# Exploring the Role of Artificial Intelligence in Digital Value Networks as the Driver of Digital Transformation

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*„Hoffnung ist nicht die Überzeugung, dass etwas gut ausgeht, sondern die Gewissheit, dass etwas Sinn hat, egal wie es ausgeht.“*

*Vaclav Havel*

*Mit der Fertigstellung dieser Dissertation geht für mich eine überaus lehrreiche, fordernde und glückliche Phase meines Lebens zu Ende. Daher möchte ich die Gelegenheit nutzen, um einige Worte denen zu widmen, die diesen Weg ermöglicht und mich darauf begleitet haben.*

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*Danke.*

## Copyright Statement

The following sections are partly comprised of content taken from the research articles included in this doctoral thesis. To improve the readability of the text, I omit the standard labeling of these citations.

# Abstract

Digital technologies drive the emergence of highly interdependent networks of organizations that collaborate to keep up with ever faster-changing environments, jointly face the challenges of digital transformation, and create new digital value propositions together. The resulting digital value networks build on digital technologies that enable individual incumbents to share and combine various internal and external resources, providing the basis for new products and services. Among various resources shared in digital value networks, data exchange poses one promising source of new digital value propositions for incumbent organizations by unfolding the potential of modern artificial intelligence (AI) approaches. However, connecting to others to exchange data as the basis for providing new AI-driven value propositions represents, despite its anticipated benefits, also various challenges for incumbents. In this vein, this doctoral thesis examines the risks of networking with others to create new value propositions, how to leverage AI-driven services' potential in digital value networks, and how digital value networks can drive digital transformation.

With this aim in mind, this thesis explores the challenges of connecting to others for joint value creation. Research Article #1 presents the results of a Delphi study that examines the challenges of adopting industrial internet of things (IIoT) platforms, which represent a critical technical backbone of digital value networks. Research Article #1 finds that practitioners and academics deem IT security and data privacy challenges extremely relevant for adopting IIoT platforms. Building on these results, Research Article #2 presents a decision-support model that enables decision-makers from the manufacturing industry to estimate the impact of IT security incidents on their digital value networks as a basis for selecting suitable mitigation measures. Research Article #3 then presents a taxonomy of federated learning applications as a new promising approach for securely sharing data for AI approaches in digital value networks.

Beyond the risks of connecting to others for data exchange, incumbents also face the challenge of considering the statistical nature of modern AI algorithms when designing meaningful services. Here, Research Article #4 presents a decision-support model that enables decision-makers to select payment structures and design meaningful service-level agreements (SLAs) for AI-driven services in the manufacturing industry. Complementary, Research Article #5 explores the potential of combining supervised machine learning with reinforcement learning when making meaningful decisions based on the short-term predictions of AI approaches that must be aligned with the long-term service objectives of overarching SLAs.

Finally, this doctoral thesis provides a new perspective on digital transformation that balances the prevalent agency-centric narratives of managers who design their organization's digital transformation path with a view to the external environment of an organization. Therefore, Research Article #6 provides the results of a specific theorizing review in the form of convergent assumptions and avenues for future research at the intersection of research on digital transformation and digital ecosystems – an important subform of digital value networks. Building on these convergent assumptions, Research Article #7 utilizes a phenomenon-based theorizing approach to present a path constitution theory on digital transformation that shows how managers, an organization's history, and its digital ecosystem shape its digital transformation path.

In sum, this doctoral thesis examined how incumbents can manage the complexities of forming digital value networks that drive data exchange and enable the provision of new AI-driven value propositions as a central theme of digital transformation.

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# I Introduction

## 1 Motivation

Darwin informs us that the continuous adaptation to an environment drives the evolution of species through competing with others for available resources (Darwin, 1859). Over the last decades, this notion of "competing with others" to thrive in changing environments has been a central theme in many management disciplines. However, also stemming from evolutionary thought, the last decades witnessed the rise of a new narrative that challenges Darwinism: Symbiotic relationships in ecosystems and joining forces with others to overcome the challenges of changing environments (Moore, 1993, 2006). In nature, joining forces with others is a successful strategy for many species, with examples far outnumbering the more known classic showcases of predator-prey relationships (Harris, 2013). Analogously, while management research also had its primary view focusing on competition between organizations for most of its existence, rapid technological progress and respective challenges for incumbents have led to a more nuanced balance between competition and collaboration with others to overcome the challenges of an ever-faster-altering environment (Gnyawali & Park, 2011; Zacharia et al., 2019).

In this vein, this doctoral thesis focuses on the impact of digital technologies that accelerate dramatic change on an organizational level for incumbents in recent years (Yoo, 2013). In response to this ever-faster altering business landscape, we are witnessing a marked shift as more and more incumbents try to keep up with technological progress and face the phenomenon of digital transformation (DT) – the redefinition of how they provide value for their customers using digital technologies (Bharadwaj et al., 2013; Venkatraman, 1994; Vial, 2019; Wessel et al., 2020). This redefinition of how to provide value enables incumbents to keep up with new digital competitors, meet increasing customer expectations, and generate increasing margins on digital products that counter shrinking returns on non-digital offerings (Vial, 2019). DT differs from traditional IT-enabled organizational transformation in several fundamental ways. First, concerning the significance of change (Markus & Rowe, 2023), DT actions leverage digital technologies in (re)defining an organization's value proposition, which also involves a new organizational identity (Wessel et al., 2020). In contrast, IT-enabled organizational transformation leverages digital technologies to support an existing value proposition and enhances an organization's identity (Wessel et al., 2020). Second, compared to IT-enabled transformation, the impetus for DT goes far beyond individual organizations, comprising "society and industry trends" (Vial, 2019, p. 132).

However, the implications of digital transformation and the goal of creating new digital value propositions are profound: Digital technologies and the manifold changes they bring about require and enable the formation of highly interdependent networks of organizations that join forces to keep up with their changing environments and master the challenges of DT by creating new forms of value (Brynjolfsson & McAfee, 2014; Iansiti & Lakhani, 2020). In these emerging digital value networks, companies integrate their information systems and production facilities into cross-company networks (Oberländer et al., 2018; Vial, 2019). By embedding their value creation into multiple organizations' overarching digital value networks, incumbents gain access to various external resources that provide novel opportunities to utilize digital technologies for new value propositions (Oberländer et al., 2021). Accordingly, this doctoral thesis defines a digital value network as an alliance of at least two interdependent organizations co-creating value through digital technologies (Adner, 2017; Jacobides et al., 2018; Tan et al., 2020). Digital value networks subsume various subconstructs, such as digital ecosystems, in which multiple organizations align to create a focal digital value proposition for end customers (Jacobides et al., 2018) and are based on digital technologies such as Internet of Things (IoT) platforms (Arnold et al., 2023; Oberländer et al., 2018; P. Wang, 2021). The resulting interdependency of multiple organizations collaborating for value creation but competing for value capture forces organizations to evolve with their environment by seeking new ways of providing value (Hanelt et al., 2021; Nischak et al., 2017). Concerning the intersection of digital value networks and DT, scholars agree that the external environment, such as digital value networks, is decisive for DT as digital technologies cannot be restricted to the boundaries of a specific organization or industry (Hanelt et al., 2021; Yoo et al., 2010).

Central to this doctoral thesis is that digital value networks and their technical infrastructure (e.g., IoT platforms) enable two or more parties to exchange and accumulate large amounts of data (e.g., Gawer and Cusumano (2014)). This abundance of data within digital value networks and recent advances in artificial intelligence (AI), especially machine learning (Davenport, 2018; Russell & Norvig, 2016), proliferate new AI-driven services that complement existing products and services (Gregory et al., 2021; Iansiti & Lakhani, 2020). In this thesis, AI presents an umbrella term for subsets, such as supervised machine learning or reinforcement learning (Agrawal et al., 2018; Brynjolfsson & Mitchell, 2017; Raisch & Krakowski, 2021). Most of these subsets are rooted in statistics and use algorithms to solve specific cognitive tasks, such as image recognition based on predictions derived from available data (Agrawal et al., 2018; Domingos, 2012; Mitchell, 1997). In this context, the term 'prediction' describes generating missing information using available information (Agrawal et al., 2018; Shmueli & Koppius, 2011). Predictions pave the way for a new generation of highly efficient services that deliver new customer value (Agrawal et al., 2018; Schüritz, Seebacher, Satzger, & Schwarz, 2017; Weking et al., 2018), e.g., providing predictive maintenance services that save costs and increase machine availability (Dalzochio et al., 2020). Further, new AI-driven services allow incumbents to deepen their relationships with customers and other organizations and gain even more data regarding the activities and interactions within these relationships (Iansiti & Lakhani, 2020). Additionally, the more organizations share data within digital value networks, the more value can be created for each participating organization (Gregory et al., 2021). These data-driven network effects within digital value networks alter the scale and scope of business models by enabling ever more effective AI-driven services for existing and new customers (Iansiti & Lakhani, 2020). Especially for incumbents, the data shared in digital value networks and AI-driven services built on it can shield against digital competitors or competitors with similar physical products or non-AI-driven services but no access to equal amounts of contextual business data (Agrawal et al., 2018).

Recent DT research has highlighted the role of digital value networks and AI for DT (Vial, 2019). Numerous industry examples show that incumbents undergoing DT deepen their relationships with others by collaborating through digital technologies and using AI to provide novel value propositions based on the data gathered within these relationships (Baesens et al., 2016; Iansiti & Lakhani, 2020). In this course, manufacturing companies increasingly form digital value networks with their customers and other organizations, such as cloud providers, to provide the AI-optimized usage of their products as a service instead of selling them (Opresnik & Taisch, 2015). For example, the famous power-by-the-hour full-service business model introduced by Rolls-Royce is based on multiple airlines that share data on the usage of their aircraft turbines (and further infrastructure). Through these insights, Rolls-Royce provides advanced data analytics services that complement and optimize its maintenance operations and are monetarized through an innovative pay-per-use model (Smith, 2013). While these airlines can provide their passengers with higher flight frequencies due to more efficient maintenance, Rolls-Royce benefits from a deepened relationship with a network of airlines, providing further services and a competitive advantage against other turbine manufacturers. Analogously, car companies utilize digital value networks and AI to provide their customers with new mobility services based on cars that are now highly connected physical assets and continuously collect data that provide vast opportunities for networked AI-driven services (Iansiti & Lakhani, 2020; Tschiesner et al., 2019). The customers of such services benefit from highly efficiently operated physical products and convenient, complementary services enabled by data analysis from countless connected devices that pose a competitive advantage for service providers (Opresnik & Taisch, 2015). Such developments in the course of DT are not limited to the automotive or manufacturing industry but can be found in almost all industries. A further example from the financial sector is the Chinese banking company Ant Financial: The company utilizes the data gathered from its customers and various actors within its digital value network, such as Alibaba, a Chinese consumer webshop, and Alipay, a Chinese payment service provider, to offer various services including consumer lending, money market funds, wealth management, health insurance, credit-rating services (Iansiti & Lakhani, 2020).

However, incumbents that aim to follow these examples and undergo their DT through joint value creation in digital value networks that enable AI-driven value creation must overcome various obstacles examined in this doctoral thesis. First, incumbents must manage challenges regarding digital value networks as enablers for new AI-driven value propositions. For example, technological complexity due to high security requirements, highly heterogeneous organizations (e.g., end users, device manufacturers, complementors), or unclear data privacy requirements hinder data sharing and AI-driven value creation (Arnold et al., 2023; Pauli et al., 2021). Further, new security challenges arise as the value creation process becomes more networked and AI-driven with external organizations. While customers benefit from services that rely on AI and data network effects through the connection of various actors (Gregory et al., 2021), the eroding organizational boundaries result in an increased interdependence of different value-creation actions (Bürger et al., 2019). The high interconnectivity between the information systems of different companies increases the attack surface and the potential for propagating damage within the value-creation activities of digital value networks (Bürger et al., 2019; Schrödl & Turowski, 2014; Yang et al., 2009). Additionally, regarding the use of AI, the need of most AI approaches to transfer, store, and analyze large amounts of potentially confidential data from various sources makes it challenging to reconcile these data needs with legal requirements such as the General Data Protection Regulation (GDPR) of the European Union (Li et al., 2020). Incumbents aiming to leverage data sharing in digital value networks for AI must explore new AI approaches that enable secure and trustful data exchange among multiple partners (Karnebogen et al., 2023).

Second, besides the challenges of digital value networks as an enabler of AI, incumbents must also manage the challenges regarding AI as a driver of new digital value propositions. Here, while customers expect reliable value provision, the fundamental statistical nature of present-day AI applications makes their predictions fallible (Agrawal et al., 2018; Clarke, 2016; Lazer et al., 2014). Thus, incumbents must consider AI's fallibility in designing new value propositions. Accordingly, companies eager to introduce new AI-driven services must assess and consider their AI’s predictive performance, design meaningful service level agreements (SLAs), and select suitable payment structures to realize the intended advantages. Aiming at these goals, companies must balance the advantages of investing in better AI approaches that enable improved services with the associated costs of operating such approaches to satisfy their customers and partners within their digital value networks (Beyer et al., 2016; Goo et al., 2009; Halbheer et al., 2018). A challenge further complicating AI-driven service provision is that while AI predictions improve individual decisions, they do not necessarily align with the goals formulated in long-term SLAs. Thus, incumbents must balance the divergences between short-term and long-term planning horizons. These sequential decisions must be aligned with the long-term service level objectives (SLOs) to satisfy customers' expectations and avoid financial losses (Häckel et al., 2022).

