs will have increased substantially due to more regional production and higher inventory levels to cope with global crises (e.g., pandemics).	2.5	37.90	20.37	2.94
Accessible capabilities	13	Digital services	In 2030, for production machinery and other hardware assets, for example, tractors, equipment, and so forth, competition will shift from hardware capabilities and functionality to differentiation by (digital) services, supplementing the traditional transactional business logic with a data-driven business model.	3.0	65.00	19.85	3.65
	14	Expert knowledge	In 2030, implicit expert knowledge, which traditionally could only be gained by collecting experience, will increasingly be explicitly preserved in form of digital models, interactive guides, or instructions, facilitated by technologies like augmented or virtual reality. As a result, the knowledge is also made available to novices and eliminates the dependency on experienced production employees.	3.5	52.07	20.95	3.28
	15	Environmental sustainability	In 2030, the environmental sustainability of production will have increased significantly as compared to today.	2.0*	67.24	19.14	3.59
	16	Production transparency	In 2030, full transparency based on a complete digital twin of all production machines, lines, and plant engineering and a complete digital twin of their operations will increase production efficiency significantly.	3.0	65.17	20.82	3.62
	17	University degrees	In 2030, the application of biological principles (e.g., cybernetics, biomimicry) of manufacturing has created a demand for new multidisciplinary university degrees between engineering, the life sciences, and computer science.	3.0	50.69	23.48	2.66
	18	Production resilience	In 2030, AI-based decision systems will enable larger resilience in production networks in the event of a global crisis (e.g., a pandemic).	2.9	40.52	19.88	2.90
Interfaces	19	Implicit HMI	In 2030, human-machine interaction will have evolved away from explicit interaction, where the human operator has full control of the actions of the production system's entities, towards implicit interaction, where the system automatically adapts to human behavior by means of activity detection and prediction of actions and modifies the actions accordingly.	3.0	52.07	17.93	3.07
	20	Open interfaces	In 2030, regulatory requirements will demand open and standardized interfaces for data exchange for all kinds of manufacturing equipment.	3.6	44.48	21.77	3.17

(Continues)

TABLE 4 (Continued)

Attribute	No.	Projection	Description	Probability of occurrence			Firm impact
				IQR	Mean	SD	
	21	Data sharing	In 2030, organizations that share usage and production data with suppliers, customers, and other partners will obtain a competitive advantage over an organization that does not share this data.	3.0	62.58	21.89	3.55
	22	Production from HO	In 2030, production employees will operate their workstations from their home office, controlling, for example, remotely operated robots.	3.0	38.10	24.93	2.83
	23	Plant mgmt. from HO	In 2030, plant directors will manage multiple factories centrally from their home office due to complete and real-time transparency of all operations in a digital system.	4.0	46.03	25.61	2.90
	24	Decentralization	In 2030, supply chains will have become more decentralized with production and sourcing moving closer to the end customer to cope better with global crises (e.g., pandemics).	2.0*	56.55	21.34	3.17

Note: * indicates projections where final consensus was reached (i.e., IQR of ≤2.0). $N = 35$.
Abbreviations: IQR, interquartile range; SD, standard deviation.

IDTs become key enablers for more environmental sustainability. "Through data availability, transparency for holistic sustainability will be available" (Expert 27, industry). Catena-X (Case no. 17) aims to build accessible capabilities through IDTs that integrate data and analytical models along the products' lifecycle across all stakeholders in one data space of the European automotive industry. The IDTs create higher transparency and traceability along the entire value chain to facilitate collaboration and innovation for greater sustainability. Based on shared data, various actors connected to the Catena-X data space can perform simulations and analytics to make the environmental impact measurable and identify mitigation efforts.

The *organization attribute* relates to the structural management of decision-making within the manufacturing system for which we reached a consensus for the projection of workforce reduction (P11). Simulation models and data analytics support autonomous decision-making so that more tasks on the shop floor can be automated. For example, Chinese manufacturer Foxconn built a DT of interconnected production plants that connects sensors, robots, and data analytics to automate production and supply chain processes. In these "lights-off factories," the interconnection through the DT technology enables the automation of decision-making, which lowers the required workforce for controlling production processes manually (Case no. 10). Similarly, an application on PTC's platform ThingWorx can automate machine inspections (Case no. 13). Here, IDTs serve as the backbone that connects and integrates data and feeds from different machines into a platform to perform automated analyses and automate machine inspection, a task previously done manually by humans. Despite these efficiency gains through automation, experts did not predict a dramatic workforce reduction, but rather a shift of required capabilities: "It is likely that interindustry and interfirm shifts in labor automation will lead to heterogeneous

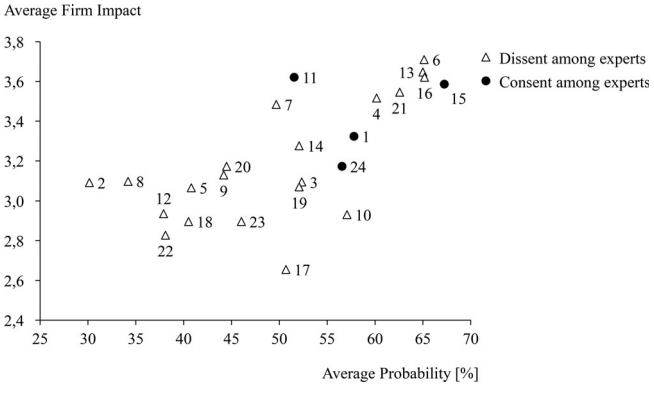

FIGURE 1 Spread of Delphi projections

changes in workforces. Agriculture and manufacturing have, for instance, already become highly mechanized, and these trends will continue" (Expert 19, academia).

For the *governance attribute* regarding the coordination mechanisms of collaborative value creation (innovation) and capture (commercialization), subscription models (P1) emerged as a consensus. IDTs enable continuous synchronization between virtual and physical systems, that is, IDTs with an execution engine in the form of an embedded simulation model can adapt physical systems based on virtual simulations. Consequently, production machines can be adjusted continuously according to changing user needs to create value, addressing the desire for more flexible and customizable production. For machine vendors, adjustable machinery based on IDTs allows the introduction of new collaborative coordination mechanisms to create value but also to capture value differently—for example, where manufacturers pay for their use by volume or outcome, instead of investing in the asset upfront. "Today we are already ordering production lines and equipment based on contractual KPIs (OEE, FPY, cycle times, changeover times, etc.). We buy guaranteed production capabilities and not just machines" (Expert 34, industry). Such "as-a-service" models change the forms of collaboration, ownership, and risk when machine vendors become operators who collaborate automatically via IDTs with manufacturing firms. Manufacturers, in turn, give up some control but reduce their investment requirements and share the risk with the vendor.

In the transport sector, Hitachi Rail monitors the IDTs of its trains via the platform Lumada IoT. This allows the manufacturer of railways to offer and collaboratively coordinate "trains-as-a-service" in the United Kingdom. Hitachi Rail keeps ownership of the trains and is paid by railway operators for on-time transportation (Case no. 11). Such a model is only feasible economically by utilizing a set of interconnect composite DTs that not just allow the provider (Hitachi) to monitor usage, utilization, and performance of the assets but also to cooperate with the operator (e.g., British Rail) and continuously increase the performance by providing advise how to operate or maintain the trains in a better way.

Our base scenario shows that in the future of digital manufacturing, IDTs facilitate (data) platforms that are decentralized by offering interfaces to connect and share data and applications across locations, stakeholders, and lifecycles. Through increased integration and transparency along the value chain, external capabilities are more easily incorporated to increase environmental sustainability. These decentralized yet integrated digital manufacturing platforms allow for new collaboration modes and revenue models. At the same time, IDTs shift the required skills internally by reducing the workforce while making it easier to incorporate new skills from third parties.

4.3 | IDTs in digital manufacturing: Alternative futures

In addition to our baseline scenario, which is grounded on the consensus projections (of our experts), Table 4 indicates that our diverse set of experts evaluated most of our projections controversially. These disagreeing evaluations reflect the uncertainty about the future of digital manufacturing but also point to different options for future development (Beiderbeck et al., 2021; Markmann et al., 2013). Hence, we extended our analysis to a broader range of projections (P2, P3, P4, P6, P9, P10, P13, P16, P20, and P21). For each projection, we especially analyzed the experts' qualitative arguments which substantiated their quantitative evaluations (refer to Appendix B for our coding scheme and information on the rationale for why we included a specific projection in this analysis). Combined, the quantitative and qualitative analysis revealed alternative predictions of the impact of IDTs. Different design choices of platforms emerge, and the resulting setup of the platform will differ. These design choices denote opposing alternatives that arise from the extreme positions in our Delphi study. In the following, we elaborate on these divergent options, referring again to Gawer's (2014) framework of platform attributes to structure our analysis. Figure 2 depicts these choices along with the attributes and illustrative use cases.

