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Designing Digital Business Models for Manufacturing Companies

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Copyright Statement

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

“Der beste Weg, die Zukunft vorauszusagen, ist, sie zu gestalten”

(Willy Brandt)

Von ganzem Herzen danke ich meinen Eltern und meinem Bruder für die bedingungslose Unterstützung.

Abstract

The design of digital business models is an integral part of the socio-technical phenomenon known as digitalization – the adoption of digital technologies by individuals, organizations, and society. The manufacturing industry, which is a crucial sector in the global economy, stands to unlock substantial value by harnessing the vast amounts of data generated by customers' machines and systems through digital technologies. Redefining value creation, delivery, and capture mechanisms allow manufacturers to establish novel revenue streams, distinguish themselves from competitors, and cultivate enduring customer relationships. As servitization gains momentum, manufacturers are embracing the transition from product-centric to service provider business models, bolstered by helping customers to operate their machines. However, the design of digital business models poses significant challenges for the manufacturing industry. Adopting a socio-technical perspective, this doctoral thesis comprises five research articles and outlines a comprehensive pathway for addressing the three primary challenges of initiating, developing, and implementing digital business models, which requires an integrated perspective across organizational layers.

Amidst a myriad of digital opportunities, firms need to identify ways to create value through digital technologies that go beyond the usual incremental improvement of existing products. Manufacturers, therefore, face the challenge of initiating the exploration of digital opportunities, given the multitude of new possibilities, changing customers' demands, and unknown technical requirements, leading to high uncertainty. Thus, manufacturers need a structured approach to explore digital business models that meet customers' expectations (desirability), are technically realizable (feasibility), and are supported by a robust monetization strategy (viability). Research article #1 presents a four-phase approach for identifying and levering digital opportunities, using a case study on WashTec, a market-leading manufacturer of car wash systems, to provide a blueprint for other manufacturers.

Further, as manufacturers embrace servitization, they face the challenge of generating value for their customers while ensuring profitable business models. This entails developing aligned value creation and capture mechanisms to successfully realize the shift from traditional one-time sales of physical products to the provision of outcome-based service offerings. Against this backdrop, research article #2 presents a decision support system for predictive maintenance services, incorporating real options analysis to exploit the value of an outcome-based service provision, where the service provider guarantees a certain machine availability using digital technologies for failure prediction. Research article #3 provides insights for manufacturers as services providers utilizing artificial intelligence in offering outcome-based services.

The study deals with the effects of algorithms' predictive power on a digital business model's revenue, depending on the underlying payment structure, such as subscription-based or usage-based. The resulting decision support system exemplifies the development of aligned value creation and value capture mechanisms.

Implementation of new business and technological capabilities is also imperative if manufacturers are to exploit digital business' long-term value. Research article #4 introduces a maturity model for the capabilities necessary for implementing specific digital business model archetypes. Further, manufacturers need guidance if they are to effectively translate digital business model concepts into operational processes. Considering business process management's role in facilitating the allocation of resources and capabilities to successfully implement novel digital business models, research article #5 presents a taxonomy of business process management governance setups as a tool for better understanding potential design options when implementing or adjusting business process management practices.

This thesis contributes novel artifacts for both research and practice, bridging the gap between conceptualizing strategic target states and providing guidance for digital business model design. By extending descriptive and prescriptive knowledge at the intersections of the information systems domain, the business model innovation research, and the servitization literature, the thesis supports manufacturing companies in their digital transformation. Lastly, the thesis responds to calls for research by delving into the transformation of manufacturing companies in the business-to-business context.

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I Introduction

In the dynamic landscape of the digital era, organizations widely acknowledge the significance of digital business models spurred by digital technologies such as the industrial internet of things (IIoT), cloud computing, and artificial intelligence (AI). These technologies present a plethora of novel opportunities for value creation. On the one hand, they enable organizations to enhance operational efficiency and optimize existing processes (*exploitation*) (Beverungen, Buijs, et al., 2021). On the other hand, digital technologies empower organizations to offer their customers novel or adapted value beyond existing products or service offerings (*exploration*) (Knote et al., 2020; Kotarba, 2018; Nambisan et al., 2017; Ranjan & Foropon, 2021). Capturing the potential of data-driven value creation is pivotal if organizations are to thrive in the – complex – digital environment. The adoption of digital technologies by individuals, organizations and society is an integral part of the socio-technical phenomenon known as digitalization (Legner et al., 2017; Vial, 2019). This doctoral dissertation focuses on the digital transformation of organizations in the context of digitalization, with an emphasis on the redefinition of an organization’s value proposition (Wessel et al., 2021). The opportunities and potentials of digital technologies go far beyond the traditional focus on information and communication processes (Teubner, 2013). Digital technologies continually produce increasing amounts of structured and unstructured data, driving the *big data* trend (Buhl et al., 2013; Wu et al., 2014). Scholars argue that the new value lies in collecting and analyzing data generated by individuals, machines, or systems (Chen et al., 2012; Constantiou & Kallinikos, 2015). For instance, AI models trained on large-scale data-sets enable new applications such as image classification, voice recognition, and pattern detection (Agrawal et al., 2018; Krogh, 2018). Companies can utilize digital technologies and a vast array of potential applications as enablers to modify or redefine their course of value creation, value delivery, or value capture to design successful digital business models (Chen et al., 2012; Davenport et al., 2012).