With a view at the outlined challenges, the fundamental subject of this doctoral thesis relates to the perspective of digital value networks that drive an incumbent’s DT and how to manage risks and leverage the potential of networking with others to provide AI-driven services.

## 2 Structure of the Thesis and Overview of Embedded Research Articles

This doctoral thesis is cumulative and consists of seven research articles addressing its fundamental subject by applying different qualitative and quantitative methodological approaches, different forms of empirical evidence, and varying perspectives. Additionally, through a phenomenon-based theorizing approach, according to Fisher et al. (2021), this thesis provides a new theoretical perspective on an incumbent’s DT driven not by an executive agency but by overarching value networks, i.e., its digital ecosystem. As a result, all research articles in this thesis are assigned to the overarching topic of the role of AI in digital value networks for DT or subtopics, as presented in Figure 1: Challenges of Digital Value Networks as a Driver of Artificial Intelligence, Challenges of Artificial Intelligence as a Driver of New Digital Value Propositions, and Digital Value Networks as Driver of Digital Transformation. By providing new perspectives on and decision-support for an incumbent's DT, this thesis provides valuable contributions for research and practitioners and an impetus for future research.

Despite the potential of digital value networks that enable the provision of AI-driven services, research, and practice still need to address the risks posed by the close dependence on others and the exchange of data for an individual organization. In this course, Section II.1 – including Research Articles #1, #2, and #3 provides insights on assessing and mitigating risks arising from digital value networks. Specifically, Research Article #1 presents an overview of challenges to be considered when integrating an organization's information systems and production facilities into overarching industrial IoT platforms. These challenges were identified by collecting empirical data during a Delphi study with experts from various industries. Security concerns remain one of the most common risks of this deepened networking. Thus, Research Article #2 provides a decision-support model developed based on a design science research approach that assists decision-makers from the manufacturing industry in economically assessing the threats of IT security incidents within their digital value networks. Concerning the risks arising through the data exchange necessary to train AI algorithms, Research Article #3 highlights how to use federated learning to balance trade-offs between privacy, performance, and fairness when sharing data securely between different parties.

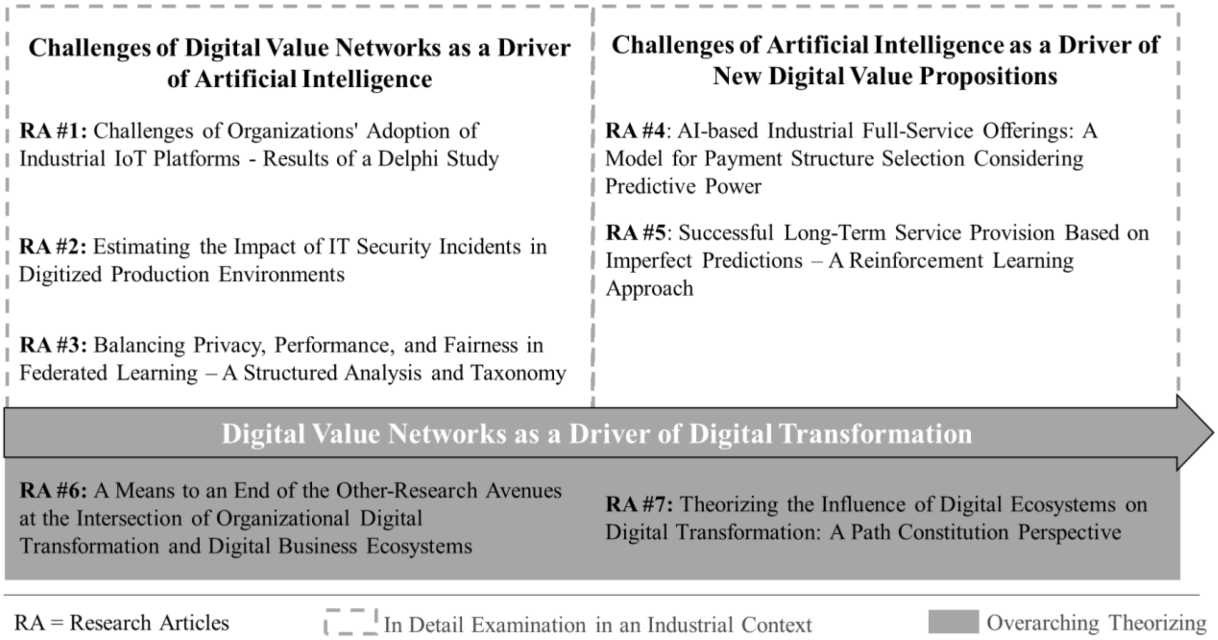


**Figure 1: Assignment of the Research Articles to the Topics Structuring this Doctoral Thesis**

Beyond a risk-centered perspective, incumbents aiming to implement AI-driven services within their value creation need decision-support on how to meaningful consider the characteristics of AI in the design of their services. Therefore, this thesis provides two quantitative decision-support models developed based on a design science research approach to assist decision-makers in tailoring their services to underlying AI algorithms' characteristics and derive meaningful decisions from AI’s predictions (Section II.2 – including Research Articles #4 and #5). Therefore, Research Article #4 provides a decision-support model that helps practitioners to tailor their SLAs and payment structures to the achievable predictive power of their underlying AI algorithms. Research Article #5 shows how reinforcement learning can turn multiple predictions into meaningful decisions aligned with long-term commitments toward customers.

Overarching, Section II.3 – including Research Articles #6 and #7 – provides a new perspective on DT as a phenomenon that is more driven by an organization's external environment than recently discussed in current research by employing a specific theorizing review and a phenomenon-based theorizing approach. Therefore, Research Article #6 presents a research agenda along four themes and convergent assumptions that drive the relationship between DT and digital ecosystems as an essential subform of digital value networks for theorizing this relationship. Following these assumptions, Research Article #7 presents overarching propositions on how digital value networks drive an organization’s DT path along three phases.

Section III summarizes this doctoral thesis and provides an outlook on future research. Section IV contains the publication bibliography, and Section V provides additional information on all research articles (V.1), my contributions to each research article (V.2), and the research articles themselves (V.3 - 9).

# II Research Overview

## 1 Challenges of Digital Value Networks as a Driver of Artificial Intelligence

While digital technologies provide the basis for building digital value networks and co-creating value propositions with others (Hanelt et al., 2021; Nischak & Hanelt, 2019), decision-makers must balance the potential and the challenges that arise through these connections. Identifying, assessing, and addressing these challenges is essential for leveraging the potential of AI-driven services in digital value networks with economically justifiable risks.

**Research Article 1# - Discovering the Challenges of Joining Digital Value Networks**

Digital platforms, such as industrial IoT platforms, build a crucial technical backbone for joining forces with others, exchanging data, and providing digital services. However, industrial IoT platforms have not yet met the associated expectations in the business-to-business (B2B) domain (Graff et al., 2018). Given the growing research interest involving digital technologies in different industrial settings, research so far has mainly focused on understanding how to set up the technical infrastructure for digital value networks (Arnold et al., 2022; Mirani et al., 2022; Moura et al., 2018), govern the ecosystem of complementors for value creation (Jacobides et al., 2018; Pauli et al., 2021), or guide incumbents in their DT toward co-creating value with others (Hanelt et al., 2021; Karnebogen et al., 2021). Nevertheless, while current research has identified different critical challenges impeding the adoption of IoT platforms, it comes up short in three ways: First, many challenges known so far have been mainly identified in isolated or different contexts, missing out on their interdependencies and implications. Second, many challenges known so far are technical-oriented, leaving industrial IoT platform providers, complementors, and incumbents in the dark about organizational, economic, and other overarching challenges they might have to address. Third, a compilation of the status quo and its assessment regarding the actuality and validity of different challenges is missing. As industrial IoT platforms constantly face new challenges due to an ever-growing variety of devices, technologies, and a continuously evolving environment, researchers and practitioners need an overview of relevant challenges. Therefore, Research Article #1 poses the research question: *What challenges impede industrial organizations' adoption of industrial IoT platforms?*

To answer this question, Research Article #1 presents a ranking-type Delphi study with industrial IoT experts from academia and practice to answer this question. This Delphi technique, exploratory in nature, is suitable as it aims to uncover challenges (Okoli & Pawlowski, 2004; Paré et al., 2013; Schmidt, 1997) and has proven its applicability for this effort on different occasions (Hanelt et al., 2021; Hodapp et al., 2019; König et al., 2019). The resulting challenges are structured along the technological, organizational, and environmental (TOE) perspectives, according to Tornatzky and Fleischer´s (1990) TOE framework. Further, the results show the comparative relevance of the challenges derived through two rating rounds, uncovering differences in the assessment between academia and practice.

In sum, Research Article #1 presents results from 22 surveyed experts leading to a holistic set of 29 challenges, of which nine have not been mentioned in the previous literature. Table 1 presents the specific challenges academics and practitioners rated as extremely relevant (ER) on an ordinal scale when adopting industrial IoT platforms (refer to Appendix V.3 for all identified challenges).

**Table 1: Challenges Rated as Extremely Relevant by Each Subpanel**

| **Academics** | | **Practitioners** | |
|---|---|---|---|
| **Challenge** | **ER ratings** | **Challenge** | **ER ratings** |
| Complex data preparation | 80% | Unwillingness to adopt platform thinking | 66.7% |
| Insufficient system interoperability | 70% | Lack of management support | 66.7% |
| **Poor platform security**[1] | 70% | **Unclear business privacy** | 66.7% |
| Changing technological standards and methods | 70% | Connectivity issues of old machines | 55.6% |
| Unclear data access and usage rights | 70% | Insufficient semantic interoperability | 55.6% |
| **Poor data security** | 60% | | |
| Employees’ insufficient technical skills | 60% | | |

[1] Challenges highlighted in bold are particularly relevant to the following Research Articles #2 and #3.

Table 1 elucidates how differently the researchers and practitioners assessed the challenges' relevance and shows clearly, that there was no agreement on the key challenges. The results motivate Research Articles #2 and #3, showing that academics and practitioners tend to focus on security and privacy-related issues (e.g., academics rating poor platform security, poor data security, or practitioners rating business privacy as extremely relevant).

The distinction between academics and practitioners is precious for illuminating the result's potential for real-world impact by recognizing industrial IoT platforms as complex, rapidly evolving socio-technical phenomena. The results sharpen the knowledge in this field by confirming pertinent challenges and disclosing novel ones. The research article indicates that industrial IoT platform adoption is determined by the characteristics of the underlying technologies and factors relating to the readiness of platform providers, platform users, and the external environment. Further, the results present an update and analysis of the literature with the most current knowledge from researchers and industry experts. Concerning ever-shorter digital technology cycles, the information systems community needs to identify challenges that hamper the diffusion of digital platforms to resolve existing barriers and identify the necessary pathways to contribute research with real-world impact. Further, Research Article #1 contributes insights into the comparative relevance of challenges the academic and practitioner communities perceive. The literature had not yet considered these different perspectives of academics and practitioners, which opens new perspectives for diverse industrial IoT platform research strands by elucidating the commonalities and differences of these groups.

**Research Article 2# - Estimating the Impact of IT Security Incidents in Digitized Production Environments**

Table 1 clearly shows that academia and practice see security and data privacy challenges as extremely relevant to address as a basis for joining digital value networks and co-creating joint value propositions. Therefore, Research Article #2 investigates how to estimate the impact of IT security incidents in digitized production environments. As digital value networks erode boundaries between organizations and their operational technology (OT) and information technology (IT) systems (Hein et al., 2020; Hein et al., 2019), the complexity of value creation in digitized production environments increases. These digitized production environments consist of two interconnected main networks: an information network spreading across the information systems of multiple organizations and a production network consisting of OT equipment. The interconnectivity of digitized production environments creates an increased attack surface and more opportunities for the propagation of attacks (Schrödl & Turowski, 2014, p. 22). Higher interconnectivity between the information and production networks, in particular, also increases the potential for damage as value creation is highly reliant on the availability of IT services, both within production processes and at the customer interface (Yang et al., 2009). Here, the essential difference between cyber attacks and conventional machine failures is the uncertainty about the attacker's behavior. A simple machine breakdown is usually a specific event followed only by consequential damage in the production network and hampers value creation for a limited time until the machine breakdown is resolved. In contrast, a cyber attack can spread through the whole information network (Yang et al., 2009) and cause extensive damage within the broader cross-organizational information and production networks.

To protect their business against cyber attacks, incumbents must thoroughly assess the potential for damage and develop an approach that enables them to simulate both (a) the spreading effects of individual cyber attacks within the information network and (b) the consequential spread of damage within production networks and value creation. The example of AI-driven services that run on an external cloud highlights the potential effects of damage to the information network: If the cloud is attacked, services running on it cannot function, causing potential outfalls in the production network and a subsequent lower value creation, which means the damage is spread to other actors within the digital value network (Zissis & Lekkas, 2012). Additionally to these consequences of a single cyber attack, the attacker might spread through the cross-organizational IT systems and cause further damage to operational and IT systems. Whereas in the past, researchers have widely investigated how to model multi-stage attacks (Atluri et al., 2008; Frigault et al., 2008; Munoz-Gonzalez et al., 2017b; Muñoz-Gonzalez et al., 2017a; Poolsappasit et al., 2012; Xie et al., 2010), there remains a lack of approaches that enable companies to measure the impact that cyber attacks would have on value creation (Bendovschi, 2015). Therefore, Research Article #2 aims to support decision-makers' attempts by posing the following research question: *How can companies estimate the impact of IT security incidents which harm availability in digitized production environments?*

To answer this research question, Research Article #2 presents a quantitative model, developed following a design science research approach according to Peffers et al. (2007), to assess the IT security risk of availability incidents in digitized production environments and support decision-making. The model uses Bayesian networks, Bayesian attack graphs, and stochastic distributions for risk analysis in digital value networks to illustrate how an attack can spread and measure the associated damage within the information and production networks.