4.3.1 | Design choices of IDTs: Interfaces

The projections on open interfaces (P20) and data sharing (P21) cover the interface attribute. While P20 refers more to expected regulatory actions concerning a "forced" openness of interfaces, especially the lack of consensus for P21 is interesting. It covers the competitive consequences of a firm's strategic decisions with whom and how to share data in the form of IDTs. Some experts argued that data sharing with external organizations threatens one's competitive advantage: "Production data are mostly sensible so that a share of data endangers our business model" (Expert 2, industry). Thus, data sharing will only be done selectively, if it provides a concrete benefit in return: "Sharing data out of production has no value in itself for producing firms. There needs to be a clear contractual agreement of what firms are sharing data get in return and in the end it all needs to clearly

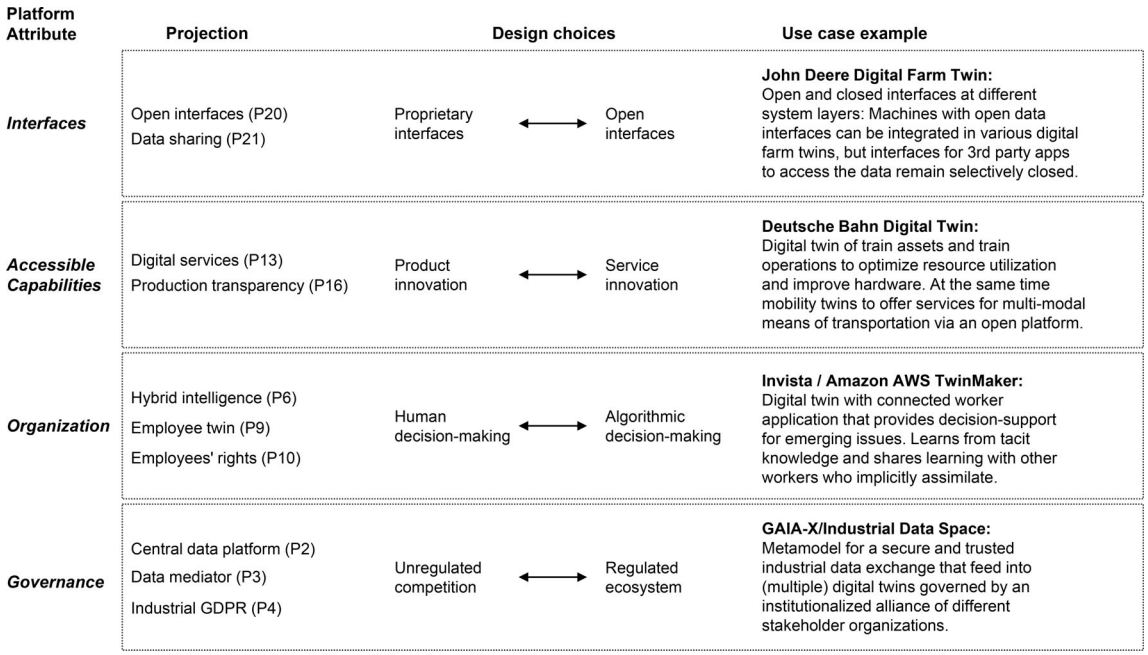

FIGURE 2 Design choices of interconnected digital twins in digital manufacturing.

translate into either lower cost or better quality of the products they are producing and selling" (Expert 34, industry). In terms of platform implications, this will either lead to closed interfaces where data are only shared within a firm's production network, or selectively open interfaces, where only specified partners get access to a firm's platform. Thereby, they keep control of their data but miss out on new forms of value creation and learning by integrating third-party complementors (Parker & van Alstyne, 2018).

The experts in our Delphi panel argued that data sharing and open interfaces are prerequisites to collaborate and innovate on a platform fueled by data from IDTs. "Distributed networks, which share data, can react agile on new market environments. To lift the entire potential of data in the value chain, it is necessary to share the data" (Expert 5, industry). These experts called for a *"mindset change across internal and external silos"* (Expert 34, industry) to reap the benefits of openness, such as new forms of value creation based on connected data. This would require open interfaces so that complementors can access the platform's data. While data sharing creates value on an interorganizational level, it makes value capture more difficult on the firm level.

Consequently, the design choices of platforms for future digital manufacturing resulting from the conflicting evaluations of projections P20 and P21 encompass a design-choice continuum from proprietary interfaces for internal platforms to open interfaces for cross-industry platforms. In our use cases, we can observe both approaches. BAOWU started to connect its production network across China but only selectively allowed third-party service providers to access the data for specific tasks (Case no. 7). In contrast, the open Catena-X data space was initiated to include and interconnect DTs from all actors along the automotive value chain (Case no. 17). Interestingly, the driver of data sharing in Catena-X has been the shared objective to increase ecological sustainability by providing better visibility along the entire automotive value chain.

4.3.2 | Design choices of IDTs: Accessible capabilities

Regarding accessible capabilities, the projections on digital services (P13) and production transparency (P16) provide interesting insights. Here, the design choices encompass different options of what is considered a competitive resource (digital services or the underlying hardware). Some experts pointed towards innovation opportunities to optimize existing products (machinery) and continuously improve their quality based on the increased transparency about production and usage patterns provided by IDTs. "Hardware capabilities and innovations are and will still remain critical to the success of all hardware-related products and services—you cannot sustainably sell inferior hardware covered by digital gimmicks. While software will become a nice add-on, being able to offer high-quality hardware "underneath" at low prices will lead to success for many firms (especially in

B2B) because in many cases it's simply most profitable to focus on core hardware competencies" (Expert 34, industry). Additionally, IDTs support the development and usage of innovative new materials and designs, as their embedded simulation models combined with generative algorithms expand the design space during development to a large extent (Rindfleisch et al., 2017). Consequently, some experts predicted "that we will see a return to much more competition based on hardware capabilities due to innovations in materials, design, functionality, and shrinking of global value chains" (Expert 19, academia). Firms that follow these assumptions will likely focus on building the required digital capabilities in-house, as here the analytical and simulation models in the DTs are closely related to a specific internal manufacturing setup. This is in line with observations that investments into new technologies in manufacturing have mainly been triggered by improvements in operational efficiency or quality—developments that do not require a fundamental change of the organization (Björkdahl, 2020). These firms would focus on building internal digital platforms with closed proprietary interfaces of their IDTs.

As a catalyst for digital platforms, IDTs provide many opportunities for open innovation. Specifically, experts predict that competitive resources and differentiating factors will be rather based on data-driven service innovation: "The software is the complex part to operate the hardware. Hardware only remains valuable in niches with critical infrastructure" (Expert 5, industry). These digital services will often be jointly developed and deployed with external partners in collaborative models facilitated by data platforms. By incorporating third-party complementors, firms benefit from learning effects they would not be able to realize on their own: "For many industries (not all), having a deep process and machine know-how collected at the machine manufacturer is more efficient than building up large decentralized expert teams yourself. Also, it's easier for machine manufacturers to level their workload over multiple customers worldwide regarding the development of turnkey solutions and services. Furthermore, lessons learned can be transferred from a large number of use cases" (Expert 11, academia).

As a result, the design-choice continuum ranges from a focus on continuous data-driven product and process improvements to a focus on new business models around service innovations jointly developed with partners leveraging ecosystem data via IDTs. Firms have the choice of exploiting existing hardware resources independently or exploring data-based service innovations jointly with partners (van Dyck et al., 2021). Doosan (Case no. 20) developed IDTs for its wind farms to design new turbines based on a comparison of predicted performance and actual production output. Foxconn (Case no. 10) started offering its digital manufacturing platform BEACON to customers and suppliers. Customers can upload their DTs to Foxconn's digital platform, and Foxconn analyzes the data using 1 of the 30 apps it has developed for this platform. Foxconn communicates necessary adjustments or maintenance needs back via the apps and improves its analytics models with an increased amount of data. Suppliers can use this data to customize and/or innovate their machinery and services based on usage patterns. Consequently, Foxconn benefits from new service innovations and revenues generated through the interactions between suppliers and customers.

4.3.3 | Design choices of IDTs: Organization

The projections on hybrid intelligence (P6), employee twin (P9), and employees' rights (P10) address the level of the organization. All projections refer to procedures of internal decision-making and organizational learning. Specifically, connecting DTs on digital platforms enables new forms of AI-driven predictions and prescriptions for decision-making. All experts agreed that simulation models and data analytics based on IDTs will shift decision-making towards more autonomous (machine-based) decisions, but they differed in their evaluations of the remaining degree of human involvement. Some predict that core decision-making will remain with humans. The role of AI would be to provide decision support by identifying patterns and making predictions based on data from IDTs, but it will remain on human decision makers to decide on this input. In this understanding, the rise of IDTs will not impact the structure of an organization. Human leaders will be held accountable for decision-making: "In the end, someone has to be responsible, and this person will be top of the hierarchy" (Expert 2, industry). Other experts expect that algorithms will take over most parts of the decision-making process in manufacturing, leaving humans only with a veto right. In such a scenario around autonomous machines, algorithms cannot just interpret heterogeneous data sources more frequently, identify patterns unobvious to humans, and predict the upcoming incidents in manufacturing systems, but also generate and execute prescriptions of how to react to the predicted event.

A special case is the DT of humans, so-called *human digital twins*. Human IDTs in manufacturing comprise all connected data that can be assigned to human actors (e.g., patterns of behavior, knowledge, skills, and experiences) to support decision-making and enhance activities within a production system (Mertens et al., 2021). As human IDTs entail personal data and algorithmic

decisions, the protection of the affected personal rights of employees and other stakeholders becomes crucial to create acceptance when employing such technology. Some experts suggested anonymization procedures as a solution: "Advanced anonymization techniques will be a prerequisite for more data-driven production systems" (Expert 25, academia).