OpenAI is an example of a digital-born company that offers data-driven services such as ChatGPT based on digital technologies. ChatGPT is an AI-language tool that provides users with detailed responses to questions or tasks in dialogue-based interactions. The model has been trained on a vast amount of diverse text data from the Internet and is the foundation for a subscription-based digital business model (https://chat.openai.com). However, traditional incumbents, which, historically, have focused on physical products, can also leverage digital technologies for data-driven value creation. For instance, Siemens, operating in the industrial, energy, and healthcare sectors, developed an AI software suite that utilizes medical data sources to improve radiological diagnostics and patient treatment planning. Siemens also levers AI for quality prediction in the production of printed circuit boards to avoid bottlenecks in quality control by eliminating unnecessary control operations (van Giffen & Ludwig, 2023).

As a pioneering company, Siemens shows that the exploration of digital business models is very relevant for manufacturing and mechanical engineering companies.[1] The machines and systems used by customers generate vast numbers of data, which can provide value for these firms' customers (Dai et al., 2020; Opresnik & Taisch, 2015). The manufacturing industry holds a crucial position in global economies, serving as the foundation for industrial development and generating an estimated global machinery turnover of €2.945 billion in 2020 (VDMA, 2022). Among the leading manufacturing nations, Germany has a vital role in the global supply chain (Sklyar et al., 2019), underpinned by a high export ratio. In 2020, Germany accounted for 15.4% of global machinery exports, second only to China's 15.6% share (VDMA, 2022).

The potential value of digital business models in manufacturing extends well beyond traditional operations, encompassing improvements in product quality, optimized maintenance strategies, efficient inventory management, and personalized customer experiences (Bertolini et al., 2021; Hartmann et al., 2016). The value of digital technologies for manufacturing is especially discussed in the context of servitization (Ardolino et al., 2018; Baines et al., 2009; Kohtamäki et al., 2019; Kowalkowski et al., 2015; Opresnik & Taisch, 2015; Paschou et al., 2020; Struyf et al., 2021). In manufacturing, servitization refers to transforming a traditional product-centric business model into one that emphasizes providing data-driven services alongside physical products (Baines et al., 2009; Paschou et al., 2020). Particularly, IIoT offers opportunities for servitization in business-to-business customer relationships, as the connectivity provides data on the status and use of intelligent machines and devices (Ardolino et al., 2018; Rymaszewska et al., 2017). The resulting offerings from manufacturers comprise integrated and intelligent bundles of products and services, often referred to as smart service systems (Heuchert et al., 2020; Zheng et al., 2018). By providing data-driven service offerings, manufacturers can establish enduring customer relationships and can generate consistent revenues. As service providers, such manufacturers help customers to operate their machines and therefore move beyond one-time product sales by providing for instance pay-per-use payment structures (Hou & Neely, 2018; Opresnik & Taisch, 2015; Schuh et al., 2021; R. Wang et al., 2019). Especially established companies with existing connected machines in the field and trusting customer relationships have unique opportunities to provide customers with individual data-driven service offerings. The abundance of customer data, combined with domain knowledge, creates a competitive advantage that is hard for competitors to replicate (Baia et al., 2020; Usai et al., 2021).