Figure 2 provides a graphic overview of the core elements of the decision-support model and their relationships and illustrates the four critical digital value network components in a manufacturing context: *production components*, *production flows*, *service components*, and *information flows*. While the production flow only connects production components, the information flow can also connect service and associated production components.

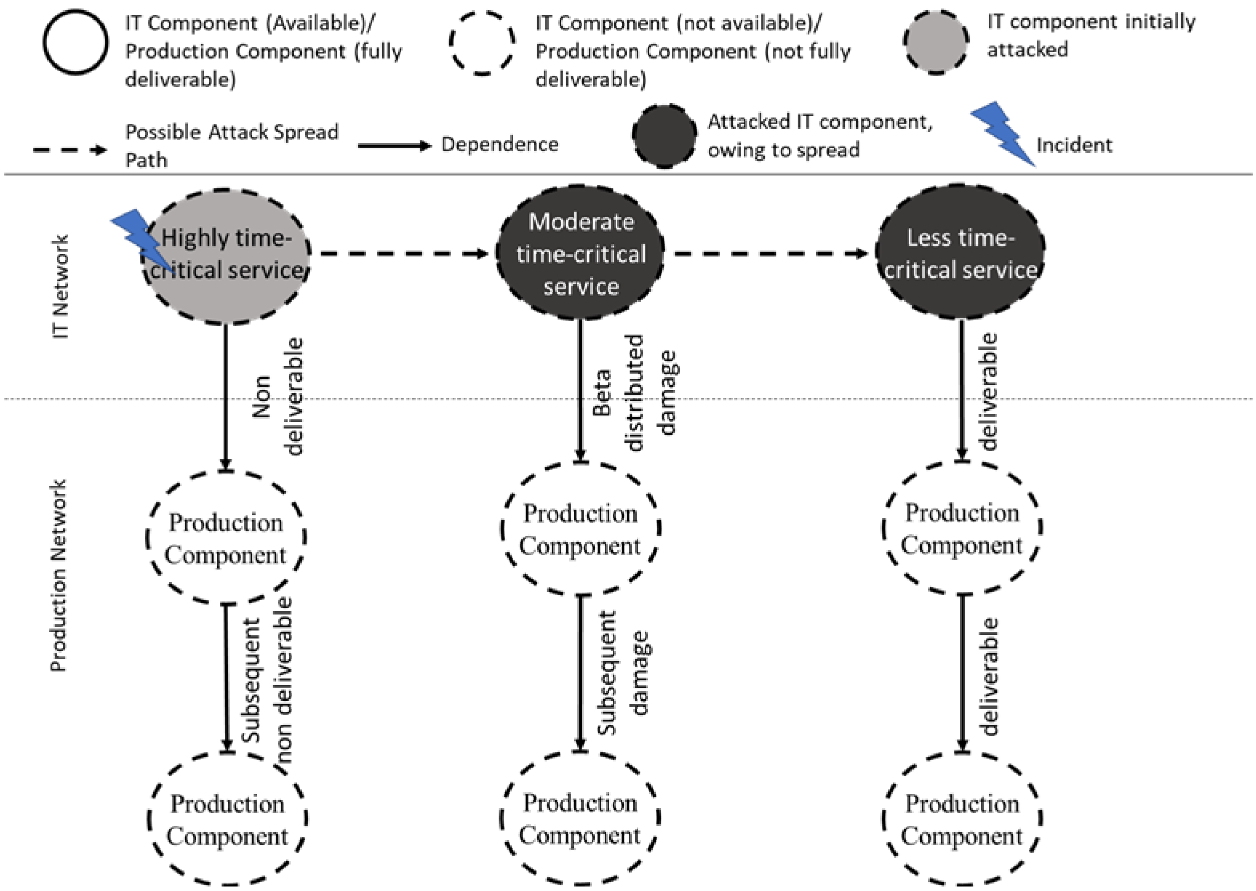


**Figure 2: Model Summary of Research Article #2**

Figure 2 also shows how a cyber attack on a service component causes damage spread within the information network and within the interconnected production network. Although the example represents an attack on a highly time-critical service, the other two services could be a starting point for the cyber attack.

To illustrate how the model applies to a real-world use case, Research Article #2 presents a concrete case discussed in an evaluation workshop involving a German company's Chief Security Officer and Director of Business Services & Solutions. The company in question is a medium-sized manufacturing company focusing on physical products, namely critical components of engines and transmissions in mechanical engineering. Additionally, the company must meet strict IT security standards due to its customer base. Consequently, the production space is designed as a high-security area, and all IT services involved in the production process must be selected and implemented according to these standards. As a first step, one selected digital value network was depicted by identifying its critical components, illustrated in Figure 3. Almost all 17 production components are linked to ten service components for the company. The colors of the service components (green, yellow, and red) express their time criticality (less time-critical, moderately time-critical, and highly time-critical). All probability values and distributions are defined monthly. The number that follows each component name expresses the order in which a component appears in the Bayesian attack graphs algorithm.

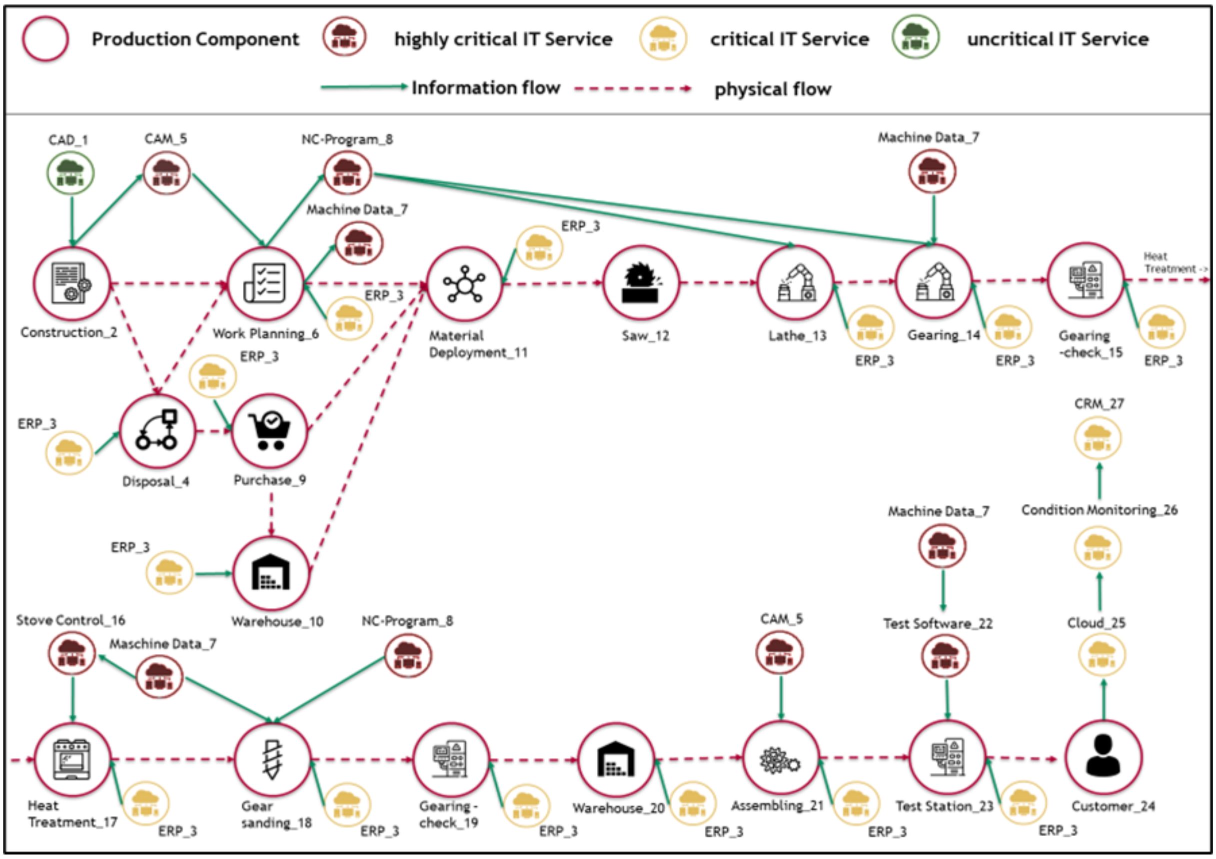


**Figure 3: Real-World Digital Value Network used for Evaluation**

The pictured digital value network was then analyzed using an R-based prototype and two simulation scenarios. First, Scenario 1 depicted the actual risk landscape for the illustrated digital value network. In Scenario 2, the company introduced a mitigation measure: it installed a protected air gap (the physical separation of different IT systems) between the office systems and systems controlling production processes (e.g., numerical control programs or machine data flows).

By analyzing both scenarios, Research Article #2 aimed to compare the simulation results with and without additional security measures. Simulating the damage caused by attacks in both scenarios, Scenario 2 shows an average deliverability of 76% concerning an availability incident, compared to an average deliverability of 71% in Scenario 1. Here, one must note that 5% more average deliverability can have a huge monetary impact on production processes. The results confirm the expectation that higher security measures will also lead to digital value networks that are more resistant to cyber attacks. Further, the results also show that the developed model can be adapted to different use cases via the parameterization of components.

After presenting these results, the company in question confirmed the applicability and usefulness (Sonnenberg & vom Brocke, 2012) of the developed model for assessing damage potentials in digital value networks. Additionally, the industry experts confirmed that the model clarified the dependencies between different network components, highlighted the potential impact of a cyber attack, and assisted decision-makers in evaluating and selecting suitable mitigation measures. Furthermore, the industry experts appreciated the possibility of adapting the model to fit various differently-structured digital value networks. At the same time, they noted that the parametrization of the model's components might be challenging and need careful planning.

**Research Article #3 – Federated Learning as Approach for Secure Data-Sharing in Digital Value Networks**

Besides the mere connectivity of digital value networks that requires a secure design and a careful selection of mitigation measures regarding cyber attacks, incumbents in digital value networks also require new secure approaches for exchanging data, especially regarding the provision of AI-driven services (see Table 1).

In this vein, Google introduced federated learning (FL) as a novel paradigm to enable collaborative AI without centrally storing sensitive training data and only sharing the parameters such as gradients or weights of local AI models instead of the actual data (McMahan et al., 2017; McMahan et al., 2016). Figure 4 shows the general structure of an FL application. The FL process starts with a global AI model (1), initialized and distributed to multiple clients within the digital value network (2) by a central instance. Each client independently updates the parameters of its received global model in multiple training rounds using locally available data and creates a local instance of the AI model (local model) (3). Each client then transmits its parameters to the central instance (4). The core of FL is then the efficient aggregation of these different local model parameters of various clients by an algorithm within an updated global model (5). The central instance sends this new global model to all clients, starting a new round of local training. This FL procedure is repeated continuously or until a specific criterion is met.

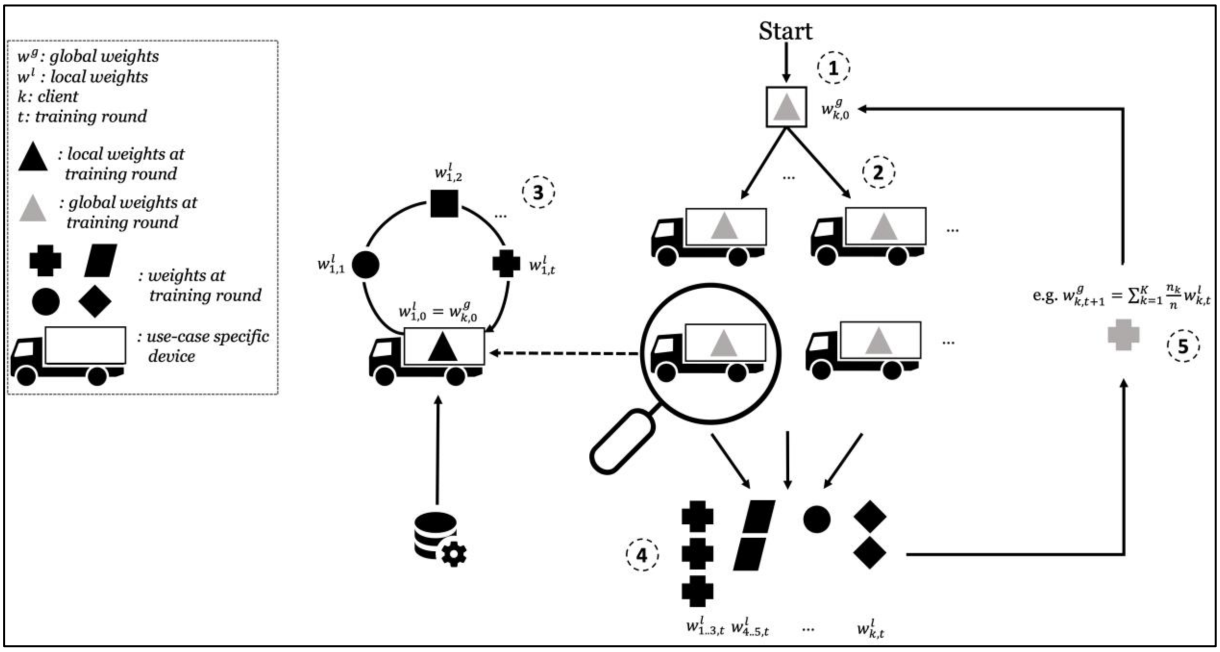


**Figure 4: The General Structure of Federated Learning Systems**

FL aims to relieve a wide range of AI applications of one of their biggest criticisms: The need to transfer, store, and analyze large amounts of potentially confidential data from various sources in a single database (Li et al., 2020). This dependence on data often makes it challenging to reconcile AI with General Data Protection Regulation (GDPR) requirements of the European Union (European Union, 2021), which is one of the main reasons AI projects fail in practice (Agrawal et al., 2018; O'Leary, 2013). FL offers significant opportunities here, especially for Western societies, e.g., in the European Union, where comparatively strict data protection requirements for individuals and companies apply (Aledhari et al., 2020; Goldsteen et al., 2022; Mourby et al., 2021).