Overall, the design-choice continuum ranges from human decision-making supported by AI to algorithmic decision-making, leaving humans just a veto right. While full algorithmic decision-making is yet to be implemented in industrial settings on a larger scale, we could observe various degrees of AI support by IDTs. For example, Foxconn equipped its industrial internet platform with features to automate decision-making for operational machine processes to reduce the reliance on human labor (Case no. 10). Similarly, HIROTEC (Case no. 13) developed IDTs for its CNC machines that enabled automated inspection of the manufactured exhaust systems, reducing the need for manual inspection and quality decisions by humans.

4.3.4 | Design choices of IDTs: Governance

The projections on the role of a central data platform (P2), data mediators (P3), and industrial GDPR (P4) address the governance attribute and deal with different approaches to competition and regulation of data exchange. Managing access to data emerged, with little surprise, as a critical issue for digital manufacturing. Thus, one question is where IDTs are stored and processed. Consider as an example the question of whether machine learning applications should run locally and decentral at the manufacturer's site or centrally in the cloud of a hyperscaler (like Amazon Web Services, Microsoft Azure, or Google Cloud). In our survey, experts perceived these technology firms to be in a favorable position to leverage the opportunities of IDTs: "In the end, AWS, MS Azure follow the trend from consumer realm to industrial realm" (Expert 23, academia), highlighting their advantage of huge economies of scale and learning concerning data storage and analytics: "Google and other providers have a strong position and for firms, it is necessary to get this data" (Expert 31, academia). Subsequently, some experts feared that large tech-savvy firms can force smaller firms to share data through IDTs: "Only very big firms can try not to return the data, smaller firms need to do so to obtain the partnership" (Expert 17, industry).

Some experts propose local data analytics using edge processing through IDTs or complementary technologies like Blockchain (distributed ledger technology) to enable decentralized platforms: "Some applications need '(near-) hard' real-time data. In this case, direct data connections and control loops are needed at the source" (Expert 34, industry). These approaches have implications for competition management on digital platforms, resembling different policy approaches. A free-market approach suggests that firms coordinate through bilateral contracts, and firms are responsible for protecting their valuable resources as "regulations move slowly" (Expert 6, academia). However, this scenario may result in detrimental effects on competition and society, favoring fewer firms at the expense of the rest (Winner-takes-all effect): "If indeed competition will shift towards the digital spectrum, data-driven network economies may benefit only a few firms, and overall firm impact will be significant, but likely negative from a societal point of view" (Expert 19, academia).

Standards and regulations for data exchange through IDTs can foster a decentralized platform setup that enables a variety of not predetermined interactions. "A legal basis would definitely address many obstacles and risks that are currently prevalent. As it is the same with other industrial goods and services that are covered by regulations, industrial data need to be considered, too. As there are currently many efforts such as GDPR [General Data Protection Regulation, author's note], it seems likely to pass over to the industrial context" (Expert 15, academia). Overall, the design-choice continuum for IDTs on the policy level spans between unregulated competition where firms compete for ways of collecting, processing, and analyzing data, and regulated ecosystem approaches where regulation and standards govern the data exchange across organizations. Large multinational providers of manufacturing equipment, such as Siemens and GE, and IT infrastructure providers, or digital hyperscalers such as Amazon and Microsoft, attempted to define the governance structures through their scaled platform designs (Cases nos. 4, 16, 20, and 21).

In contrast, approaches like the *Industrial Data Space* (*IDS*) set out to create a decentralized framework for data exchange based on open standards and consensus-driven governance rules (Case no. 19). The IDS was developed by a consortium of European manufacturing firms together with Fraunhofer Society as a response to this uncertainty and the perceived competitive threat by global platforms like AWS or Microsoft (Otto, 2022; Otto & Jarke, 2019). It provides a framework and platform for secure and trusted data exchange in large distributed system architectures of data spaces and IDTs that are governed by an institutionalized alliance of different stakeholder organizations (Silva et al., 2022). Recently, the IDS has been integrated into the European GAIA-X initiative, governed by more than

250 participating organizations from many different sectors (Braud et al., 2021; Otto, 2022).

Our analysis predicts that the use of IDTs will have a significant impact on collaboration, innovation, autonomous decision-making, and governance. IDTs can be developed with proprietary or open interfaces to share data, and firms must focus on building data spaces to create production transparency and exploit data-driven service innovation. However, there are concerns about IDTs regarding privacy, union interventions, and ethical tensions related to hybrid intelligence and human DTs. In addition, the design of IDTs has implications for governing competition and innovation in digital manufacturing, and a free market approach may have detrimental effects on competition and society, favoring a few companies at the expense of the rest.

5 | DISCUSSION AND IMPLICATIONS FOR FUTURE INNOVATION MANAGEMENT

Prior research has discussed how new digital manufacturing technologies, such as 3D printing, cloud computing, or AI, impact the innovation process (Appio et al., 2021; Björkdahl, 2020; Haefner et al., 2021; Rindfleisch et al., 2017). IDTs offer a new dimension to innovation in digital manufacturing. They connect and integrate data from different assets and resources, creating a single source of data and analytics that becomes the starting point for many different applications (West et al., 2021). Our Delphi study and complementary analysis of 22 industrial case studies contribute to a better understanding of IDTs and their impact on future digital manufacturing. The uncertainties identified within our Delphi expert panel on the exact developments and effects of IDTs helped us to identify a set of specific design choices that need to be addressed when managing future digital manufacturing and innovation.

From an innovation management perspective, IDTs exchange and integrate external data sources to create enhanced simulations along product and process life cycles (Silva et al., 2022; Stark, 2022). Any innovation project depends on the generation and evaluation of a continuous inflow of ideas, concepts, and information from internal and external sources (Beretta et al., 2018; van den Ende et al., 2015)—an inflow that can be largely complemented by IDTs. Hence, IDTs will impact the amount and quality of external knowledge inflows into the innovation process. This demands, in turn, new dedicated governance rules to balance collaborative innovation.

Accordingly, we discuss the implications of IDTs and their related data platforms (data spaces) for future innovation management. First, we structure our implications of IDTs for (digital) innovation management according to Beretta et al. (2018), who argue that innovation processes can be influenced along the dimensions of variation and selection. Afterwards, we discuss the implications of IDTs and their governance models for collaborative innovation management, followed by a discussion of the main limitations and conclusion of our research. As an overview, Table 5 summarizes major research questions for innovation management that could become part of a future research agenda on IDTs.

5.1 | IDTs and the generation of variation for innovation

Increasing *variation* through IDTs in the innovation process aims to access a wider range of knowledge inputs that raise the likelihood of innovation outputs. Many organizations open themselves to external sources to generate large, divergent, and complex knowledge spaces that drive and manage variation for innovation (Beretta et al., 2018; van den Ende et al., 2015). IDTs increase variation in the innovation process. To do so, our Delphi findings and the derived design choices imply that IDTs utilize *open interfaces* (Projection no. 20) embodied in products, services, or technologies in the production system to mediate transactions between the physical and the virtual world. IDTs with open interfaces enable the collection of engineering, production, and usage data by creating cross-organizational repositories that enable higher degrees of *data sharing* (Projection no. 21) (Damjanovic-Behrendt & Behrendt, 2019; Redeker et al., 2021; Silva et al., 2022; Stark, 2022).

Firms can utilize IDTs to increase the number of valuable knowledge inflows for their innovation process. Take as an example the generated information during a product's usage stage captured through IDTs such as in the case of *Teslas*' electric cars (Case no. 14) or trucks from *Volvo and Scania* (Case no. 15). The IDTs enable simultaneous data transfer between the vehicles and the production plants (e.g., Tesla's Gigafactories), which facilitates the real-time data integration of product and manufacturing lifecycles. This is a valuable inflow of knowledge for innovation not available before. The integrated information of the lifecycles not only provides new insights to a manufacturer on how products are actually used by its customers but also insights about the product behavior and its status, for example, the correlation between specific production parameters and the product's durability in given usage situations.

Real-time data integration of both lifecycles creates new access capabilities to improve the simulation models

TABLE 5 Future research agenda for IDTs in innovation management.