This sense of ambition is accompanied by a sense of urgency, particularly in the global manufacturing industry, which is fiercely competitive. The imperative for manufacturers to capitalize on data-driven value creation as part of digital business models, and to establish them successfully in the market, is

[1] In the following, *manufacturing industry*, *manufacturing companies* and *manufacturers* include mechanical engineering companies, for instance all organizations that contribute to the production of goods from raw materials through machinery.

intensified by external dynamics and the multiple crises that affect the global economy (Ardolino et al., 2022). The convergence of factors – such as supply shortages caused by the COVID-19 pandemic, rising energy costs, and inflationary increases in raw material prices – are increasing cost pressure and squeezing profit margins (Priyono et al., 2020). Simultaneously, the demands of existing and new customer groups are evolving, creating a need for digital solutions that simplify, automate, or enhance machine operations (Abrell et al., 2016). Further, digitalization facilitates the entry of new competitors from outside an industry, enabling them to enter new markets and exert pressure on established companies (Loebbecke & Picot, 2015; Thomas & Maine, 2019). A prime example of such a new market entrant that is utilizing disruptive technologies is Tesla, a digital-native company that entered the automotive industry with highly connected electric vehicles, focusing primarily on software (Thomas & Maine, 2019). To counteract the threat of intensified competitive pressure, incumbent manufacturers must lever their established market position, experiences, and competences to explore customer-centric digital solutions and to transform their business model accordingly. By collaborating with customers and partners, ecosystems can be created that bridge the gaps between physical and digital products offering long-term benefits to manufacturers, partners, and customers (Pagani, 2013). In sum, digital business models design creates strategic opportunities to meet two requirements that are necessary if one is to thrive in a competitive industry: first, one must outperform established competitors; second, one must protect against disruption from emerging digital competitors (Athanasopoulou & Reuver, 2020; Oberländer et al., 2021).

Scholars argue that data's potentials, which companies can unleash, depend on their business model and how it is changed by digital technologies (Arnold et al., 2016; Chesbrough et al., 2018; Paiola & Gebauer, 2020). However, the business model concept lacks a uniform definition, resulting in a wide range of interpretations in the literature (e.g., Chesbrough, 2002; Johnson et al., 2008; Osterwalder & Pigneur, 2013). This dissertation adopts Teece's definition of business models as the "design or architecture of the value creation, delivery, and capture mechanisms of a firm" since it covers both internal and external aspects of a business model (Teece, 2010, p. 172). When at least one of these dimensions of value changes, the literature calls this *business model innovation* (Ritter & Lettl, 2018). Thus, the business model innovation process entails exploring and developing novel possibilities associated with an organization's value creation, value delivery, and value capture mechanisms (Foss & Saebi, 2017). If changes in value creation, delivery, or capture are the result of the use of digital technologies, the literature refers to this as *digital innovation*. Notably, the outcomes are not purely digital – they can be a combination of physical and digital products, forming, for example, new product-service systems. (Kohli & Melville, 2019; Vega & Chiasson, 2019; Yoo et al., 2010).

The socio-technical phenomenon of digital transformation offers considerable potentials for research in the fields of information systems (ISs), digital business model innovation, and servitization, since resulting artifacts help organizations, particularly manufacturers, to overcome challenges (Arnold et al., 2016; Gregor & Hevner, 2013; Kohtamäki et al., 2020; Loebbecke & Picot, 2015). This doctoral thesis focuses on three challenges faced by manufacturing companies when they seek to initiate, develop, and implement digital business models (Kohli & Melville, 2019).

Manufacturers face the challenge of identifying suitable opportunities for digital innovation that are crucial for the success of their innovation endeavors (Kohli & Melville, 2019). The research indicates that organizations need a structured approach to analyze the internal and external environments to identify suitable opportunities for digital innovation, given the multitude of new possibilities, changing customer demands, and unknown technical requirements, leading to high uncertainty (Haftor & Climent, 2023). Thus, traditional hardware-centric companies need guidance if they *initiate the exploration of digital opportunities* – finding ways to create value through digital technologies that go well beyond the usual incremental improvement of existing products (Favoretto et al., 2022).

Further, existing business model innovation literature emphasizes the need for research on aligning value creation and value capture mechanisms (Chesbrough et al., 2018; Dyer et al., 2018; Sjödin et al., 2020). *Digital value creation* refers to enhancing customer value by means of digital technologies. In contrast, *value capture* involves securing and distributing the profits derived from value creation among various stakeholders such as manufacturers, customers, and partners (Chesbrough et al., 2018). Understanding these mechanisms' interconnectedness is critical in the context of servitization since manufacturers must generate value for their customers while ensuring a profitable business model. Thus, manufacturers need to *develop aligned value creation and value capture mechanisms*. An example that highlights the importance of such alignment is Trumpf, a manufacturer that specializes in laser technologies. Trumpf devised a pay-per-part model as a novel business model, wherein customers utilize its machines for their manufacturing requirements while it remotely monitors these machines and is responsible for the production planning, programming, and maintenance (*value creation*). Instead of purchasing the machines, customers pay a predetermined price for each produced part to Trumpf, which acts as a service provider (*value capture*) *(https://www.trumpf.com/)*. For a profitable digital business model, the mechanisms of value creation (e.g., increased output, decreased personnel capacity) and value capture (e.g., service contract, revenue model, pricing) must align in a way that renders the service offering valuable for customers, while also being financially viable for Trumpf. Despite initial practical applications and the existing literature, a knowledge gap remains regarding designing and implementing digital value creation and value capture processes across organizational boundaries (Chesbrough et al., 2018; Dyer et al., 2018; Sjödin et al., 2020).