However, as a relatively new approach, FL still poses significant challenges related to a tense field between the privacy, performance, and fairness of FL applications (Gu et al., 2022). For example, smartphone users who speak the same language may still have different dialects, and FL applications must find meaningful ways to integrate such heterogeneous clients into a single AI model without having access to the underlying data. Not solving this challenge would lead to a better service level for some dialects than others and raise fairness concerns. Additionally, if some client groups provide hyperparameter updates less frequently, this might impede the resulting predictions of FL applications. In the case of Google's Android keyboard, while the restriction of analyzing the underlying data is essential regarding the privacy of personal messages, the application focus may lean more towards ensuring fairness between the different participating clients and providing good prediction performance results. However, as in this example, “limiting” fairness in favor of privacy may not be unfeasible in other application areas. To illustrate, the trade-offs of FL pose far more significant risks in medical applications, where ethical considerations prohibit enhancing performance and fairness at the expense of less privacy. Thus, applying FL in a business use case involves an interconnection of the considered use case and the technological and business foundations of FL to navigate the trade-offs between privacy, performance, and fairness. Thus, Research Article #3 aims to advance the use of FL and the understanding of those trade-offs by posing the following research question: *What are the technical and business characteristics of federated learning applications and their inherent trade-offs concerning privacy, fairness, and performance?*

Following Webster and Watson (2002) and Templier and Paré (2018), Research Article #3 first synthesizes the existing knowledge on FL and its applications in different use cases and industries through a structured literature review. Research Article #3 focuses on the sociotechnical information systems (IS) perspective since related work mainly targets technical aspects, such as algorithms and datasets (e.g., Lo Kit et al., 2020; Yin et al., 2021; Abdulrahman et al., 2021) and publications from the IS community on FL are still scarce.

The results of the literature review of Research Article #3, shown in Figure 5, reveal that the number of publications related to FL has increased explosively in the last three years. Starting with the first publication of McMahan et al. (2016) that introduced the first general principles of FL, a substantial increase in publications with use cases from a wide range of industries can be seen, especially since 2020. A further motivating factor for Research Article #3 is that there are only a few IS community publications; therefore, a sociotechnical view of FL in interaction with its application in different areas is still missing. However, given the profound social implications of trade-offs between privacy, fairness, and performance, such an investigation is highly relevant to leverage the potential of FL in a meaningful way.

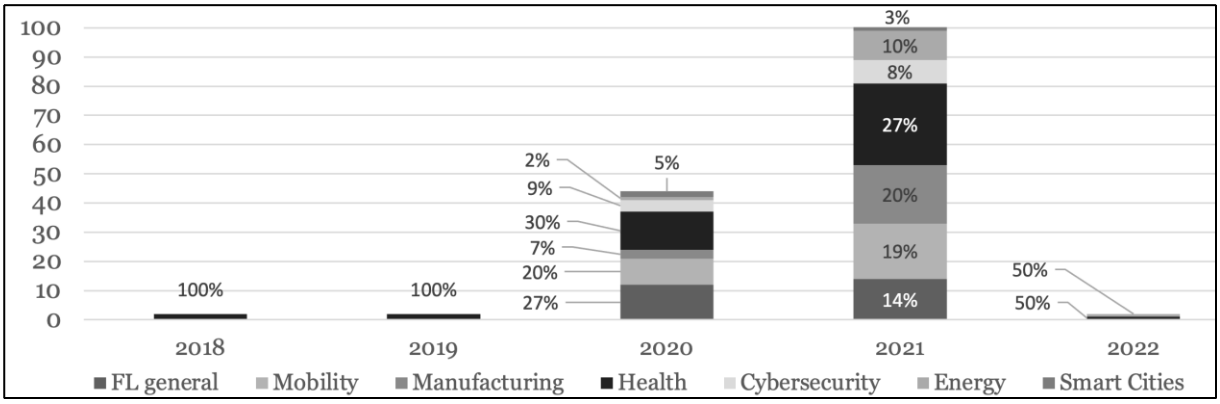


**Figure 5: Analysis of Publications Regarding FL in Different Industries**

In the next step, the article analyzes the literature regarding different use cases, builds a taxonomy of FL characteristics according to Nickerson et al. (2013), and discusses how these characteristics impact the FL-specific trade-offs concerning privacy, performance, and fairness. The 152 found articles also formed the basis for the taxonomy development: The authors combined theoretical findings from 26 publications of the structured literature review concerning conceptual research on FL with empirical findings from the remaining 126 papers that examined individual applications of FL in different industries. Therefore, Research Article #3 presents a multidimensional taxonomy to structure the diversity of FL applications. Research Article #3 introduces three perspectives, namely Business, Coordination, and Execution, each consisting of dimensions and characteristics, each influencing privacy, performance, and fairness in varying degrees depending on the specific application.

The resulting taxonomy of Research Article #3, shown in Table 2, is a supporting tool in designing, developing, and improving FL applications in different industry branches to navigate the trade-offs between the mentioned aspects. Since insights from multiple industries were considered, Research Article #3 aimed to achieve granular characteristics. The structured literature review found many conceptual and technical articles but lacked a more sociotechnical IS perspective, especially when discussing privacy, performance, and fairness. Thus, Research Article #3 showed how FL's characteristics impact this existent field of tension.

The perception of privacy, performance, and fairness differs significantly from different viewing points. For example, to ensure fairness, all clients in a training process might agree that the inclusion of underrepresented groups (delivering parameters of the local ML model to update the global ML less frequently) is needed, leading to some better-performing clients that may feel “disadvantaged”. A higher level of fairness impacts performance and may even over-prefer underperformers. Hence, good-performing clients (delivering parameters of the local ML model to update the global ML frequently) might not get incentivized and lose the purpose of further participating in the training. It is difficult to grasp this phenomenon, as the importance of privacy, performance, and fairness factors must be determined in the context of the use case since it is highly dependent on external factors.

**Table 2: A Taxonomy of Federated Learning Applications**

<table>
<tr><th></th><th>Dimension</th><th colspan="12">Characteristic</th><th>E/N[1]</th></tr>
<tr><td rowspan="3">Business</td><td>Value Capture</td><td colspan="4">Focus on Underperformers</td><td colspan="4">Balanced</td><td colspan="4">Focus on Overperformers</td><td>E</td></tr>
<tr><td>Customer Type</td><td colspan="6">B2B</td><td colspan="6">B2C</td><td>E</td></tr>
<tr><td>Participant Structure</td><td colspan="6">Single Participant Network</td><td colspan="6">Multiple Participant Network</td><td>E</td></tr>
<tr><td rowspan="3">Coordination</td><td>Distribution</td><td colspan="4">Centralized Network</td><td colspan="4">Decentralized Network</td><td colspan="4">Full P2P Network</td><td>E</td></tr>
<tr><td>Update Mode</td><td colspan="4">Real-time</td><td colspan="4">Scheduled</td><td colspan="4">Asynchronous</td><td>E</td></tr>
<tr><td>Orientation</td><td colspan="4">Horizontal</td><td colspan="4">Vertical</td><td colspan="4">Transfer</td><td>E</td></tr>
<tr><td rowspan="3">Execution</td><td>Hardware Agnostic</td><td colspan="6">Yes</td><td colspan="6">No</td><td>E</td></tr>
<tr><td>Statistical Heterogeneity</td><td colspan="6">Imbalanced data</td><td colspan="6">Non-iid</td><td>N</td></tr>
<tr><td>System Heterogeneity</td><td colspan="3">Storage</td><td colspan="3">Connectivity</td><td colspan="3">Client power supply</td><td colspan="3">Homogeneous Systems</td><td>N</td></tr>
</table>

Notes: [1]Exclusivity: E = Mutually exclusive, N = Non-exclusive

From a theoretical point of view, Research Article #3 is the first to investigate FL from an IS perspective based on the sociotechnical constructs of privacy, performance, and fairness (for details on the individual impact of the presented characteristics, please see Research Article #3 in the Appendix). Our taxonomy is thus a contribution to the discussion on how trade-offs between privacy, algorithmic performance, and algorithmic fairness can be examined from different angles for FL use cases. Hence, Research Article #3 leads to a better understanding of the different aspects of FL and thus outlines common differences from AI architectures. Research Article #3 can also act as a basis for developing application patterns and archetypes, enabling researchers to limit the number of possible realizations from the beginning of the development of an FL application. Most importantly and despite its limitation, Research Article

#3 aims to incentivize more extensive research on application areas in which FL and its potential for sharing data securely.

## 2 Challenges of Artificial Intelligence as a Driver of New Digital Value Propositions

After overcoming the challenges of forming complex digital value networks to exchange data with others, incumbents must decide how to create value from the shared data. In this vein, besides efficiency gains, AI applications also promise innovative AI-driven services in the manufacturing industry (Opresnik & Taisch, 2015; Schüritz, Seebacher, Satzger, & Schwarz, 2017). For incumbents in the manufacturing industry, complementing products with AI-driven services is a key revenue driver in markets with decreasing margins and offers firms an opportunity to differentiate themselves from competitors, especially in contexts where non-data-driven services are standard (Heuchert et al.; Huber et al., 2019; Schüritz, Seebacher, Satzger, & Schwarz, 2017). Examples of such applications include cost-minimizing predictive maintenance (Weking et al., 2018) and automated predictive quality control (Benardos & Vosniakos, 2002).

However, most AI algorithms' decisions or recommendations are based on fallible predictions, and incumbents must consider this fallibility within their service design (Lazer et al., 2014) to create value for the service recipients while providing a profitable service (Agrawal et al., 2018). Incumbents eager to introduce new AI-driven must, therefore, face the following three challenges to introduce valuable data-driven services: First, incumbents must consider the fallibility of AI predictions in their design of SLAs to realize the intended advantages (Lazer et al., 2014). Second, incumbents must choose reasonable payment structures for their AI-driven services. A service provider's revenue varies in response to the varying predictive power-dependent service level. Nevertheless, different payment structures of an AI-driven service react differently to varying service levels. A subscription-based payment structure is mainly unaffected by low predictive power and, thus, offers service providers reliable revenue. In contrast, a usage-based payment structure can benefit from high predictive power that increases revenue by raising service levels (Häckel et al., 2022). Third, incumbents must derive reasonable decisions from AI predictions during the SLA's runtime to achieve the promised service level and satisfy customers. Deriving meaningful multiple sequential decisions from an AI’s predictions to achieve a long-term goal is a complex challenge (Hu et al., 2021). For example, many predictive maintenance applications can predict machine breakdowns. Still, decision-makers face complex challenges when transforming these predictions into maintenance decisions aligned toward long-term service objectives at reasonable costs.

**Research Article #4 – AI-Based Industrial Full-Service Offerings: A Model for Payment Structure Selection Considering Predictive Power**

Concerning the challenges of considering the fallibility of AI predictions in an SLA design and choosing suitable payment structures, Research Article #4 provides decision support for industrial full-service provider business models (Fabri et al., 2019). Full-service providers (FSPs) in the manufacturing industry remain the owner of their products (e.g., industrial systems) and sell their use as a service. Customers of FSPs benefit from converting acquisition costs into usage- or time-based costs and eliminating operating costs while shifting the risks of product ownership to the FSP. On the contrary, the FSP benefits from increased customer loyalty (Baines et al., 2009; Baines et al., 2017; Guajardo et al., 2012) and unlocks new revenue streams by adopting new payment structures (Cachon, 2020; Schüritz, Seebacher, & Dorner, 2017). Decision-makers in the manufacturing industry must, therefore, (1) assess the predictive power of their AI applications, (2) derive meaningful SLAs in alignment with their predictive power, and (3) thoughtfully select the net present value (NPV)-maximizing payment structure (Cachon, 2020). However, the current literature provides little quantitative guidance for decision-makers on developing economically substantiated FSP offerings that include AI applications. In response to this research gap, Research Article #4 poses the following research questions:

1. *What is the economic impact of the predictive power of underlying classification algorithms on the NPV of an FSP?*
2. *How can FSPs select NPV-maximizing payment structures depending on the predictive power of underlying classification algorithms?*

To answer both research questions, Research Article #4 employs a design science research approach presented by Peffers et al.'s (2007) to develop a quantitative decision support model (Arnott & Pervan, 2012). The decision-support model of Research Article #4 maps the predictive power of classification algorithms to the expected NPV of the resulting FSP offering and considers the chosen SLA design (aiming at answering research question 1) and payment structure (aiming at answering research question 2).