Innovation topics	Implication of IDTs	Example of research questions for innovation management
Innovation variation	IDTs increase the variation in the innovation process through broad, continuous, and collaborative knowledge inflows from open interfaces and data sharing. IDTs enable new approaches for open innovation, allowing firms to innovate with a larger and more diverse set of interconnected partners. IDTs generated an inherent trade-off between the benefits of openness in terms of data sharing and the risk of losing critical knowledge, necessitating the need to manage the openness paradox.	• How do IDTs change the individual risk of knowledge leakage more towards a collective risk—but also a collective opportunity for innovation? • How do data spaces create opportunities and incentives to share knowledge while being protected through IDTs? • How IDTs can balance the degree of the paradox of openness through their design choices?
Innovation selection	IDTs support the selection of knowledge inputs in the innovation process and can transfer the cognitive load of decision-making towards simulation models. IDTs enable hybrid intelligence to assist in the problem-solution fit of selection decisions for innovation. IDTs enable the automation of simulations, generating new approaches for hybrid testing with algorithm-based decision-making in the selection process.	• How do IDTs impact human-machine (AI) collaboration to facilitate organizational learning and innovation? • To what extent humans will remain part of strategic and operational decision-making in innovation management and how does that impact creativity in the innovation process? • What are the organizational tensions of digitalizing human knowledge through IDTs for hybrid intelligence in the selection process of innovation?
Innovation governance	IDTs necessitate suitable governance models that account for all divergent interests of different actors in the innovation process. Two alternatives for the orchestration of innovation activities emerge, impacting the competitive industry dynamics: IDTs could be either 1. governed by one keystone player, or 2. by an alliance of actors managing a data space together in a decentralized governance mode.	• Under which conditions will one central orchestrator emerge who disproportionally benefits from IDTs while ensuring overall ecosystem health for innovation? • How do alliance-driven approaches establish new forms of decentral innovation ecosystems through IDTs and the originating data spaces?

on the engineering stage for new product and manufacturing process innovations while increasing production adaptability. Sharing the data of IDTs create access to this knowledge beyond the manufacturer. External partners along the value chain, such as suppliers, production partners, and sales agents, can use the data of IDTs to continuously improve and innovate their processes and products or enable collaborative innovation for *digital services* (Projection no. 13). IDTs increase variation in the innovation process through real-time data integration of product and manufacturing lifecycles, generating broader, and continuous knowledge inflows. Additionally, sharing lifecycle data generate broader utilization of these data, leading to new forms of collaborative innovations. Hence, IDTs foster open innovation, allowing a larger and more diverse set of partners to search for a specific solution to a given innovation task from external sources (Niu & Qin, 2021; Silva et al., 2022).

However, to create shared data through IDTs (so that new, useful variation for innovation becomes possible), a sufficient number of companies must share their data (Michael et al., 2022; Silva et al., 2022). In this context, the literature on innovation management points to the "paradox of openness" (Arora et al., 2016; Laursen & Salter, 2014); that is, the tradeoff between the benefits of openness in terms of incentivizing more external contributors to share data and the shortcomings of openness in terms of increased uncertainties—such as the risk of revealing critical knowledge to competitors (Moschko et al., 2023). The paradox of openness suggests that if too little is shared through IDTs, others might not be willing to contribute and share data through the IDT network. Opening up to outside sources of knowledge to innovate may weaken the firm's power to capture rents from that knowledge. Data openness through IDTs, for example, poses a risk for machine manufacturers that physical production assets and their IP are commoditized, when other actors appropriate the assets' value by capturing its process or application knowledge and providing complementary *digital services* (Projection no. 13). Firms are more

likely to seek external collaborators if they can protect their innovation through patents, and more generally, guard against unintended knowledge spillovers to partners. However, a focus on patenting and exclusivity makes a firm less efficient in developing collaborative innovations and, thus, a less attractive partner (Arora et al., 2016; Foege et al., 2019). Hence, the degree of *data sharing* (Projection no. 21) through IDTs is a critical design choice of our Delphi findings. It impacts the variation of possible innovation opportunities for value creation on an interorganizational level while making value capture through IP protection more difficult on the firm level (Michael et al., 2022).

Formal (e.g., patents, copyrights) and informal (e.g., secrecy/anonymity, selective revealing) IP protection practices are focusing on guarding a single firm to manage the paradox of openness (Arora et al., 2016; Foege et al., 2019). The increasing interconnectedness through open interfaces of IDTs generates large and complex data spaces among all connected actors. In this context, the question arises of how IDTs change the individual risk of knowledge spillovers more towards a collective risk—but also a collective opportunity for innovation (Michael et al., 2022; Otto, 2022). This value constellation bears new interesting implications in the context of variation for innovation that complement prior debates in the (open) innovation literature.

For instance, Catena-X (Case no. 17) integrates and shares data in the form of IDTs through a federated data space to foster collaboration and innovation for more environmental sustainability, illustrating Projection no. 15 from our base scenario. The ambition of the partners behind Catena-X is to increase production transparency (Projection no. 16) by tracking components and products along the entire automotive value chain and measuring their social and ecological footprint. A central feature of the Catena-X architecture (or other data space initiatives like GAIA-X, Case no. 19) is sovereign, cross-organizational data exchange—that is, the actor sharing data via IDTs retains control and decides independently who is involved in the data exchange, how, when, and where. IDTs can be complemented with other digital technologies (e.g., Blockchain) to share, control, and protect the production data, its IP, and the identity of data owners for greater data sovereignty (Braud et al., 2021; Otto, 2022; Redeker et al., 2021). In turn, the higher level of control over data and capabilities contained in IDTs increases companies' willingness to share production and usage data for innovation.

In consequence, IDTs create innovation opportunities concerning measures and governance schemes to balance data sharing, distributed data control, and decentral interactions in IDSs (Otto, 2022; Silva et al., 2022). Future research can investigate the effects of such developments from the perspectives of competitive strategy and novel ways of generating innovation collectively. In this context, a major question arises of how IDTs can balance the paradox of openness through potential design choices in such data spaces, following the established concept like selective revealing or strategic openness (Alexy et al., 2013; Alexy et al., 2018)—that is, strategically opening and revealing nonsensitive manufacturing data (e.g., from machine and product commodities) while simultaneously ensuring the protection of sensitive component and process information in the physical and virtual manufacturing system. Besides the data space initiatives of *Catena-X* and *GAIA-X*, we could only observe very early other practices of such behavior in our case data (e.g., in Case no. 22, DataConnect). Further research, perhaps following a design science paradigm, needs to investigate this development in more detail.

5.2 | IDTs and the selection of innovation

Research has shown that too much variation is problematic because it generates countless knowledge inputs that might be of low quality and are difficult to evaluate (Beretta et al., 2018; van den Ende et al., 2015). *Selection*, hence, involves analytical and reflective convergence of knowledge inputs from different sources into the innovation process. According to cognitive load theory (Paas et al., 2004), selection quality suffers as evaluators face cognitive overload and are not able to identify the most promising knowledge inputs for innovation among the wide range of alternatives (Beretta et al., 2018; Cheng et al., 2020; van den Ende et al., 2015). In this context, IDTs can facilitate the offloading of all or some of the cognitive load for decision-making towards the simulation models embedded in IDTs (Fukawa & Rindfleisch, 2023; Tao et al., 2018; Xia et al., 2021).

Our identified Delphi design choice for organization shows that machine intelligence coupled with IDTs offers greater information processing capacity and decision accuracy for organizing innovation through *hybrid intelligence* (Projection no. 6; Dellermann et al., 2019; Fuller et al., 2020; Xia et al., 2021). IDTs utilize algorithms to integrate and process large amounts of data required to analyze performance and make predictions. They support humans in connecting different data sources, but also actors with resources and information to support collective and better-informed decision-making within a production system (Hoffmann et al., 2019; West et al., 2021; Xia et al., 2021). Industrial applications such as *ABB Ability* (Case no. 3), *Foxconn BEACON* (Case no. 10), or *PTC's*

ThingWorx (Case no. 13) use IDTs to automate simulations of manufacturing by taking inputs from sensors, machines, and other production sources to improve and innovate production processes. For example, a DT of a production line with its machines can simulate how its elements will behave under different conditions or designs and identify potential issues before they occur. The simulation intelligence generated by IDTs links problem and solution information in an automated way, supporting decision-making about the appropriate problem-solution fit in a production system. Automated simulation models provided by IDTs allow for new approaches to experimentation and trial-and-error learning in innovation management—for example, combining human and machine intelligence (AI) in the form of hybrid testing approaches (Fuller et al., 2020; West et al., 2021; Xia et al., 2021).

In this context, future research has to identify ways in which firms can organize such decision-making for innovation selection between humans and algorithms and allocate prototyping and testing tasks to either humans or AI embedded in IDTs (Piller et al., 2022). Based on these results, we propose to investigate how different design choices of IDTs can impact human–machine collaboration for selection and decision-making to facilitate organizational learning and innovation. Investigating different sets of design choices that determine the extent to which humans remain part of strategic and operational decision-making in innovation management could be at the heart of such future research. For instance, IDTs allow for more (autonomous) AI-based decision-making and thus a potential reduction of human contributions and *workforce* (Projection no. 11). However, this future development also reduces the autonomy of teams in their freedom to innovate, which might hamper creativity in the innovation process. How to find the right balance between contributions from machines and humans remains an open question for future research, asking also for a reconsideration of the established literature on team composition in innovation management (Bouschery et al., 2023).

An extreme design choice from our Delphi findings is the comprehensive virtualization of human resources and decisions in manufacturing by *Human DTs* (Mertens et al., 2021). *INVISTA* (Case no. 16) builds IDTs by using *AWS IoT TwinMaker* to capture and interconnect the tacit knowledge and experience of employees working in the production system, but also in engineering and development. Such interconnected *employee twins* (Projection no. 9) can share learning with others who implicitly assimilate and benefit from the collective insights to improve the decision-making in the selection process of innovation. The digitalization of human knowledge and learning by IDTs facilitates new possibilities for company-wide and cross-organizational knowledge management and *hybrid intelligence* (Projection no. 6; Brauner et al., 2020; Fuller et al., 2020), but might also create new organizational tensions (Dellermann et al., 2019; Raisch & Krakowski, 2020). For instance, our Delphi findings show issues regarding *employee rights* (Projection no. 10) in terms of data privacy conflicts and the need to anonymize human-related production data—potentially impacting the application scope and decision-making capabilities of hybrid intelligence through IDTs in the innovation process.