Further, manufacturers face a significant challenge when designing digital business models since they need to *implement capabilities to exploit digital business' long-term value.* The literature highlights various digital business model archetypes that manufacturing companies can adopt (Bergman et al., 2022; Pieroni et al., 2020). For instance, some manufacturers strive to become *data providers* by making data (e.g., production data to track performance) accessible and valuable to their customers. In contrast, other manufacturers seek to self-position as *recommendation providers*, utilizing advanced data processing and analytics to derive actionable recommendations (Hunke et al., 2022; Zonta et al., 2020). Especially for incumbents and product-centric manufacturers, this implies a tremendous shift in the organizational rationale and requires the structured development of new capabilities that are both of a business and technological nature (Azkan et al., 2021; Hunke et al., 2022; Rashed & Drews, 2021). The research indicates that an integrated, organization-spanning perspective integrating business and technology is essential for successfully developing digital business models, as Hausladen and Schosser (2020) demonstrated for the aviation sector. However, an understanding of the technical and business capabilities required for designing certain digital business model archetypes in manufacturing is lacking (Favoretto et al., 2022).

To delve deeper into the essential capabilities needed for exploiting digital business' long-term value, it is vital to acknowledge that several business processes need to be developed and adopted to realize novel digital business models. This is exemplified by Mendling et al. (2020), who highlight that Uber's value creation is not merely in transporting customers from one locale to another, but in the processes surrounding how customers discover, book, and pay for rides. Within the range of business processes, business process management (BPM) has emerged as a proven management method for enhancing operational efficiency (Benner & Tushman, 2003). Dumas et al. (2018, p.6) define BPM as "body of methods, techniques, and tools to identify, discover, analyze, redesign, execute, and monitor business processes." By enabling organizations to understand how work is performed, BPM ensures consistent results and capitalizes on improvement opportunities (Dumas et al., 2018). Multiple studies at the intersection of digital innovation and BPM indicate that BPM can enable the digital transformation (Ahmad & van Looy, 2020; Fischer et al., 2020; Friedrich et al., 2023; Grisold et al., 2021). Through establishing responsibilities, methodologies, and capabilities, BPM helps practitioners address the challenge of *implementing capabilities to exploit digital business' long*-term value. BPM facilitates the design of business processes that are key for implementing novel digital business models. It also supports continual process improvements by harnessing digital technologies' potentials (Fischer et al., 2020). This approach emphasizes that digital innovation requires ongoing effort rather than being a once-off project (Mendling et al., 2020). Thus, BPM has a crucial role in implementing digital business models, while also ensuring the effective utilization of digital technologies in operational processes (Legner et al., 2017; Vial, 2019).

As illustrated in Figure 1, this thesis addresses the three abovementioned challenges and the knowledge gaps surrounding the design of digital business models for manufacturing companies. To achieve this, the thesis takes a cumulative approach, comprising five research articles that employ different conceptual, methodological, and theoretical lenses, qualitative and quantitative research methods, and varying levels of granularity.