Developing the decision support model, Research Article #4 followed Peffers et al.'s (2007) established iterative design science research process. In the first phase of the design science research process, Research Article #4 justifies its research questions as decision-makers face considerable risks if these services are not tailored to the characteristics of the AI algorithms applied (Gregor & Hevner, 2013). Therefore, practice and research require studies on balancing the risks of AI with the benefits of its added value. In the second phase, Research Article #4 presents design objectives that guided the development of its decision support model. Based on this guidance, the third phase employed normative analytical modeling (Keeney & Raiffa, 1993; Meredith et al., 1989) as a widely established method for finding solutions to decision-making problems (Bürger et al., 2019; Kreuzer et al., 2020). The constructs of the decision support model (Such as the considered SLA characteristics or payment structures) are based on qualitative research on the role of SLAs in service success (Goo et al., 2008; Goo et al., 2009) and payment structures for data-driven services (Cachon, 2020; Neely, 2008; Schüritz, Seebacher, Satzger, & Schwarz, 2017; R. Wang et al., 2019). Thus, SLAs are defined as measuring instruments for specific service dimensions (e.g., service availability), which quantify the performance of the service in these dimensions using service level indicators (SLIs) (Beyer et al., 2016; Goo et al., 2008; Goo et al., 2009; Halbheer et al., 2018). The respective target value in each dimension is called SLO. The decision support model considers the effects of these SLA characteristics and payment structures in an integrated manner by calculating the expected NPV of a service as a standard approach for decision-making (Kreuzer et al., 2020).

In the fourth phase of the research process of Peffers et al. (2007), Research Article #4 demonstrates and evaluates the decision support model using the framework proposed by Sonnenberg and vom Brocke (2012). After implementing a Python prototype of the decision support model and conducting multiple simulations with synthetic data, the article presents the application of its decision support model to the real-world case of a German manufacturing company. Research Article #4 presents the case of a real-world medium-sized mechanical engineering company with the pseudonym ENGINEERING to showcase the real-world application of its decision-support model. This showcase validated the model’s applicability and usefulness in a naturalistic setting.

ENGINEERING has 3,000 employees, reports annual revenue of 400 MEUR in 2019, and is a market leader in car wash systems. ENGINEERING acts as an FSP, providing and operating washing systems as a service to ensure high customer loyalty and continuous revenues. Most of ENGINEERING’s customers are large petrol station chains, requiring car wash systems that meet their customers’ demands. The availability of the car wash systems is, thus, crucial for ENGINEERING’s customers, meaning that the service dimension ‘availability’ determines the service level. In this context, ENGINEERING considered introducing a predictive maintenance application based on a binary classification algorithm to increase the expected NPV of its FSP offering. The predictive maintenance application sought to increase the service level of ENGINEERING by decreasing downtime, as unforeseen breakdowns of the car wash system could be predicted and prevented. Further, the predictive maintenance application was meant to reduce necessary maintenance costs via the improved plannability and efficiency of maintenance operations. For this purpose, the predictive maintenance application determined the condition of the car wash system as either maintenance-requiring (positive condition) or non-maintenance-requiring (negative condition). Nevertheless, misclassifications (false negatives and false positives) led to lower service levels, higher maintenance costs, and shrinking revenues, whereby the extent of these negative effects on the NPV depends on the selected payment structure. Therefore, assessing the predictive power of the underlying classification algorithm to determine expected service levels and select suitable payment structures was highly relevant for the economic success of ENGINEERING's FSP offerings. Research Article #4 demonstrates the applicability of its model, using different predictive power scenarios to compare the resulting NPV depending on the selected payment structure and SLA design.

The results illustrated by Figure 6 show that, despite rising operating costs, higher predictive power (expressed by the area under the curve value of the precision-recall curve (AUC), see Davis and Goadrich (2006)) makes economic sense if revenues increase more than these costs due to increasing service levels. However, too-high AUC values are no longer economically meaningful due to high operating costs. Furthermore, the advantageousness of a payment structure also depends on the negotiated premium or penalty payments and the agreed SLO.

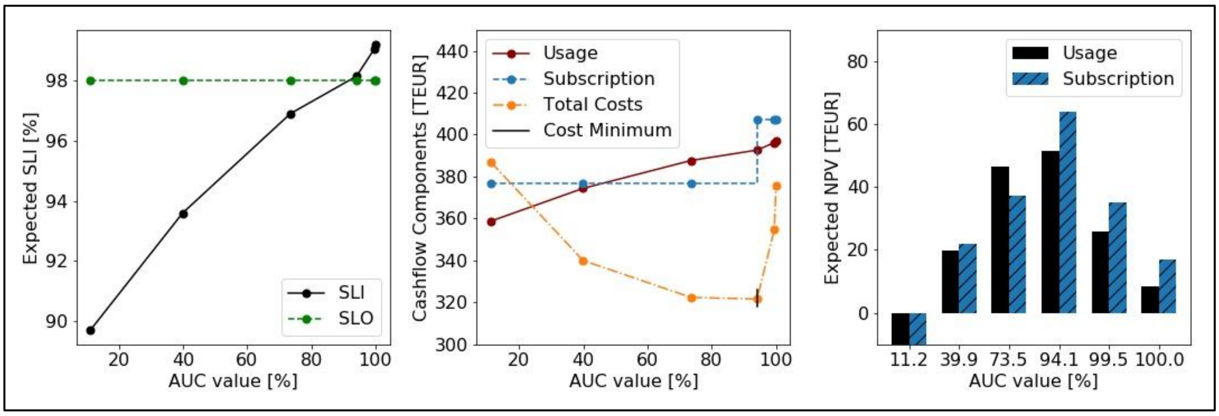


**Figure 6: Analyses of the ENGINEERING Data**

To validate the results illustrated by Figure 6, Research Article #4 includes a robustness analysis of the model in the face of fluctuating some of its unique parameters analogously to the analyses of other recent quantitative decision-support models (Bürger et al., 2019; Kreuzer et al., 2020).

In sum, the results of Research Article #4 were regarded by ENGINEERING and all other interview partners as economically reasonable and helpful for evaluating the effects of varying predictive power and different payment structures on the expected NPV of a data-driven service. Furthermore, the developed decision-support model can derive conclusions about the advantageousness of specific payment structures under certain parameter configurations, and the evaluation confirmed the decision-support model's applicability and added value for decision-makers. Additionally, the results verify existing studies by showing that increasing the predictive power of AI algorithms decreases misclassification costs (Bock et al., 2020; Domingos, 1999, 2012; Fabri et al., 2019). Nevertheless, Research Article #4 extends existing research by including the operating costs for achieving high predictive power, modeling the resulting revenues, and showing that increasing predictive power does not have to make economic sense regarding the expected NPV in an FSP context.

**Research Article #5 – Deriving Decisions Aligned to SLA Objectives Based on Imperfect Predictions**

Besides optimizing SLA design, decision-makers still face the challenge of aligning decisions derived from fallible predictions with a short-term optimization horizon to long-term SLOs. Today, AI algorithms from the field of supervised machine learning (SML) are the source of the predictions of most AI algorithms, ranging from recommending new products for customers to predicting patients' cancer risk in healthcare (Agrawal et al., 2018; Collins et al., 2021; Iansiti & Lakhani, 2020). Further, especially for long-term services formalized by SLAs, it is unreasonable for SML to make predictions in dynamic environments for an arbitrarily long period ahead, as new data acquired during service provision may alter its predictions. This newly acquired data during service provision may lead to changed or refined predictions, resulting in improved decisions and, thus, an improved service (Häckel et al., 2022). Additionally, a series of short-term optimal (periodic) decisions do not necessarily have to be long-term optimal (Robichek et al., 1965). For example, when providing a customer with the availability of a machine deriving each maintenance decision over multiple periods following accurate predictions might be optimal regarding each decision, but not necessarily from the long-term perspective of the multiperiod SLA. In this long-term perspective of the SLA, it might be more beneficial to bring forward or postpone maintenance to achieve less effort over the entire contract period while maintaining the same level of system availability (Häckel et al., 2022; Panzer & Bender, 2022). In sum, to offer successful services in the long term, service providers face the challenge of making multiple and sequential decisions during service provision that are based on predictions made from the available short-term data. These multiple and sequential decisions must be aligned with the long-term SLOs to satisfy customers' expectations and avoid financial losses (Häckel et al., 2022).

A promising solution strategy – Hu et al. (2021) introduced – relies on combining SML and reinforcement learning (RL), which allows for optimizing multiple and sequential decisions in dynamic environments regarding a long-term goal (François-Lavet et al., 2018; Mnih et al., 2015). Following this vein, the envisaged solution strategy of Research Article #5 combines SML's short-term prediction capabilities and RL's capability to translate sequential and short-term predictions into decisions that pay off for successful services in the long term. Despite Hu et al. (2021) presenting the technical approach to combining RL and SML to derive optimal decisions from imperfect predictions, research, and practice have not yet recognized its combination's potential for optimizing long-term SLA-related decisions. Neglecting this potential may lead to the case that short-term predictions made by SML are not best aligned with the negotiated long-term SLOs to satisfy customers at low costs. Therefore, Research Article #5 presents a decision-support model that combines both and illustrates their potential for long-term optimization of SLA-related decisions, following the research question: *How can the combination of supervised machine learning and reinforcement learning enable optimized decision-making to provide successful long-term services?*

To answer this question, Research Article #5 also follows the design science research process of Peffers et al. (2007) to develop a decision support model that combines the strengths of SML and RL with the SLA formalization of Häckel et al. (2022) to derive meaningful decisions related to long-term SLOs. The development and evaluation of the decision support model again included a software-technical implementation of the real-world use case of a medium-sized mechanical engineering company, referred to using the pseudonym ALPHA. Analogously to Research Article #4, this evaluation aimed to validate the model's applicability and usefulness in a naturalistic setting, according to Sonnenberg and vom Brocke (2012). ALPHA has 2,000 employees, reports annual revenue of 400 MEUR in 2023, and is a market leader in providing car wash systems. Most of ALPHA's customers are large petrol station companies that require high availability of their respective car wash systems to service customers whenever they arrive at a petrol station. Hence, the car wash systems' availability is the decisive factor determining the service level.

With this in mind, ALPHA considered introducing a predictive maintenance application to increase the achievable service level and lower costs for ALPHA as the service provider. The predictive maintenance application sought to decrease downtimes, as unforeseen breakdowns of the car wash system could be anticipated leading to reduced necessary maintenance costs via the improved plannability and efficiency of maintenance operations. For this purpose, the decision support model of Research Article #5 expresses the status of a car wash system through its machine runtime, the time since ALPHA performed the last maintenance activities within the SLA runtime, and the prediction of failures for the subsequent three periods (a total period of three weeks). The predictive maintenance application translated the status of a respective car wash system into a reasonable decision aligned with the underlying SLA to achieve high service levels and low costs. Therefore, to fulfill customer expectations at reasonable costs, aligning decisions derived from predictions to the long-term goals negotiated in the SLA contract is highly relevant for the economic success of ALPHA’s SLA-related offers.

The evaluation was based on four different prediction qualities of the underlying SML algorithm to show how the decision support model reacted to different input predictions. For this, we decreased the prediction accuracy with an area under the curve value of the receiver operating characteristic (ROC-AUC) from close to perfect predictions of 0.96 to lower prediction qualities with ROC-AUC values of 0.84, 0.74, and 0.68. Further, Research Article #5 compares its decision-support model to two other decision strategies to evaluate its performance. First, the *Reactive* approach represents the execution of no preemptive services and sticking to the classical decision-making concept of performing reactive maintenance services when actively demanded. Second, the *Naïve* approach represents the strategy of performing preemptive services based on the mere predictions of an SML algorithm. In the case of ALPHA, we employed an eXtreme Gradient Boosting model to obtain machine breakdown probabilities for the next three time steps. As the *Naïve* approach sticks to a pure prediction-driven maintenance strategy, service decisions were triggered as soon as the breakdown probabilities for the next time step surpassed a certain threshold.

Figure 7 shows the evaluation results obtained in Research Article #5. The number of SLA penalties (at an SLO of 90 % machine availability) and the average achieved service level for all four ROC-AUC value scenarios. Again, the *Reactive* approach shows the worst results, with

262 penalties and an average SLI of 86%. The *Naïve* approach leads to ambiguous results, with, by chance, a lower number of penalties and a reasonably high SLI at the ROC-AUC value scenarios of ROC-AUC = 0.677 and ROC-AUC = 0.736. This results from an increased number of services through random predictions that were not necessarily required when executed but prevented later machine breakdowns (at higher costs than the presented decision-support model). The decision support model of Research Article #5 generates an average SLI of 87% (with 252 penalties) at the worst ROC-AUC value and an SLI of 96% (with 96 penalties) at the best ROC-AUC value. While keeping the lowest costs in all ROC-AUC scenarios, the decision-support model fulfills the underlying SLA only with reasonably high prediction accuracy. This dependency on a high predictive accuracy is due to a conflicting divergence of SLO fulfillment and low cost: In the event of poor predictive power, the model reacts in a risk-averse manner and minimizes the costs by adopting a rather reactive maintenance strategy by only performing necessary maintenance services and accepting contractual penalties to a certain extent.