5.3 | IDTs and innovation governance

A third implication of IDTs for innovation management originates from the alternatives of orchestrating digital platforms (Otto, 2022; Xu et al., 2020). IDTs distributed among different actors necessitate suitable *governance* models that account for all divergent interests in the innovation process (Silva et al., 2022). From our Delphi findings, we imply that manufacturing firms must manage the positive and negative effects of evolving IDTs. Similar to other digital platforms, we see two alternatives for the orchestration of innovation activities. IDTs could be either governed by one keystone player (Iansiti & Levien, 2004), the established model for many *central data platforms* (Projection no. 02), or by an alliance of actors managing a data space together in a decentralized and federated governance mode (Otto, 2022; Silva et al., 2022; Xu et al., 2020).

In the case of IDTs *managed by one keystone player*, a single entity is orchestrating value creation and capture from exchanged data (Otto, 2022; Redeker et al., 2021). This is the typical model of *central data platforms* (Projection no. 02) in consumer markets, but also a model that many operators of industrial data platforms originally follow (van Dyck et al., 2021)—for example, Cases no. 4 *GE Predix*, no. 12 *John Deere Operations Center*, or no. 13 *PTC ThingWorx*. A keystone player acts as a *data mediator* (Projection no. 03), who forces strong centralization of data and knowledge within an ecosystem to create "winner takes all" platform business models (Eisenmann, 2006). Keystone players act within unregulated competition and aim to control the network effects and also new value capture mechanisms—such as *subscription models* (Projection no. 01) for industrial machines (e.g., Case no. 8 *Munich Re and Bosch*), data or new digital services (e.g., Case no. 10 *Foxconn BEACON*), and so forth. In this context, innovation management research could investigate the issue of how one central orchestrator will emerge who disproportionally benefits

from IDTs while ensuring overall ecosystem health for innovation, that is, fairly regulating the value appropriation of the innovation variation and selection, protecting the network knowledge, and addressing the openness paradox.

But some of the case studies complementing our Delphi research indicate an interesting alternative approach to a platform managed by one keystone player: *an alliance-orchestrated or federated data space*. In this case, IDTs and their underlying data space are designed and jointly orchestrated by multiple actors from a specific industry domain under common rules and standards. Examples of such federated data spaces are *DataConnect* (Case no. 22), *GAIA-X* (Case no. 19), or Catena-X (Case no. 17), which foster *decentralization* (Projection no. 24) of value creation and capture (Braud et al., 2021; Otto, 2022). Drivers of such an approach are the need to utilize domain-specific contextual knowledge for better predictions and prescriptions, but also a desire for data sovereignty and distributed control, which is based on a future *Industrial GDPR* (Projection no. 04) to create regulated ecosystems in digital manufacturing (Cappiello et al., 2020; Otto, 2022). Future research should investigate how these alliance-driven approaches establish new forms of decentral innovation ecosystems through IDTs.

Hence, alliance-driven approaches governing IDTs provide many interesting options for future research (Fukawa & Rindfleisch, 2023) and build the foundation of creating data spaces that increase the *decentralization* (Projection no. 24) of digital platforms (Braud et al., 2021; Otto, 2022). In practice, manufacturers have different design choices that shape the IDT network and its complements in a way they perceive as a fair balance in their participation and share between value creation (innovation) and value capture. The aim is to foster, incentivize, and protect collaborative innovation activities among all interconnected actors, which drive innovation variation and selection collectively in an ecosystem.

5.4 | Limitations and conclusion of the Delphi study

Our research is not without limitations. First, our Delphi survey was conducted during the COVID-19 pandemic. While we could use this to our advantage to assess the impact of the pandemic on operations, it is also possible that experts rated projections higher which were of greater importance or presence to them. A further analysis of the lower-rated projections could thus be fruitful. Second, the real-time Delphi method relies on the subjective input and opinions of those involved. As with any subjective data collection technique, the risk of bias exists. Participants' responses may be influenced by self-selection, perspective, experience, or personal bias. This subjectivity can potentially have an impact on the generalizability and objectivity of the findings. As our scenarios are based on qualitative data and supported by quantitative assessments, the inclusion of more secondary statistical data alongside the Delphi estimates could improve the accuracy of our predictions and address potential biases (Jiang et al., 2017).

Third, while Delphi panels do not require a representative sample and our expert panel is in line with other Delphi studies in terms of size and heterogeneity (Beiderbeck et al., 2021), the generalization should be considered against the demography of our sample and our implication should be validated by larger scale surveys among manufacturers. For example, our research did not aim to statistically analyze differences between the subgroups of our experts. When analyzing the data, we did also not find any differences or patterns in response behavior that could be explained theoretically. Future research could leverage a larger panel with distinct subgroups to analyze significant differences (e.g., depending on geography or nationality). This could be particularly fruitful given, for example, the different philosophies of data privacy across the globe as a factor in shaping views on digital manufacturing.

Digital manufacturing in general and IDTs in particular are phenomena that are just beginning to emerge. IDTs have the potential to revolutionize innovation in digital manufacturing by enabling the generation of diverse knowledge inputs and facilitating informed decision-making through hybrid intelligence. However, successful implementation and management of IDTs require addressing challenges related to data sharing, striking a balance between human and machine contributions, and developing robust governance models to balance value creation (innovation) and value capture among interconnected entities. Besides many open and emerging technical issues, various managerial questions will shape the development in this area. Our study design could not capture these organizational and individual-level dynamics. But, innovation management research has a rich methodological toolbox and experience to study these questions in future research. With this in mind, we hope that our study can encourage more research in this important and fascinating field.

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REFERENCES

Aengenheyster, S., K. Cuhls, L. Gerhold, M. Heiskanen-Schüttler, J. Huck, and M. Muszynska. 2017. "Real-Time Delphi in Practice: A Comparative Analysis of Existing Software-Based Tools." *Technological Forecasting and Social Change* 118: 15–27.

Alexy, O., G. George, and A. J. Salter. 2013. "Cui Bono? The Selective Revealing of Knowledge and Its Implications for Innovative Activity." *Academy of Management Review* 38(2): 270–91.

Alexy, O., J. West, H. Klapper, and M. Reitzig. 2018. "Surrendering Control to Gain Advantage: Reconciling Openness and the Resource-Based View of the Firm." *Strategic Management Journal* 39(6): 1704–27.

Appio, F. P., F. Frattini, A. M. Petruzzelli, and P. Neirotti. 2021. "Digital Transformation and Innovation Management: A Synthesis of Existing Research and an Agenda for Future Studies." *Journal of Product Innovation Management* 38(1): 4–20.

Arora, A., S. Athreye, and C. Huang. 2016. "The Paradox of Openness Revisited. Collaborative Innovation and Patenting by UK Innovators." *Research Policy* 45(7): 1352–61.

Beiderbeck, D., N. Frevel, H. von der Gracht, S. Schmidt, and V. Schweitzer. 2021. "Preparing, Conducting, and Analyzing Delphi Surveys: Cross-Disciplinary Practices, New Directions, and Advancements." *MethodsX* 8: 101401.

Beretta, M., J. Björk, and M. Magnusson. 2018. "Moderating Ideation in Web-Enabled Ideation Systems." *Journal of Product Innovation Management* 35(3): 389–409.

Björkdahl, J. 2020. "Strategies for Digitalization in Manufacturing Firms." *California Management Review* 62(4): 17–36.

Bokrantz, J., A. Skoogh, C. Berlin, and J. Stahre. 2017. "Maintenance in Digitalised Manufacturing: Delphi-Based Scenarios for 2030." *International Journal of Production Economics* 191: 154–69.

Bouschery, S. G., V. Blazevic, and F. Piller. 2023. "Augmenting Human Innovation Teams with Artificial Intelligence: Exploring Transformer Language Models." *Journal of Product Innovation Management* 40(2): 139–53.

Braud, A., G. Fromentoux, B. Radier, and O. Le Grand. 2021. "The Road to European Digital Sovereignty with Gaia-X and IDSA." *IEEE Network* 35(2): 4–5.

Brauner, P., F. Brillowski, H. Dammers, P. Königs, F. Kordtomeikel, H. Petruck, A. K. Schaar, et al. 2020. "A Research Framework for Human Aspects in the Internet of Production." In *Advances in Manufacturing, Production Management and Process Control*, edited by B. Mrugalska, S. Trzcielinski, W. Karwowski, M. Di Nicolantonio, and E. Rossi, 3–17. Cham: Springer.

Cappiello, C., A. Gal, M. Jarke, and J. Rehof. 2020. "Data Ecosystems: Sovereign Data Exchange among Organizations (Dagstuhl Seminar 19,391)." *Dagstuhl Seminar* 19(391): 9.

Cennamo, C. 2021. "Competing in Digital Markets: A Platform-Based Perspective." *Academy of Management Perspectives* 35(2): 265–91.