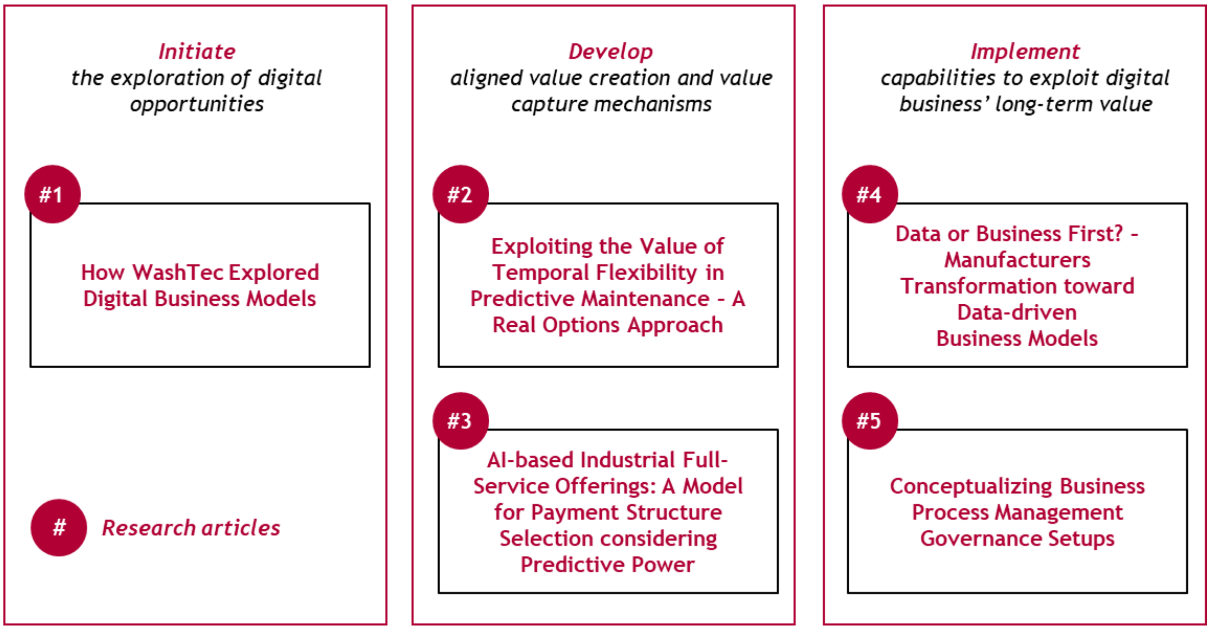

Figure 1. Research articles in this dissertation

The five research articles contribute to four digital innovation research streams, identified by Kohli and Melville (2019), and encompass the initiation, development, implementation, and exploitation of digital innovation. Figure 1 summarizes the implementation and exploitation research streams, as research papers #4 and #5 contribute to the interfaces of these streams by implementing capabilities for exploiting digital business' long-term value.

Further, considering that manufacturing traditionally revolve around the production and sales of physical products, the successful integration of digital business models depends on multiple layers within the organization (Hausladen & Schosser, 2020). While overcoming the abovementioned challenges in the context of digital innovation primarily requires attention at the *business model* layer, these changes also affect other organizational layers, such as *business processes*, *people and applications*, *data and information*, and *infrastructure*. To provide the necessary socio-technological perspective on digital transformation, this dissertation sheds light on the transformation of manufacturers toward digital business models across multiple organizational levels, as outlined in the enterprise architecture model proposed by Urbach et al. (2021). Figure 2 presents the focal points of each research contribution, highlighting the interfaces between organizational levels and digital innovation research streams.