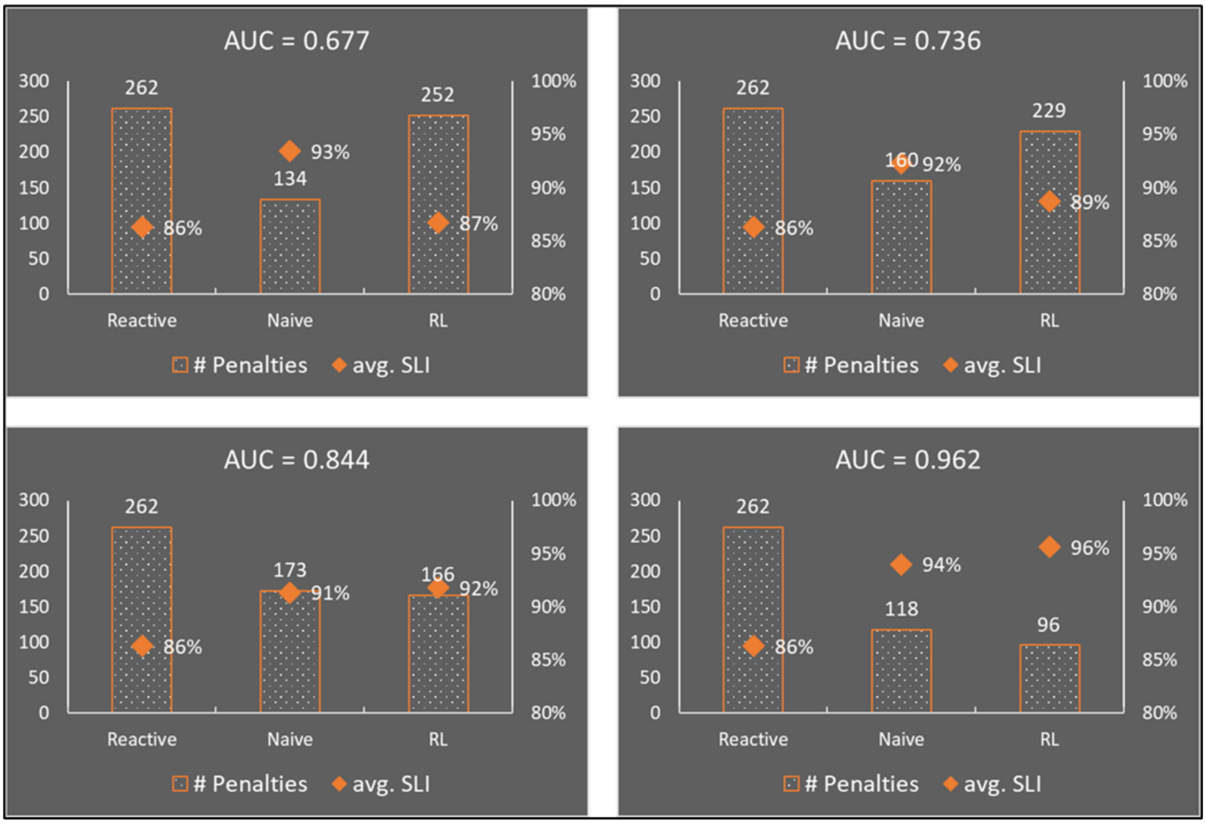


**Figure 7: Comparison of Average Service Level and Number of SLA Penalties**

Overall, the results show that with reasonably high predictive power, the decision-support model of Research Article #5 can align multiple short-term decisions to a long-term SLA while reducing service costs. Further, the case evaluation illustrated how the decision support model of Research Article #5 identifies meaningful decision strategies based on data and learns to anticipate the statistical nature of the SML algorithm's predictions.

## 3 Digital Value Networks as a Driver of Digital Transformation

While the previous two chapters focused on the challenges of connecting an organization's value creation with other partners (Research Articles #1 and #2), discussed approaches on how to exchange data securely (Research Article #3), and presented decision support models, that assisted the provision of data-driven services (Research Articles #4 and #5) this chapter focuses on providing a new theoretical perspective on DT: DT as a phenomenon not driven merely by an organization's managerial agency as discussed in most previous works, but DT as a phenomenon driven by overarching value networks and specifically digital ecosystems (DEs).

In a DE, all member organizations aim to maximize the value creation of a particular value proposition (Adner, 2017; Kapoor, 2018). To do so, the DE members must combine their resources in a way that they are complementary. Such complementary resources are either unique or supermodular. Unique resources are difficult to reproduce by other organizations, while supermodular resources provide disproportionate benefits when combined (Jacobides et al., 2018; Teece, 2018). In line with this understanding, we define a digital ecosystem (DE) as a network of at least two (inter-)dependent organizations co-creating a joint value proposition through digital technologies (Adner, 2017; Jacobides et al., 2018; Tan et al., 2020). In a DE, at least one of the specific complements is built on digital technologies. For example, the infrastructure of a digital platform can enable two or more parties to co-create value (e.g., Gawer and Cusumano (2014)).

### Research Article #6 – A Means to an End of the Other - Research Avenues at the Intersection of Organizational Digital Transformation and Digital Business Ecosystems

While the relevance of the intersection of an organization's DT and DEs' is becoming more and more apparent in empirical research, as outlined by various case studies (e.g., by Hansen and Kien (2015), El Sawy et al. (2016), Alfaro et al. (2019), Stamas et al. (2014), or Du et al. (2020)), a deeper theoretical understanding of the intersection of both constructs is still missing. With this in mind, Research Article #6 proposes the following research question: *What is a shared foundation for theory on DT's and DEs' intersection, and what are corresponding avenues for future research?*

Following Leidner (2018), Research Article #6 first extracts underlying assumptions of both research streams and derives convergent ones that point toward future research avenues. In detail, Research Article #6 identifies and summarizes four individual assumptions of DT and DEs in isolation, of which three are depicted in Table 3. The research article then elaborates on the convergence of the respective assumptions, having discovered that they represent a 'missing link' between the research streams of DT and DEs, following the example of Mendling et al. (2020). These assumptions do not represent an exhaustive set of assumptions within both research streams and do not suggest that something is "misunderstood". Instead, the convergent assumptions take a step toward a theory of why, where, and how research on DT and DEs intersect (Bacharach, 1989).

**Table 3: Derived Convergent Assumptions of DT and DEs**

| Nr. | Topic of Assumption | Assumption in DT Literature | Assumption in DEs Literature | The Missing Link in Assumptions | Convergent Assumption |
|---|---|---|---|---|---|
| *1* | ***Resource*** *interde-pendence* | Organizations require external resources for digitally-enabled value creation. | Organizations mutually share resources for digitally-enabled value (co-) creation. | Organizations can leverage resources from DEs for DT. Vice versa, DEs require organizations to contribute resources for mutual, digitally-enabled value (co-) creation. | *DT requires and enables resource-sharing in DEs.* |
| *2* | ***Coopetition*** *dynamics* | Organizations must act due to digitally-driven competition and disruption. | Organizations balance collaboration and competition (coopetition). | Organizations engage in DT to protect against disruption. In DEs, organizations shield each other from digital disruption through coopetition. | *DT seeks protection that can be provided by the coopetition dynamics of DEs.* |
| *3* | *Locus of* ***control*** | Organizations need to overcome hierarchy-based value creation and static control paradigms. | Organizations are engaged in ecosystem-based value (co-) creation and dynamic holarchies. | Organizations need to develop dynamic control for activities across DEs. That offers a way forward for hierarchy-based control mechanisms, which DT aims to overcome. | *DEs facilitate dynamic control structures that organizations need to develop within DT.* |

Based on its results, Research Article #6 posits that incumbent organizations may start their DT without a deliberate focus on DEs or overarching digital value networks, yet in doing so, they learn that digitalization is “a game played by partners.” Otherwise, the multiple challenges of DT, especially the adoption of digital technologies to open up new ways of value creation (Vial, 2019), may not be feasible. Nevertheless, so far, there is little theoretical dimension to this discussion. Research Article #6 argues that DT and DEs share a foundation for theory in at least the identified convergent assumptions and concludes that further theorizing on DT and DEs is essential to understand phenomena related to organizations and DEs.

**Research Article #7 – Theorizing the Influence of Digital Ecosystems on Digital Transformation: A Path Constitution Perspective**

Based on the results of Research Article #6 and following a phenomenon-based theorizing approach (Fisher et al., 2021; Gregory et al., 2021), Research Article #7 provides a path constitution theory of DT explicating the role of a digital ecosystem on the generation, continuation, and termination of an organization’s DT path. This article seeks to push the frontier of current DT research from an agency-centric to an environment-centric perspective and mobilize future DT research and practice by providing a foundation for environment-centric studies. To achieve this, Research Article #7 asks: *“How a digital ecosystem influences an organization’s digital transformation?”*

Research Article #7 builds its results on path constitution theory, which explains how an organization’s history, external environment, and decisions by managerial actors influence its possible actions (Meyer & Schubert, 2007; Singh et al., 2015). In the past two decades, path constitution theory has evolved into an influential theory for explaining technological and organizational paths (Meyer & Schubert, 2007; Sydow et al., 2020). Additionally, Research Article #7 refers to a DT path not on the level of a particular digital technology but on the level of an organization’s value proposition. A path is driven by self-reinforcing processes, which reproduce specific action patterns (e.g., positive feedback loops or increasing returns) (Sydow et al., 2009).

Translating Sydow et al.’s (2012) constitutive features of a path to the context of DT, Research Article #7 defines the DT path as a progression of organizational transformation actions that leverage digital technologies in (re-)defining an organization’s value proposition over time (Sydow et al., 2020; Wessel et al., 2020). Theorizing the DT path at the organizational level requires examining an organization’s interrelation with its external environment (Plekhanov et al., 2022), i.e., the influence of a DE. A DT path is triggered by a digital technology-driven change in the environmental or organizational context that significantly influences an organization's actions and gradually transforms its value proposition (Vial, 2019; Wessel et al., 2020). While various new digital value propositions are imaginable at the generation of the DT path, the range of options narrows down as a new digital value proposition concretizes over time. The development of this digitally-enabled value proposition further stabilizes the embarked path through a progressive alignment of possible transformation actions driven by internal and external stakeholders, which intentionally or unintentionally influence the development of the digitally-enabled value proposition over time. This DT path becomes (temporarily) congealed or even locked in when a digitally-enabled value proposition establishes and limits an organization's flexibility regarding further DT actions (Adner, 2017; Hanelt et al., 2021).

As depicted in Figure 8, Research Article #7 theorizes the role of a DE on an organization's DT path in three phases covering the generation of a DT path, outlining how the DT path continues, and demonstrating how the DT path terminates in the face of an exogenous shock.

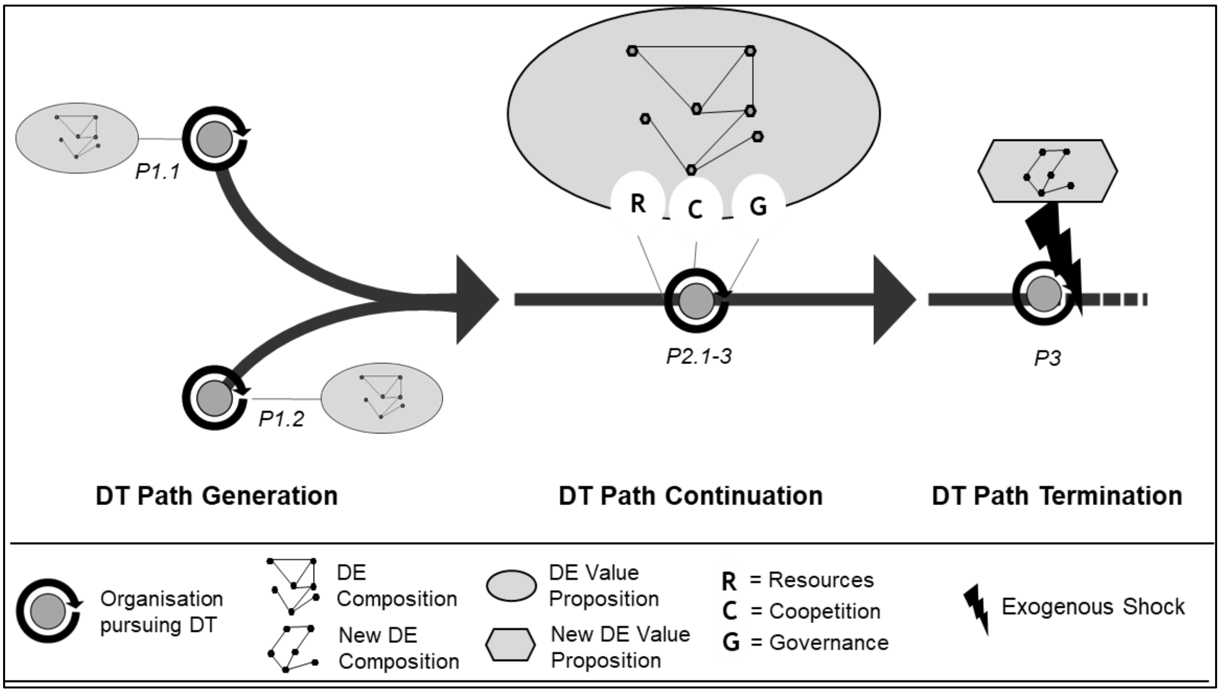


**Figure 8: Overview of the Path Constitution Theory of Digital Transformation Across Three Phases**

The theory explains how DEs influence all phases of the DT path and drive both continuous and episodic change concerned with DT (Hanelt et al., 2021). The primary contribution of Research Article # 7 is a theory that brings the external environment in general and the influence of DEs in particular to the focus of DT research (Gregor, 2006). While the significance of the external environment in influencing an organization's DT is already widely acknowledged (Hanelt et al., 2021; Verhoef et al., 2021), there is a potential of failing to recognize the pivotal role played by DEs guiding and limiting managerial agency. Thus, the theory serves as a sensitizing device to view an organization's DT and its influences from an environment-centric perspective which complements current agency-centric work and aligns with recent calls by Markus and Rowe (2021) on concurrent DT research. By pushing the frontier of DT research to account for the influence of DEs, we pick up the calls to explicitly consider the external environment, which dates back to Venkatraman (1994).