Cheng, X., S. Fu, T. de Vreede, G.-J. de Vreede, I. Seeber, R. Maier, and B. Weber. 2020. "Idea Convergence Quality in Open Innovation Crowdsourcing: A Cognitive Load Perspective." *Journal of Management Information Systems* 37(2): 349–76.

Cloutier, C., and D. Ravasi. 2021. "Using Tables to Enhance Trustworthiness in Qualitative Research." *Strategic Organization* 19(1): 113–33.

Damjanovic-Behrendt, V., and W. Behrendt. 2019. "An Open Source Approach to the Design and Implementation of Digital Twins for Smart Manufacturing." *International Journal of Computer Integrated Manufacturing* 32(4–5): 366–84.

Dellermann, D., P. Ebel, M. Söllner, and J. M. Leimeister. 2019. "Hybrid Intelligence." *Business & Information Systems Engineering* 61(5): 637–43.

Deutsche Bahn. 2020. *Trend Study Digital Twin*. Berlin: DB Systel GmbH. https://www.dbsystel.de.

Digital Twin Consortium. 2020. The Definition of a Digital Twin. https://www.digitaltwinconsortium.org/initiatives/the-definition-of-a-digital-twin.htm.

Eisenhardt, K. M., and M. E. Graebner. 2007. "Theory Building from Cases: Opportunities and Challenges." *Academy of Management Journal* 50(1): 25–32.

Eisenmann, T. R. 2006. "Internet companies' Growth Strategies: Determinants of Investment Intensity and Long-Term Performance." *Strategic Management Journal* 27(12): 1183–204.

Foege, J. N., G. D. Lauritzen, F. Tietze, and T. O. Salge. 2019. "Reconceptualizing the Paradox of Openness: How Solvers Navigate Sharing-Protecting Tensions in Crowdsourcing." *Research Policy* 48(6): 1323–39.

Fukawa, N., and A. Rindfleisch. 2023. "Enhancing Innovation Via the Digital Twin." *Journal of Product Innovation Management* 40 (Special Issue on "The Impact of Digital Manufacturing on Innovation"). https://doi.org/10.1111/jpim.12655.

Fuller, A., Z. Fan, C. Day, and C. Barlow. 2020. "Digital Twin: Enabling Technologies, Challenges and Open Research." *IEEE Access* 8: 108952–71.

Gartner. 2019. What to expect when you're expecting digital twins. https://www.gartner.com/en/documents/3905979/what-to-expect-when-you-re-expecting-digital-twins.

Gawer, A. 2014. "Bridging Differing Perspectives on Technological Platforms: Toward an Integrative Framework." *Research Policy* 43(7): 1239–49.

Gioia, D. A., K. G. Corley, and A. L. Hamilton. 2013. "Seeking Qualitative Rigor in Inductive Research." *Organizational Research Methods* 16(1): 15–31.

Gnatzy, T., J. Warth, H. von der Gracht, and I.-L. Darkow. 2011. "Validating an Innovative Real-Time Delphi Approach: A Methodological Comparison between Real-Time and Conventional Delphi Studies." *Technological Forecasting and Social Change* 78(9): 1681–94.

Goduscheit, R. C., and R. Faullant. 2018. "Paths toward Radical Service Innovation in Manufacturing Companies. A Service-Dominant Logic Perspective." *Journal of Product Innovation Management* 35(5): 701–19.

Gordon, T., and A. Pease. 2006. "RT Delphi: An Efficient, "Round-Less" Almost Real Time Delphi Method." *Technological Forecasting and Social Change* 73(4): 321–33.

Haefner, N., J. Wincent, V. Parida, and O. Gassmann. 2021. "Artificial Intelligence and Innovation Management: A Review, Framework, and Research Agenda." *Technological Forecasting and Social Change* 162: 120392.

Hasson, F., and S. Keeney. 2011. "Enhancing Rigour in the Delphi Technique Research." *Technological Forecasting and Social Change* 78(9): 1695–704.

Hoffmann, J. B., P. Heimes, and S. Senel. 2019. "IoT Platforms for the Internet of Production." *IEEE Internet of Things Journal* 6(3): 4098–105.

Iansiti, M., and R. Levien. 2004. "Strategy as Ecology." *Harvard Business Review* 82(3): 68–78.

Jiang, R., R. Kleer, and F. Piller. 2017. "Predicting the Future of Additive Manufacturing: A Delphi Study on Economic & Societal Implications of 3D Printing for 2030." *Technological Forecasting & Social Change* 117: 84–97.

Jovanovic, M., D. Sjödin, and V. Parida. 2021. "Co-Evolution of Platform Architecture, Platform Services, and Platform Governance: Expanding the Platform Value of Industrial Digital Platforms." *Technovation* 118: 102218.

Keller, J., and H. A. von der Gracht. 2014. "The Influence of Information and Communication Technology (ICT) on Future Foresight Processes — Results from a Delphi Survey." *Technological Forecasting and Social Change* 85: 81–92.

Laursen, K., and A. Salter. 2014. "The Paradox of Openness. Appropriability, External Search and Collaboration." *Research Policy* 43(5): 867–78.

Linstone, H. A. 1981. "The Multiple Perspective Concept. With Applications to Technology Assessment and Other Decision Areas." *Technological Forecasting and Social Change* 20(4): 275–325.

Linstone, H. A., and M. Turoff, eds. 2002. *The Delphi Method. Techniques and Applications*. Reading, Mass: Addison-Wesley.

Markmann, C., I.-L. Darkow, and H. von der Gracht. 2013. "A Delphi-Based Risk Analysis: Identifying and Assessing Future Challenges for Supply Chain Security in a Multi-Stakeholder Environment." *Technological Forecasting and Social Change* 80(9): 1815–33.

Markmann, C., A. Spickermann, H. von der Gracht, and A. Brem. 2021. "Improving the Question Formulation in Delphi-Like Surveys: Analysis of the Effects of Abstract Language and Amount of Information on Response Behavior." *Futures & Foresight Science* 3(1): e56.

Mertens, A., S. Putz, P. Brauner, F. Brillowski, N. Buczak, H. Dammers, et al. 2021. Human Digital Shadow: Data-Based Modeling of Users and Usage in the Internet of Production. In 2021 14th International Conference on Human System Interaction (HSI). IEEE.

Michael, J., J. Pfeiffer, B. Rumpe, and A. Wortmann. 2022. Integration Challenges for Digital Twin Systems-of-Systems. In 2022 IEEE/ACM 10th Int. Workshop on Software Engineering for Systems-of-Systems and Software Ecosystems (SESoS), pp. 9–12.

Michelfelder, I., and J. Kratzer. 2013. "Why and how Combining Strong and Weak Ties within a Single Interorganizational R&D Collaboration Outperforms Other Collaboration Structures." *Journal of Product Innovation Management* 30(6): 1159–77.

Moschko, L., V. Blazevic, and F. T. Piller. 2023. "Paradoxes of Implementing Digital Manufacturing Systems: A Longitudinal Study of Digital Innovation Projects for Disruptive Change." *Journal of Product Innovation Management* 40 (Special Issue on "The Impact of Digital Manufacturing on Innovation"). https://doi.org/10.1111/jpim.12667.

Niu, X., and S. Qin. 2021. "Integrating Crowd−/Service-Sourcing into Digital Twin for Advanced Manufacturing Service Innovation." *Advanced Engineering Informatics* 50: 101422.

Noy, C. 2008. "Sampling Knowledge: The Hermeneutics of Snowball Sampling in Qualitative Research." *International Journal of Social Research Methodology* 11(4): 327–44.

Ogden, J. A., K. J. Petersen, J. R. Carter, and R. M. Monczka. 2005. "Supply Management Strategies for the Future: A Delphi Study." *Journal of Supply Chain Management* 41(3): 29–48.

Otto, B. 2022. "The Evolution of Data Spaces." In *Designing Data Spaces: The Ecosystem Approach to Competitive Advantage*, edited by B. Otto, M. ten Hompel, and S. Wrobel, 3–15. Cham: Springer.

Otto, B., and M. Jarke. 2019. "Designing a Multi-Sided Data Platform: Findings from the International Data Spaces Case." *Electronic Markets* 29(4): 561–80.

Paas, F., A. Renkl, and J. Sweller. 2004. "Cognitive Load Theory: Instructional Implications of the Interaction between Information Structures and Cognitive Architecture." *Instructional Science* 32(1/2): 1–8.

Parker, G., and M. van Alstyne. 2018. "Innovation, Openness, and Platform Control." *Management Science* 64(7): 3015–32.

Parrot, A., B. Umbenhauer, and L. Warshaw. 2020. Digital Twins - Bridging the Physical and Digital. Deloitte Insights. https://www.deloitte.com/us/en/insights/focus/tech-trends/2020/digital-twin-applications-bridging-the-physical-and-digital.html.

Piller, F. T., and V. Nitsch. 2022. "How Digital Shadows, New Forms of Human-Machine Collaboration, and Data-Driven Business Models Are Driving the Future of Industry 4.0." In *Forecasting Next Generation Manufacturing* 1–31. Cham: Springer.

Piller, F. T., V. Nitsch, and W. van der Aalst. 2022. "Hybrid Intelligence in Next Generation Manufacturing." In *Forecasting Next Generation Manufacturing* 139–58. Cham: Springer.