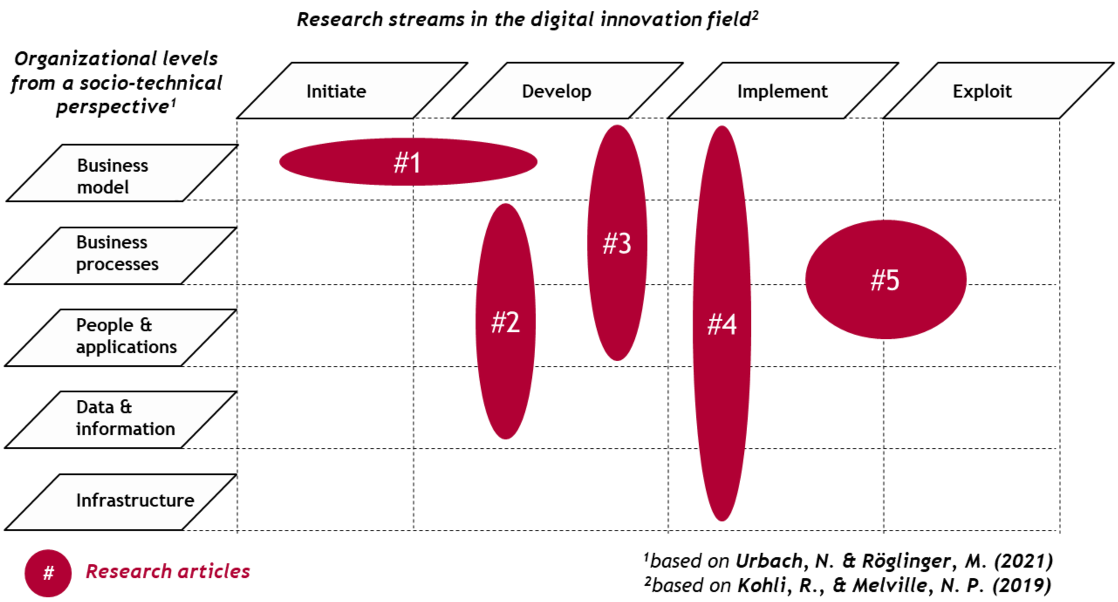

Figure 2. Structure of this dissertation

As manufacturers struggle with *initiating the exploration of digital opportunities*, this thesis presents a structured approach to identify and lever digital opportunities. Research article #1 is a case study on WashTec, a market-leading manufacturer of car wash systems, which use a four-phase approach to develop concrete digital business models. Research papers #2 and #3 contribute knowledge regarding the challenge of *developing aligned value creation and value capture mechanisms*. Research article #2 develops a decision support system (DSS) for a predictive maintenance (PM) service using real options analysis (ROA). Research article #3 supports manufacturers as providers of AI-services such as PM in deciding between usage-based or subscription-based payment structures. The paper focuses on the cross-organizational alignment of multiple organizational layers of the enterprise structure, as the DSS examines the effects of the predictive power (PP) of an AI-algorithm developed at the *People and Applications* level on the performance of an outcome-based service at the *Business Processes* level. The socio-technological perspective is complemented by considering the impact of the achieved service level on the applied payment structure and the resulting revenue at the *business model* level. Research articles #4 and #5 tackle the challenge of *implementing capabilities to exploit digital business' long-term value*. Research article #4 provides a maturity model (MM) for the capabilities necessary to implement specific digital business model archetypes. To ensure an integrated perspective on business and technology capabilities, the MM levers all organizational levels of the enterprise architecture (EA) model by Urbach et al. (2021). Further, considering the role of BPM in facilitating the allocation of resources and capabilities for a successful digital transformation, research article #5 introduces a taxonomy of BPM-governance setups toward better understanding potential design options when implementing or adjusting BPM practices.

II Research Overview

1 Initiate the exploration of digital opportunities

Digital innovation has emerged as a critical catalyst for manufacturing companies to maintain their market positions and expand into new markets. The process of identifying digital innovation possibilities for new digital business models is referred to as business model exploration (Athanasopoulou & Reuver, 2020). However, for many manufacturers, the challenge *of initiating the exploration of digital opportunities* is associated with significant uncertainty (Haftor & Climent, 2023). On the one hand, exploration requires adopting digital technologies beyond a company's core domain and capabilities, such as data analytics. On the other hand, exploration aims to capitalize on unaddressed customer requirements or new customer groups. A well-known example is that by enabling their customers to configure and order cars online, car manufacturers have gained direct contact with end-customers without an intermediary dealer. Stacey's (1996) matrix (Figure 3) visually presents this area of uncertainty and emphasizes the need for structured exploration.

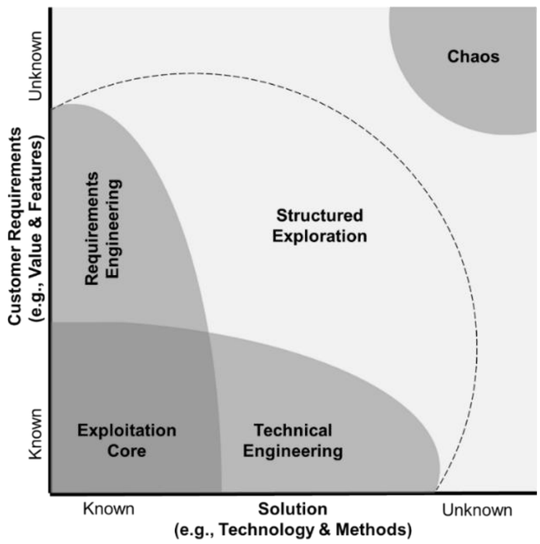

Figure 3. The Stacey matrix (based on Stacey, 1996)

Manufacturers often hesitate to depart from their exploitation core, which involves enhancing established solutions that have been tested for their existing customer base. Traditionally, these companies focus on tangible, physical products, limiting their innovation process to developing new physical solutions or making incremental improvements (Christensen, 1997).

However, as stated in section I, changing customer requirements, increasing competitive pressure, and shrinking margins have led manufacturers to recognize the limitations of relying solely on hardware-centric enhancements (Baines et al., 2009; Favoretto et al., 2022). A common approach is lacking to guide the exploration of digital business models beyond the product core (Athanasopoulou & Reuver, 2020).