The secondary contribution of Research Article #7 is to conceptualize DT as a path drawing from path constitution theory (Meyer & Schubert, 2007; Singh et al., 2015; Sydow et al., 2009) and break down the abstract phenomenon of DT into three different phases. The theory answers previous calls for conceptualizing DT as a path, i.e., a particular type of process characterized by a limited scope of meaningful or even a lock-in on specific DT actions (Drechsler et al., 2020; Nambisan et al., 2017). Research Article #7 builds upon and expands existing research that understands DT as a (change) process (Soluk & Kammerlander, 2021). Further, as Hanelt et al. (2021), an organization's DT is a dynamic process with no static but moving target, including continuous and episodic change phases. Our theorizing adds to that by suggesting that within a phase of continuous change, the DT path continues and stabilizes through self-reinforcing processes related to resources, coopetition, and governance. In a phase of episodic change, a DT path terminates driven by a change in a DE's joint value proposition or composition. DT does not necessarily end from there, but a new DT path may be generated. Finally, a path constitution perspective of DT also helps to address the implicit assumption of concurrent research, which treats DT "as a binary outcome of transformed vs. non-transformed" (Fabian et al., 2023). By conceptualizing DT as a path of three major phases, Research Article #7 offers a more fine-grained understanding of examining an organization's DT between the non-transformed and transformed states.

# III Summary and Limitations

## 1 Summary

Moving beyond competing with others' narratives to form digital value networks and face the challenges of ever-faster changing environments due to rampant DT involves profound challenges for organizations. Here, through joining forces with others, digital value networks provide access to various external resources, especially substantial amounts of data, that pave the way for new AI-driven services (Gregory et al., 2021; Oberländer et al., 2021). Motivated by these opportunities, this doctoral thesis addresses three overarching topics: Firstly, the *challenges of digital value networks as a driver of artificial intelligence* pose significant obstacles for incumbents. In this vein, this doctoral thesis identifies the challenges of adopting IoT platforms, provides a decision support model to manage particularly critical IT security concerns, and highlights the opportunities for FL to share data in digital value networks. Secondly, the *challenges of artificial intelligence as a driver of new digital value propositions* force incumbents to consider the stochastic nature of most AI-driven services in their service design. Therefore, this doctoral thesis provides two decision-support models for supporting the monetization of data-driven services and successfully providing new digital value propositions that fulfill customer expectations. Thirdly, acknowledging the significant role of the external environment in an incumbent's DT, this doctoral thesis provides a new theoretical assertion on *value networks as a driver of digital transformation* that balances the prevalent view that an organization's agents design its DT path with a more nuanced perspective on the influence of its external environment (Markus & Rowe, 2021, 2023).

Concerning the *challenges of digital value networks as a driver of artificial intelligence*, Section II.1 provides an overview of the challenges practitioners and academics deem relevant when companies adopt IoT platforms as a prerequisite for connecting forces with others to provide new digital value propositions (Research Article #1). Section II.1 reveals several extremely relevant rated challenges of adopting industrial IoT platforms and using digital technologies to exchange data with others in an IT security context. Therefore, this doctoral thesis provides a decision-support model that assists decision-makers in quantitatively assessing the risks of connecting to other organizations and overseeing the complexity of their digital value network (Research Article #2). Applying the decision-support model to the case of a German gearing manufacturer provides promising results regarding its usefulness and applicability. While this decision-support model allows for assessing the impact of IT security incidents on information systems and value flows, Section II.1 further provides an overview of FL applications as a promising way to share data safely (Research Article #3).

Concerning the *challenges of artificial intelligence as a driver of new digital value propositions*, Section II.2 provides two decision-support models that assist decision-makers in designing AI-driven services. Both decision-support models are driven by challenges incumbents face when turning data-driven predictions into meaningful services. The first decision-support model of Section II.2 thereby enables decision-makers to derive meaningful SLAs with reasonable SLOs and select suitable payment structures for their services based on the predictive power of their underlying AI algorithms (Research Article #4). The second decision support model of Section II.2 utilizes new reinforcement learning approaches to turn predictions into meaningful decisions aligned with the long-term goals of overarching SLAs (Research Article #5). The applicability of both decision support models is evaluated by the case of a German car wash system manufacturer that aims to use its customers' data, i.e., the data of large petrol station chains, to improve its maintenance services and provide higher availability of its systems. The decision-support models broaden the prescriptive knowledge on implementing AI-driven services in the manufacturing industry by combining and extending existing solutions to a relevant research problem. Furthermore, both decision-support models offer novel approaches to assess the economic value of data-driven services for service providers in the manufacturing industry.

Concerning *digital value networks as a driver of digital transformation*, Section II.3 provides a new theoretical foundation on the influence of an organization's external environment on its DT. This new theoretical foundation consists of four convergent assumptions illuminating the intersection of DEs and an organization’s DT and a new theoretical perspective on an organization's DT using path constitution theory. The four convergent assumptions represent possible constructs for building future theory and serve as the first step toward a more profound theoretical explanation of how a DE influences an organization’s DT (Research Article #6). Building on the convergent assumptions, the path constitution theory of digital transformation spotlights the role of a DE on an organization’s DT. Following a phenomenon-based theorizing approach and drawing from path constitution theory, this new perspective explicates a DE’s role in DT path generation, continuation, and termination and pushes the frontier of organizational DT research from an agency-centric to an environment-centric perspective (Research Article #7).

## 2 Limitations and Future Research

The results of this doctoral thesis have limitations that provide an impetus for future research endeavors. This section provides an overview of these limitations and spotlights resulting avenues for future scholars that examine the role of digital value networks and AI for an incumbent's DT. Further, the individual research articles provide a detailed perspective on the limitations of this research endeavor and their potential for future research (see the Appendix section).

First, the developed decision-support models of Research Articles #2, #4, and #5 consider multiple input parameters as deterministic or expected values. In reality, however, parameters such as costs resulting from misclassifications or IT incidents can fluctuate, and, therefore, the stochastic modeling of input parameters would further increase the validity of the decision-support models. Furthermore, it is challenging to determine input parameters such as expected costs, e.g., resulting from AI-based misclassifications, or expected revenues, especially for manufacturing companies with little experience in DT or AI. However, I must note that increasing the validity of the presented decision-support models comes with increased requirements for underlying data. The decision-support models of this doctoral thesis are intended for use in industry settings and, therefore, focus on the effects of specific parameters such as network complexity or predictive power. This spotlighting of specific parameters facilitates the applicability of the presented decision-support models and allows a closer investigation of different scenarios by varying input parameters. Further, performing robustness analyses can compensate for the uncertainty of input parameters, and joining forces with others in digital value networks may provide the opportunity to meet the increased requirements for underlying data.

Second, concerning applying FL to share data within digital value networks, Research Article #3 omitted certain aspects from the chosen perspectives of the developed taxonomy due to a lack of data. For example, balancing fairness and privacy in an FL use case is mainly an issue regarding incentives for training performance. This limitation opens a vast research avenue from a business perspective on possibly commercializing FL applications through payments to the clients while providing proof of their training benchmarks without disclosing their identity. Here, research like Rückel et al. (2022) provides a promising approach but still needs to be extended by field tests. Gu et al. (2022) also show promising results in navigating trade-offs between privacy, performance, and fairness on an algorithm level.

Third, the theorizing efforts presented in Research Articles #6 and #7 may have missed relevant publications despite the best attempts at rigorous research. The literature reviews of both research articles are not aimed to be comprehensive within the individual research streams but rather to provide a representative sample of the current discourse in literature (Leidner 2018). Literature unknown to the authors might offer further valuable insights. However, this doctoral thesis emphasized the first steps to theoretical development and focused less on the full-fledged review of prior literature (Leidner 2018; Rivard 2014). Thus, my work supports an early stage of theory building, i.e., in line with Bacharach (1989), who stated that "during the early stages of theory building, there may be a fine line between satisfying the criteria of the internal logic of theory and achieving a creative contribution" (P. 513).

Fourth, this doctoral thesis does not operationalize the presented *path constitution theory of digital transformation* regarding variables, hypotheses, and quantitative empirical analysis. Instead, the path constitution theory of DT provides a basis for operationalizing and empirically assessing an organization’s DT path in future research following explicit propositions along three phases. When empirically examining the theory, future research should also consider specific contingencies along an organization’s DT path, e.g., an organization’s size, age, industry, geography, and culture. Moreover, future empirical agency-centric DT research should account for control variables that consider the external environment's influence in general and DEs and digital value networks in particular.

In sum, the velocity of change in many industries induced by ever-faster-evolving digital technologies will almost certainly increase further and spur the emergence of more complex networks of organizations cocreating data-driven value propositions. Therefore, I sincerely hope this doctoral thesis will support researchers and practitioners in navigating the opportunities and risks of DT in digital value networks.

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# V Appendix

## 1 Index of Research Articles

**Research Article #1: Challenges of Organizations' Adoption of Industrial IoT Platforms - Results of a Delphi Study**

Arnold, Laurin; Karnebogen, Philip; Urbach, Nils. Challenges of Organizations' Adoption of Industrial IoT Platforms - Results of a Delphi Study. *International Journal of Innovation and Technology Management* (2023).

(VHB-Jourqual 3: Category C | Impact Factor (2023): 1.917)

**Research Article #2: Estimating the Impact of IT security incidents in digitized production environments**

Bürger, Olga; Häckel, Björn; Karnebogen, Philip; Töppel, Jannick. Estimating the impact of IT security incidents in digitized production environments. *Decision Support Systems* (2019).

(VHB-Jourqual 3: Category B | Impact Factor (2023): 6.969 | Part of the Senior Scholars' List of Premier Journals)

**Research Article #3: Structuring Federated Learning Applications – A Literature Analysis and Taxonomy**

Karnebogen, Philip; Kaymakci, Can; Willburger, Lukas; Häckel, Björn; Sauer, Alexander. Structuring Federated Learning Applications – A Literature Analysis and Taxonomy. *Proceedings of the 31st European Conference on Information Systems (ECIS 2023). Kristiansand, Norway.*

(VHB-Jourqual 3: Category B)

**Research Article #4: AI-based Industrial Full-Service Offerings: A Model for Payment Structure Selection Considering Predictive Power**

Häckel, Björn; Karnebogen, Philip; Ritter, Christian. AI-based industrial full-service offerings: A model for payment structure selection considering predictive power. *Decision Support Systems* (2022).

(VHB-Jourqual 3: Category B | Impact Factor (2023): 6.969 | Part of the Senior Scholars' List of Premier Journals)

**Research Article #5: Successful Service Provision Based on Imperfect Predictions – A Reinforcement Learning Approach**

Karnebogen, Philip; Markgraf, Moritz; Hofmann; Peter; Häckel, Björn. Successful Service Provision Based on Imperfect Predictions – A Reinforcement Learning Approach. *Working paper submitted to the Decision Support Systems Journal*.

**Research Article #6: A Means to an End of the Other-Research Avenues at the Intersection of Organizational Digital Transformation and Digital Business Ecosystems**

Karnebogen, Philip; Oberländer, Anna Maria; Rövekamp, Patrick. A Means to an End of the Other-Research Avenues at the Intersection of Organizational Digital Transformation and Digital Business Ecosystems. *Proceedings of the 42nd International Conference on Information Systems (ICIS 2021). Austin, Texas.*

(VHB-Jourqual 3: Category A | Nominated for Best Theory Development Paper Award)

**Research Article #7: Theorizing the Influence of Digital Ecosystems on Digital Transformation: A Path Constitution Perspective**

Oberländer, Anna Maria; Karnebogen, Philip; Rövekamp, Patrick; Röglinger, Maximilian; Leidner Dorothy. Theorizing the Influence of Digital Ecosystems on Digital Transformation: A Path Constitution Perspective. *Submitted working paper in the second round of revision at Information Systems Journal (ISJ).*

(VHB-Jourqual 3: Category A | Impact Factor (2023): 7.767 | Part of the Senior Scholars' List of Premier Journals)

## 2 Individual Contribution to the Research Articles

This cumulative dissertation comprises seven research articles representing the main body of work. All articles were developed in teams with multiple co-authors. This section details the respective research settings and highlights my individual contributions to each article.

**Research article #1:** I co-authored this research article with Laurin Arnold and Nils Urbach. Regarding the development of the manuscript, I co-developed the initial draft of the research article and was engaged in conceptualizing the results and crafting their implications for theory and practice. Additionally, I was involved in further developing and revising the research article and textual elaboration. Laurin Arnold is the lead author of this research paper.

**Research article #2:** I co-authored this research article with Olga Bürger, Jannick Töppel, and Björn Häckel. All co-authors jointly developed the decision-support model for estimating the impact of IT security incidents in the manufacturing industry. I was involved in all stages of developing this research article, from crafting the initial research idea and manuscript to multiple rounds of textual refinement throughout multiple revisions. Further, I was responsible for a multistaged evaluation consisting of several interviews with industry experts, a software implementation in R of the developed decision-support model, and showcasing it in a case study at a German manufacturing company.

**Research article #3:** This research article was developed by a team of five co-authors (Philip Karnebogen, Can Kaymakci, Lukas Willburger, Björn Häckel, and Alexander Sauer). All co-authors jointly developed the taxonomy for federated learning applications and their implications for privacy, performance, and fairness. In line with my role as the first author, I was involved in all stages of developing this research article, from crafting the initial research idea and manuscript to multiple rounds of textual refinement and reviewing all sections. Further, I contributed significantly to the design of the research methodology.