Raisch, S., and S. Krakowski. 2020. "Artificial Intelligence and Management: The Automation-Augmentation Paradox." *Academy of Management Review* 46(1): 192–210.

Redeker, M., J. N. Weskamp, B. Rossl, and F. Pethig. 2021. Towards a Digital Twin Platform for Industrie 4.0. In *2021 4th IEEE International Conference on Industrial Cyber-Physical Systems* (*ICPS*), 39–46. IEEE.

Rindfleisch, A., M. O'Hern, and V. Sachdev. 2017. "The Digital Revolution, 3D Printing, and Innovation as Data." *Journal of Product Innovation Management* 34(5): 681–90.

Saldaña, J. 2021. *The Coding Manual for Qualitative Researchers*. London: SAGE Publications.

Schmalz, U., S. Spinler, and J. Ringbeck. 2021. "Lessons Learned from a Two-Round Delphi-Based Scenario Study." *MethodsX* 8: 101179.

Schoemaker, P. J. H. 1995. "Scenario Planning: A Tool for Strategic Thinking." *MIT Sloan Management Review* 36(2): 25–41.

Silva, H., T. Moreno, A. Almeida, A. L. Soares, and A. Azevedo. 2022. "A Digital Twin Platform-Based Approach to Product Lifecycle Management." In *Towards a Transformer 4.0 In Innovations in Industrial Engineering II*, edited by J. Machado, F. Soares, J. Trojanowska, V. Ivanov, K. Antosz, Y. Ren, V. K. Manupati, and A. Pereira, 14–25. Cham: Springer.

Stanko, M. A., G. J. Fisher, and M. Bogers. 2017. "Under the Wide Umbrella of Open Innovation." *Journal of Product Innovation Management* 34(4): 543–58.

Stark, R. 2022. *Virtual Product Creation in Industry*. Berlin: Springer.

Strauss, A., and J. Corbin. 1990. *Basics of Qualitative Research. Grounded Theory Procedures and Techniques*. London: SAGE.

Tao, F., J. Cheng, Q. Qi, M. Zhang, H. Zhang, and F. Sui. 2018. "Digital Twin-Driven Product Design, Manufacturing and Service with Big Data." *International Journal of Advanced Manufacturing Technology* 94(9–12): 3563–76.

van den Ende, J., L. Frederiksen, and A. Prencipe. 2015. "The Front End of Innovation: Organizing Search for Ideas." *Journal of Product Innovation Management* 32(4): 482–7.

van Dyck, M., D. Lüttgens, F. Piller, and K. Diener. 2021. Positioning Strategies in Emerging Industrial Ecosystems for Industry 4.0. In Proceedings of the 54th Hawaii International Conference on System Sciences (HICSS), Vol. 54, p. 6253–6262.

von der Gracht, H. A., and I.-L. Darkow. 2010. "Scenarios for the Logistics Services Industry: A Delphi-Based Analysis for 2025." *International Journal of Production Economics* 127(1): 46–59.

West, S., O. Stoll, J. Meierhofer, and S. Züst. 2021. "Digital Twin Providing New Opportunities for Value co-Creation through Supporting Decision-Making." *Applied Sciences* 11(9): 3750.

Xia, K., C. Sacco, M. Kirkpatrick, C. Saidy, L. Nguyen, A. Kircaliali, and R. Harik. 2021. "A Digital Twin to Train Deep Reinforcement Learning Agent for Smart Manufacturing Plants." *Journal of Manufacturing Systems* 58: 210–30.

Xu, Y., T. Päivärinta, and P. Kuvaja. 2020. "Digital Twins as Software and Service Development Ecosystems in Industry 4.0." In *Big Data and Security*, edited by Y. Tian, T. Ma, and M. K. Khan, 51–64. Singapore: Springer.

Yaniv, I. 2011. "Group Diversity and Decision Quality: Amplification and Attenuation of the Framing Effect." *International Journal of Forecasting* 27(1): 41–9.

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APPENDIX A

TABLE A1 Examples of use cases of digital twins.

No.	Solution/organization	Use case description/application	Industry	Source
1	Ansys Twin Builder/Kärcher	Kärcher, a German manufacturer of industrial and home cleaning equipment, built a digital twin of one of its floor cleaners using the Ansys Twin Builder. The virtual representation of the product helped the engineering team to simulate the effect of design changes on the product's performance. Due to the representation of the entire product, different scenarios of electrochemical-thermal flows could be simulated, which enabled the development of a smaller battery pack that reduces weight and heat.	Equipment manufacturing	Internal reports Press articles Literature
2	AVEVA Group/Italpresse Gauss	AVEVA Group and Italpresse Gauss developed a discrete digital twin to collect operational data and improve situational awareness through high-fidelity digital representations of their die-casting machines within an AR/VR environment. The digital twin creates a safe, reliable environment to study, inspect, and test asset maintenance and optimization strategies before implementation. Applying augmented and virtual reality layers over the discrete digital twin enables increased maintenance and asset performance optimization or training needs by using smart devices like Microsoft HoloLens.	Industrial manufacturing	Industry report Internal reports Website
3	ABB Ability/Xianglu Petrochemicals Zhangzhou	Chinese petrochemical manufacturer Xianglu Petrochemicals Zhangzhou used ABB's Ability solution to build a digital twin of its plant. The main goal was to mitigate downtime by monitoring speed drives that stir petrochemical materials. Based on condition monitoring tools, Xianglu was able to reduce downtime. In addition, energy management helps to lower the carbon footprint. By offering the Ability software, ABB itself can tap into new business models. Subscription models are planned in the future, for example, for predictive maintenance services of cloud-connected robots.	Process industry	Literature Website
4	GE/Conglomerate manufacturer	GE developed a process digital twin for the cement division of a China-based conglomerate manufacturer using its industrial analytics software Proficy CSense which runs on GE's Predix platform. The conglomerate manufacturer wanted to control the cooling process. By collecting and analyzing data from the cooler, GE could simulate the effect of input changes on the cement cooler's performance and recommend adjustments to maximize heat recovery and energy-efficient cooling in real-time.	Process industry	Literature Website
5	Haier COSMOPlat/Tongyi Ceramic	Tongyi Ceramic, a manufacturer in the ceramic industry, developed a digital twin of the full design and production process using Haier's COSMOPlat solution. Its goal is to engage users in the full production process. Users can design their products in a mass-customized manner and monitor production and delivery throughout the process. Collaboration with users in the design phase ensures market fit and higher quality products. At the same time, streamlined processes due to increased transparency resulted in cost reductions for Tongyi.	Industrial manufacturing	Industry report Literature

(Continues)

TABLE A1 (Continued)

No.	Solution/organization	Use case description/application	Industry	Source
6	SWIM.AI/Cubic	Cubic, a US technology company in the transportation industry, built a digital twin of transportation infrastructure in selected cities using Swim's software. Cubic wanted to connect infrastructure with vehicles to deliver data services, but a centralized approach was not viable due to the enormous data volume generated by transportation networks. Swim combines local data processing, analytics, edge computing, and machine learning to deal with raw data locally and decentrally. Connected, it can provide real-time insights to optimize processes.	Mobility	Industry report Website
7	BAOWU Carbon Materials & Technology	BAOWU created a digital twin of its production network across China. Each production site was equipped with sensors that generate data that is aggregated into a digital twin. The digital twin feeds the data and analytics into a platform that operates as a virtual factory. Managers can remotely manage the decentralized plant locations and maintenance schedules via this platform. Thereby, the need for managers at the locations was reduced. In addition, production capacity can more easily be distributed to increase capacity and allocate production according to operational cost and lower lead times for customers. The real-time data also enables predictive maintenance.	Industrial manufacturing	Industry report Website
8	Bosch/Munich Re	Munich Re, a multinational insurance company, cooperated with industrial equipment provider Bosch to create digital twins for small and medium-sized manufacturers (SMEs). Bosch retrofitted SME machines with sensors and connectivity devices to create a digital twin that feeds to a platform. Munich Re is the owner of this equipment and leverages its expertise in risk models to run data analytics on the platform and ensure that the equipment is performing as agreed. If necessary, Bosch executes maintenance. The SMEs pay Munich Re with a "per-use" pricing model, reducing their risk and minimizing capital investments.	Industrial manufacturing	Industry report Website
9	Dassault Systèmes "Build to Operate"/ Airbus	Aviation manufacturer Airbus used Dassault Systèmes' software to build a digital twin of its manufacturing line for helicopters. It connected its production machinery across assembly lines to simulate production changes in a virtual factory using 3D design. The digital twin helped to increase the transparency of the production process, leading to higher efficiency and improved product quality.	Aerospace/Defense	Literature Website
10	Foxconn BEACON	Chinese contract manufacturer Foxconn built a digital twin of production plants connecting sensors, robots, and data analytics to automate production and supply chain processes. In these "lights-off factories," digital twins enable the automation of decision-making which lowers the required workforce for controlling production processes manually. In addition to optimizing its internal processes, Foxconn started offering these digital services to its suppliers and customers. Customers upload their data to Foxconn's digital twin, and Foxconn analyzes the data and communicates necessary adjustments or maintenance needs via apps back to the customer. Customers benefit from increased efficiency, and suppliers can use the data to customize their machinery based on usage	Industrial manufacturing	Industry report Website

TABLE A1 (Continued)