Exploration must be characterized by broad and creative idea generation as well as by strategically guided prioritization, with a clear focus to prevent the results from being inconsistent with the firm's business strategy and core competencies. Existing innovation methods focus either solely on the technical improvement of the product core, or on creative exploration beyond the product core without the necessary strategic guidance. For instance, structured and strategy-backed innovation processes such as the stage-gate model focus on technological, incremental enhancements but lack broader creativity phases that explore unmet customer demands (Cooper et al., 2002). Conversely, customer-driven and creative approaches such as design thinking often lack strategic alignment, resulting in a lack of measurable results necessary for a structured exploration approach (Baden-Fuller & Morgan, 2010). Companies need measurable results from technical, strategic, and financial perspectives if they are to take informed decisions regarding funding and the timely abandonment of unsuccessful exploration initiatives. A successful digital business model should encompass value propositions that meet the demands of current and/or future customers, technically feasible solutions based on the firm's resources and capabilities, and a viable business case that ensures economic profitability (Bocken et al., 2022; Dennehy et al., 2019). Implementing an iterative review and refinement process that challenges these requirements based on measurable results mitigates the investment risks, enabling the early termination of unsuccessful initiatives while avoiding neglecting promising initiatives due to perceived high costs (Chasin et al., 2022).

In sum, manufacturing companies need a structured approach to exploring digital business models that meet customer expectations (desirability), are technically realizable (feasibility), and are supported by a robust monetization strategy (viability).

Research article #1: How WashTec Explored Digital Business Models

Research article #1 presents a case study on WashTec, a leading car wash systems manufacturer, and its successful exploration of digital business models. Like other incumbent manufacturers, WashTec traditionally focused on improving its physical machines as the main component of its business model (*exploitation*). However, driven by the CEO's vision of becoming the digital pioneer in the car wash industry, the company embarked on identifying and developing novel digital business models (*exploration*). The authors employed an action design research (ADR) approach, working through the activities of problem diagnosis, action planning, taking action, evaluating, and specifying learning (Baskerville, 1999). All the authors – five academics and two WashTec executives – participated in the 12-month applied research project, which provides a blueprint for other incumbents that are exploring digital business models. The developed exploration approach has four phases: *Activation*, *Inspiration*, *Evaluation*, and *Monetization*

In the *Activation* phase, WashTec focused on developing strategic guidelines and capturing digital innovation opportunities through a digital target picture. The senior managers, supported by the researchers, used a value pool concept to identify digital business model opportunities that are aligned with the corporate strategy. This top-down approach in the first phase established the foundation for further exploration by providing strategic directions (Hutchison et al., 2005).

In the *Inspiration* phase, WashTec involved its workforce in communicating the digital target picture and gaining buy-in for the exploration endeavors. Employees across hierarchies were invited to contribute concrete ideas based on the prioritized value pools of the *Activation* Phase, utilizing methods such as value proposition design (Osterwalder et al., 2015).

In the *Evaluation* phase, prioritized value proposition ideas were conceptualized and detailed into multidimensional value propositions. Drawing on design thinking principles, WashTec developed assumptions regarding the three evaluation dimensions desirability, technical feasibility, and viability. These assumptions were tested and validated through prototypes of the value propositions (Eisenmann et al., 2012).

In the *Monetization* phase, WashTec formulated a monetization strategy for the validated value propositions. It analyzed the frontstage value received directly by customers (e.g., increased revenue) and the backstage value generated indirectly by WashTec (e.g., efficiency gains, data-based insights) (Baltuttis et al., 2022). This analysis facilitated the financial viability and operational feasibility assessment of different revenue models and payment structures, such as pay-per-use or subscription.

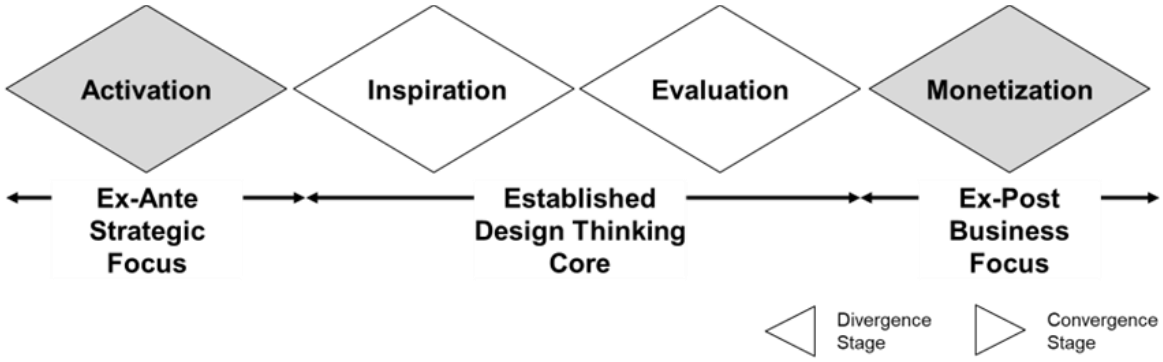

Figure 4. WashTec´s four-phase approach to the exploration of digital business models