**Research article #4:** I co-authored this research article with Christian Ritter and Björn Häckel. All co-authors jointly developed the decision-support model for selecting suitable payment structures for AI-based industrial full-service offerings. I was involved in all stages of developing this research article, from crafting the initial research idea and manuscript to multiple rounds of textual refinement throughout multiple revisions. Further, I was responsible for a multistaged evaluation consisting of several interviews with industry experts, a software implementation in Python of the developed decision-support model, and showcasing it in a case study at a German manufacturing company.

**Research article #5:** This research article was developed by four co-authors (Philip Karnebogen, Moritz Markgraf, Peter Hofmann, Björn Häckel). As the leading author of this research article, I developed its research idea and concept and contributed significantly to the design of the research methodology. Further, I had a leading role in the model development, evaluation, and writing all sections of the manuscript. Additionally, I was in charge of preparing the article’s refinement and preparing it for submission. While, to a large extent, this article reflects my work, all co-authors promoted the advancement of the paper throughout the entire project.

**Research article #6:** This research article was developed by a team of three co-authors (Philip Karnebogen, Anna Maria Oberländer, and Patrick Rövekamp). Thereby, all three co-authors jointly developed the key contributions, i.e., the convergent assumptions and avenues for future research, whereas I took a crucial role in deriving literature in the research stream of digital transformation. Further, I was especially responsible for the elaboration of results as well as the conceptualization of constructs such as digital transformation or digital technologies. I also took part in revising the manuscript during the revision process and presenting the article at the *42nd International Conference on Information Systems.*

**Research article #7:** I co-authored this research article with Anna Maria Oberländer, Patrick Rövekamp, Maximilian Röglinger, and Dorothy Leidner. Based on a similar idea to Research Article #6, In line with my role as the second author of this paper, I was involved in all parts of this research article's conception, theorizing, and writing. In particular, I was also responsible for evaluating multiple theoretical lenses, framing the Path Constitution Theory as a theoretical lens, and crafting an extensive literature review of the foundational literature. Furthermore, I was involved in preparing the research article for submission and extensively revising the paper after receiving feedback during the review process.

# 3 Research Article #1

## Challenges of Organizations' Adoption of Industrial IoT Platforms - Results of a Delphi Study

Authors: Arnold, Laurin; Karnebogen, Philip; Urbach, Nils.

Published in: *International Journal of Innovation and Technology Management (2023).*

Abstract: Companies are still reticent about adopting IIoT platforms, and research has not yet explained the underlying challenges that impede such adoption. Uncovering these obstacles can open avenues for research and practice to realize the intended potential. We take a holistic perspective on technological, organizational, and environmental challenges that impede organizations’ adoption of IIoT platforms, which we identify in a Delphi study with 22 international experts from academia and practice. Besides identifying 29 challenges, our research reveals the comparative relevance of individual challenges, uncovering differences in perceptions between academics and practitioners. The study contributes to the diffusion of IIoT platforms in research and practice.

Keywords: Industrial IoT, IIoT Platform, Adoption, Challenge, Delphi Study.

# 4 Research Article #2

## Estimating the Impact of IT Security Incidents in Digitized Production Environments

Authors: Bürger, Olga; Häckel, Björn; Karnebogen, Philip; Töppel, Jannick.

Published in: *Decision Support Systems (2019).*

Abstract: Owing to digitalization, manufacturing companies increasingly integrate IT services – such as control systems – into their production environments. This increases the flexibility of production and allows them to offer new data-based services (e.g., predictive maintenance). However, stepping up production-IT system connections also leads to an increased reliance on the availability of IT services as a means to value creation, both in internal production processes and at the customer interface. More interconnectivity also increases network complexity, and thus favors the rapid spread of cyber-attacks within the information network. The potential for damage is massive, as disruptions to IT services can harm the deliverability of both, connected IT services and production components. Despite existing studies on IT security, little has been written on ways to estimate the impact that availability incidents have on digitized production environments based on the IIoT – for example, smart factories. To help close this research gap, we provide an approach that enables users to simulate cyber-attacks and measure the impact of such attacks on value creation in digitized production environments. We compare the features of our model with our specific design objectives and competing artifacts, present our prototype and the results of a sensitivity analysis for selected model parameters, and illustrate the applicability of our model using the real-life case of a German manufacturing company. Our results indicate that the degree of interconnection in digitized production environments is the most important influencing factor when estimating the impact of an IT availability incident on value creation.

Keywords: IT security, cyber attacks, Bayesian Networks, value creation.

## 5 Research Article #3

**Structuring Federated Learning Applications – A Literature Analysis and Taxonomy**

Authors: Karnebogen, Philip; Kaymakci, Can; Willburger, Lukas; Häckel, Björn; Sauer, Alexander.

Published in: *Proceedings of the 31st European Conference on Information Systems (ECIS 2023). Kristiansand, Norway.*

Abstract: Ensuring data privacy is an essential objective competing with the ever-rising capabilities of machine learning approaches fueled by vast amounts of centralized data. Federated learning addresses this conflict by moving the model to the data and ensuring the data itself does not leave a client's device. However, maintaining privacy impels new challenges concerning algorithm performance or fairness of the algorithm's results that remain uncovered from a sociotechnical perspective. We tackle this research gap by conducting a structured literature review and analyzing 152 articles to develop a taxonomy of federated learning applications with nine dimensions and 24 characteristics. Our taxonomy illustrates how different attributes of federated learning may affect the trade-off between an algorithm's privacy, performance, and fairness. Despite an increasing interest in the technical implementation of federated learning, our work is one of the first to emphasize an information systems perspective on this emerging and promising topic.

Keywords: Taxonomy, Federated Learning, Privacy, Performance, Fairness.

# 6 Research Article #4

## AI-based Industrial Full-Service Offerings: A Model for Payment Structure Selection Considering Predictive Power

Authors: Häckel, Björn; Karnebogen, Philip; Ritter, Christian.

Published in: *Decision Support Systems (2022).*

Abstract: Artificial Intelligence and servitization reshape the way that manufacturing companies derive value. Aiming to sustain competitive advantage and intensify customer loyalty, full-service providers offer the use of their products as a service to achieve continuous revenues. For this purpose, companies implement AI classification algorithms to enable high levels of service at controllable costs. However, traditional asset sellers who become service providers require previously atypical payment structures, as classic payment methods involving a one-time fee for production costs and profit margins are unsuitable. In addition, a low predictive power of the implemented classification algorithm can lead to misclassifications, which diminish the achievable level of service and the intended net present value of the resultant service. While previous works focus solely on the costs of such misclassifications, our decision model highlights implications for payment structures, service levels, and – ultimately – the net present value of such data-driven service offerings. Our research suggests that predictive power can be a major factor in selecting a suitable payment structure and the overall design of service level agreements. Therefore, we compare common payment structures for data-driven services and investigate their relationship to predictive power. We develop our model using a design science methodology and iteratively evaluate our results using a four-step approach that includes interviews with industry experts and the application of our model to a real-world use case. In summary, our research extends the existing knowledge of servitization and data-driven services in the manufacturing industry through a quantitative decision model.

*Keywords: Artificial Intelligence, Servitization, Predictive Power, Payment Structures, Full-Service Provision*

# 7 Research Article #5

## Successful service provision based on imperfect predictions – A Reinforcement Learning Approach

Authors: Karnebogen, Philip; Markgraf, Moritz; Hofmann, Peter; Häckel, Björn.

*Working paper submitted to the Decision Support Systems Journal*

**Extended Abstract:**

Decision support systems based on supervised machine learning (SML) are at the heart of various service offerings in almost all industries (Brynjolfsson & Mitchell, 2017; Schüritz et al., 2017). However, the statistical nature of modern SML approaches implies the inherent fallibility of their predictions (Agrawal et al., 2018). Additionally, while SML is suitable for optimizing single decisions, it does not provide the ability to optimize multiple decisions over a long-term service provision. To offer successful services in the long term, service providers must make multiple and sequential decisions during service provision that are based on predictions made from the available short-term data (Häckel et al. 2022).

A promising solution strategy to solve this problem and provide valuable service in the long term relies on combining SML and reinforcement learning, which allows for optimizing multiple and sequential decisions in dynamic environments regarding a long-term goal (François-Lavet et al., 2018; Hu et al. 2021). The presented decision support model combines SML's short-term prediction capabilities and RL's capability to translate sequential and short-term predictions into decisions in dynamic environments that pay off for successful services in the long term. Despite current research already indicating the potential of combining SML and RL for optimizing operations (Hu et al. 2021), research and practice have not yet recognized the potential of this combination for optimizing service-related decisions.

To date, literature has mainly focused on either RL or SML, while we present a decision support model that combines both and illustrates their potential for optimizing SLA-related decisions in the long term. Therefore, to face the challenge of how to align short-term predictions with the long-term goals of services (e.g., service level agreements ranging from two to five years) (Beyer et al., 2016; Goo et al., 2008), we formulate the following research question: How can

the combination of supervised machine learning and reinforcement learning enable optimized decision-making to provide successful long-term services?

We follow the design science research (DSR) approach that Gregor et al. (2013) proposed and develop a decision support model for combining SML and RL to optimize sequential decision-making for service provision. We continuously evaluate our results, including a real-world application case. Our decision support model guides decision-makers in identifying services that offer the potential for a combination of SML and RL and provides design knowledge on how to use RL in combination with SML for translating the short-term predictions of SML into optimized decisions for service provision.

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## 8 Research Article #6

**A Means to an End of the Other - Research Avenues at the Intersection of Organizational Digital Transformation and Digital Business Ecosystems**

Authors: Karnebogen, Philip; Oberländer, Anna Maria; Rövekamp, Patrick.

Published in: *Proceedings of the 42nd International Conference on Information Systems (ICIS 2021). Austin, Texas.*

Abstract: Digital technologies pose challenges and opportunities to individual and ecosystems of organizations. To date, two mostly isolated research streams study these related phenomena: Organizational digital transformation (ODT), focusing on the digital improvement process of individual incumbents and digital business ecosystems (DBEs), focusing on digitally-enabled value co-creation among organizations. Joining the forces of both research streams, our work aims to assess what empirical evidence and theory exist at their intersection. After conducting an assessing review, a theorizing review, and extracting assumptions in isolation, we derive four convergent assumptions for building future theory at their intersection along four topic areas: resources, coopetition, evolution, and control. We propose that ODT and DBEs can be a means to an end of the other connected in a cyclical relationship to meet digitally induced challenges. By presenting avenues for further research, our work builds a foundation for future theory at the intersection of ODT and DBEs.

Keywords: Organizational Digital Transformation, Digital Business Ecosystems, Theory Building, Digitalization, Theorizing Review.

# 9 Research Article #7

## Theorizing the Influence of Digital Ecosystems on Digital Transformation: A Path Constitution Perspective

Authors: Oberländer, Anna Maria; Karnebogen, Philip; Rövekamp, Patrick: Röglinger, Maximilian; Leidner, Dorothy.

*Submitted working paper in the second round of revision at the Information Systems Journal (ISJ)*

**Extended Abstract**:

Organizations must embark on digital transformation (DT) to integrate digital technologies into their value creation, capture, and shielding against competitors, as a fundamental and continuous change process (Hanelt et al., 2021), leading to a new value proposition (Wessel et al., 2020). Rooted in the IS research tradition around strategic IT management and IT-related change (Wessel et al., 2020), most current DT research focuses on the transformation of the organization's core, which includes organizational structures and processes controlled by managerial agents (Plekhanov et al., 2022). However, research has only recently started to unpack the influence of an organization's external environment on DT, emphasizing the role of digital ecosystems (DEs) (Plekhanov et al., 2022). Since digital technologies bridge organizational and industry boundaries (Yoo et al., 2010), they enable organizations to create value more often outside organizational boundaries in DEs (Plekhanov et al., 2022). Empirical studies highlight the benefits of value co-creation and resource-sharing in DEs (Fürstenau et al., 2019) as reasons for this phenomenon.

However, while we know that DEs are relevant for an organization's DT, we lack a deeper understanding of how DEs influence DT. We aim to provide a new perspective that focuses on the role of DEs in DT, reversing the currently prevalent agency-centric perspective to an environment-centric one. First, suppose DEs are much more central to an organization's DT than assumed. Current research risks overvaluing an organization's internal aspects in this case, resulting in a partially misguided understanding of DT. Consequently, much-needed ef-forts to conceptualize and assess DT success would become biased towards internal aspects. Second, a DE-centric theoretical foundation for DT research must balance the DT research field regarding organization-internal and external research spotlights. Future research needs to be equipped with novel theoretical DT models that establish 'a broader view on DT, one that goes beyond

organizational design' (Hanelt et al., 2021, p. 1170) as a basis to address relevant questions concerning the external environment of the organization's DT. Third, as a consequence of the first two, underestimating the influence of DEs on DT would lead to imperfect guidance for practice. With our research, we would like to trigger a fruitful discourse in DT research around the central forces shaping an organization's DT. In order to push the frontier of DT research from an agency-centric to an environment-centric perspective and to theorize the influence of a DE on an organization's DT, we ask: *How does a digital ecosystem influence an organization's digital transformation?*

To answer this research question, we present a path constitution theory of digital transformation explaining a DE's role in an organization's DT. Following a phenomenon-based theorizing approach (Fisher et al., 2021; Leidner, 2018) and drawing from path constitution theory, our theory explicates a DE's role in DT path generation, continuation, and termination. Our theory shows how DEs drive both continuous and episodic change concerned with DT (Hanelt et al., 2021). This paper aims to push the frontier of organizational DT research from an agency-centric to an environment-centric perspective and calls for more multi-level DT theorizing. We also aim to encourage a more intense dialogue among DT and DE researchers and practitioners concerned with DT strategy.

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