No.	Solution/organization	Use case description/application	Industry	Source
		patterns. Foxconn can thereby monetize the interactions between suppliers and customers and offer analytics apps.		
11	Hitachi Rail/Lumada IoT	Hitachi Rail monitors digital twins of its trains via the platform Lumada IoT. This allows the manufacturer of railways to offer "trains-as-a-service" in the United Kingdom. Hitachi Rail keeps ownership of the trains and is paid by railway operators for on-time transportation. A prerequisite for this model is to monitor the trains' usage, utilization, and performance in real-time to make necessary adjustments and maintenance and to provide advice on the operation.	Mobility	Industry report Website
12	John Deere Operations Center	Farm equipment manufacturer John Deere developed its Operation Center as a digital twin of farmers' machinery assets. John Deere equipped its machines with sensing and communication devices that feed into the Operation Center. Selected app developers can access the data and offer services to optimize farming processes in a subscription model. Since many farmers operate machines from multiple brands, John Deere decided to collaborate with two competing farming equipment manufacturers on a joint data exchange. Consequently, farmers could integrate their multi-brand machinery data into one digital twin. While John Deere opened its machinery interface, it kept its access for app complementors selectively closed. Thereby, it was able to control who had access to the digital twin's data. By separating the closed and openness choice on different layers, John Deere found an approach to create value for farmers and complementors. However, it did not monetize the services on the platform and thereby lacked proper value capture mechanisms.	Agriculture	Interviews Internal reports Press releases
13	PTC ThingWorx/HIROTEC	HIROTEC, a supplier of machinery tools for the automotive industry, developed a digital twin for its CNC machines at their Detroit plant using PTC ThingWorx. The digital twin connects real-time usage data with data from the ERP system to optimize production planning. Due to increased transparency about equipment usage, resource efficiency was improved. In addition, the quality of manufactured exhaust systems could automatically be inspected, reducing the need for manual inspection and quality decisions by humans.	Automotive manufacturing	Internal report Literature
14	Tesla	Tesla developed a composite digital twin for each electric car to enable data transfer between the car and Tesla's Giga factories. Through analytics of real-time vehicle data, the battery of electric cars can be optimized according to their usage for larger sustainability and resource efficiency. Monitoring battery health also simplifies recycling and second-life use cases. In addition, the digital twin supports future product development by generating deeper insights about usage. Software-based improvements can be delivered as over-the-air updates in a pay-per-use model.	Automotive manufacturing	Literature

(Continues)

TABLE A1 (Continued)

No.	Solution/organization	Use case description/application	Industry	Source
15	Volvo Trucks & Scania	Volvo Trucks and Scania partnered to develop a joint digital twin to develop trucks. They created a digital twin that integrates usage data from their connected trucks. Analyzing usage behaviors across companies helps to better tailor new developments to users' needs. With this specific and limited goal that provides a clear benefit to both parties, the competitors were willing to share data.	Automotive manufacturing	Literature
16	Amazon Web Services (AWS) IoT TwinMaker/INVISTA	INVISTA, a global manufacturer of fiber, resins, and chemical intermediates, built a digital twin of its manufacturing operations using AWS IoT TwinMaker. The digital twin consolidates information from disparate equipment into a connected worker application. Thereby, shop floor workers receive notifications and alerts from the plant floor in real-time and get decision support on addressing the issues. In addition, the system learns from employees dealing with emerging issues. By capturing the tacit knowledge and experience of workers, the digital twin can share this learning with other workers who implicitly assimilate and benefit from the insights of others, which facilitates company-wide knowledge management. As a result, productivity and efficiency were improved as well as workers' health and safety.	Process industry	Literature Website
17	Catena-X	Catena-X is a European automotive data network with the goal to build an interconnected digital twin integrating data from all major stakeholders in the automotive value chain. One of its key use cases is to foster collaboration and innovation for more sustainability by tracking components and products along the entire value chain in production and lifecycle of usage and measuring their social and ecological footprint. While traditionally a very closed industry not willing to share information with other stakeholders, the capability of interconnected digital twins to achieve greater environmental sustainability increased the companies' willingness to share production and usage data on a common industry platform.	Automotive manufacturing	Interviews Internal report
18	Deutsche Bahn	German railway operator Deutsche Bahn pilots digital twins at different levels, including train (components, interactions, information flows), infrastructure and operation, and multi-model means of transport. A digital twin of operations monitors rail infrastructure and operations in one region to optimize the efficiency of its deployed resources. Thereby, they were able to improve the punctuality rate of trains while reducing maintenance costs. At the same time, Deutsche Bahn builds a Digital Mobility Twin Platform to model multi-modal means of transport by aggregating composite digital twins from its own infrastructure, but also from complementors (like bus companies), and travelers to recommend the best mode of transport. These recommendations represent a new service that potentially cannibalizes DB's own means of transport.	Mobility	Interviews Internal reports

TABLE A1 (Continued)

No.	Solution/organization	Use case description/application	Industry	Source
19	GAIA-X/Industrial Data Space	Industrial Data Space, developed by a consortium of European manufacturing firms and the Fraunhofer Society, provides a decentralized framework and platform for secure and trusted data exchange that feeds into multiple digital twins, based on open standards and consensus-driven governance rules. It has been integrated into the European GAIA-X initiative that convenes more than 250 participating organizations from different sectors. A core idea is the governance of data by an institutionalized alliance of different stakeholders instead of the control by a keystone firm.	Various	Interviews Literature
20	Microsoft Azure Digital Twins/Doosan Heavy Industries & Construction	Doosan, a South Korean conglomerate, developed with Microsoft and Bentley Systems a digital twin of its wind farms using Microsoft's Azure technology. The digital twin integrates all data from the wind farm's sensors and external weather data to predict production output for each turbine. These predictions are used for operational planning and to detect deviations from expected performance. This helps to manage the wind farm and predict failures, which increases efficiency and reduces cost. In addition, Doosan built 3D models based on the digital twin, which helped design new turbines and plan new infrastructure projects.	Energy	Literature Website
21	Siemens Intosite/Automotive OEM	Intosite allows the creation of cloud-based digital twins through 2D/3D/panoramic representations of a production facility, presented in its geographical context. An automotive OEM used the production information on the shop floor and the virtual representation of the production processes to design a new production line. They could communicate their tooling needs to suppliers by providing access to the digital twin on Intosite. Change requests were updated automatically and could be simulated virtually. Thereby, they created a single data source that enabled collaboration and cooperation between departments.	Automotive manufacturing	Interviews Internal reports Literature Website
22	DataConnect	DataConnect is a data space by CLAAS, John, Case IH, New Holland, and STEYR, five large OEMs of farm equipment. It allows users (farmers) to manage all their equipment in a single system. Machine data can be centrally controlled systems via an interface provided by DataConnect. This allows the entire machine fleet to be shown live, regardless of the machine manufacturer. Users are free to choose their preferred system for managing and controlling the machine data. A cloud-to-cloud connection allows data to be exchanged automatically. Fleet management, process optimization, and resource utilization are no longer restricted to a particular system, but can instead be bundled for all machines to provide an optimal overview.	Agriculture	Interviews Internal reports Literature Website

APPENDIX B

TABLE B1 Coding scheme for design choices.

Attribute	Projections	Selection rationale	First-order codes	Second-order codes
Interfaces	Open interfaces (P20)	Black swan	• Competition of proprietary standards • Different regional standards • Open interfaces as a growth booster • Open standards as prerequisites to overcome interoperability issues	Proprietary interfaces vs. open interfaces
	Data sharing (P21)	High impact, high probability	• Sharing as a threat to a business model • Cost-benefit evaluation of sharing • Sharing required for innovations in the production ecosystem • Forced to share data by strong players	
Accessible Capabilities	Digital services (P13)	High impact, high probability	• Product competencies due to innovation in material and design required • Product capabilities for specialized equipment critical • Data-based services as a differentiating factor • Innovations based on data	Product innovation vs. service innovation
	Production transparency (P16)	High impact, high probability	• An expected increase in production efficiency • Lack of data readiness • Demand for new skills and interdisciplinary knowledge • Transparency as an enabler for simulation models	
Organization	Hybrid intelligence (P6)	High impact, high probability	• Operational decision-making, not strategic • Change in management power • Data-based decision-making • AI supplement human decision-making	Human decision-making vs. algorithmic decision-making
	Employee twin (P9)	Black swan	• Concerns due to data privacy, regulation, and unions • Only partially until 2030 • Employee information beneficial for production planning	
	Employees' rights (P10)	High dissent	• Decision support instead of digitizing humans • Anonymization is not sufficient to protect privacy • Personalized data are a prerequisite for advanced analytics	

TABLE B1 (Continued)

Attribute	Projections	Selection rationale	First-order codes	Second-order codes
Governance	Central data platform (P2)	High dissent	• Tech players are pushing for a dominant position • Fragmented market with legacy hardware • Decentral ecosystem, not a monopoly platform	Unregulated competition vs. regulated ecosystem
	Data mediator (P3)	High dissent	• Middlemen or standards • Trust and security required • Distributed ledger technology eroding middlemen	
	Industrial GDPR (P4)	High impact, high probability	• A matter between two or more partners, no regulation • Regulation too slow • Legal basis to address current obstacles • Chance for EU with GAIA-X and IDS	

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