As shown in Figure 4, each of WashTec's four phases was subdivided into two stages. In the first divergence stage, various options were developed. In the second convergence stage, these options were aggregated and evaluated to select the most promising ones. Measurable results relating to the evaluation dimensions of desirability, technical feasibility, and viability enabled WashTec's management team to effectively explore the digital opportunity space by selecting and developing the most promising digital business models. The four-phase approach's effectiveness was demonstrated through strategic, business, and transformative outcomes. WashTec established a digital target picture that reflects its digital vision for the next five years as strategic guidance. Further, WashTec developed three concrete digital business models. The firm's exploration journey also fostered its digital transformation by engaging employees, promoting collaboration, and enhancing digital competencies. Overall, WashTec's approach to exploring digital business models can serve as a blueprint for other manufacturing companies that seek to expand their non-digital business models. This research article offers five key recommendations that outline the necessary focus of exploration, the involvement of key stakeholders, and strategies for ensuring the long-term success of exploration efforts. Practitioners can use the four-phase approach and recommendations to structure and focus their exploration of digital business models. From a research perspective, the article contributes descriptive knowledge by highlighting challenges and lessons learned during WashTec's exploration journey. It outlines the necessary steps when a manufacturing company transforms from a physical products provider to digital business models from a socio-technical perspective. The developed approach extends existing prescriptive knowledge on business model development and tooling (Teece 2010) by going beyond mere documentation and description, compared to popular models such as the business model canvas (Osterwalder & Pigneur, 2013).

2 Develop aligned value creation and value capture mechanisms

In the context of servitization, manufacturers face the challenge of *developing aligned value creation and value capture mechanisms* of novel digital business models as they transition from selling physical products to providing data-driven services that deliver specific outcomes (Sjödin et al., 2020). This transition involves the transformation of manufacturers into service providers that offer performance or results guarantees through service contracts (Baines et al., 2009; Kastalli et al., 2013; Tuli et al., 2007). For instance, manufacturers guarantee a pre-determined machine availability level, wherein customers benefit from the assured machine availability and the reduced risk as the service provider covers repairs, maintenance, and machine breakdowns, including compensation if the agreed outcome is not achieved (Grubic, 2018; Kohtamäki et al., 2019). In return, customers pay for the service, cultivating enduring customer relationships and ensuring a source of ongoing income for the service provider (Huber & Spinler, 2014).

Scholars argue that this shift represents a move from a value-in-exchange perspective to a value-in-use perspective (Chesbrough et al., 2018). While the traditional value-in-exchange perspective involves selling a machine or specific maintenance operations, the value-in-use-perspective, facilitated by outcome-based service provisions, levers the services provider's expertise, customer-specific data, and derived knowledge throughout the service contract's duration (Chatain, 2011). This new value creation mechanism allows manufacturers as service providers to generate ongoing revenue streams and enhance competitive differentiation while customers benefit from improved individual value propositions and reduced risk (Chesbrough et al., 2018; Sjödin et al., 2020).

Research into business model innovation emphasizes that the successful implementation of this value-in-use perspective depends on whether it offers better customer value than the traditional value-in-exchange perspective, while being economically viable for the service provider (Chesbrough et al., 2018). For instance, manufacturers that guarantee machine availability face the challenge of meeting contractual requirements while conducting cost-efficient maintenance strategies (Wang, 2010). In this context, digital technologies such as business intelligence and analytics (BI&AI) or machine learning (ML) play crucial roles (Phillips-Wren et al., 2021; Rouhani et al., 2016). These technologies enable manufacturers to extract valuable insights from data, detect anomalies and potential machine failures, and facilitate maintenance strategies such as PM (Carvalho et al., 2019; Mobley, 2002; Zonta et al., 2020). By proactively scheduling maintenance operations, manufacturers can prevent machine breakdowns, avoid penalties, and achieve cost savings and increased resource efficiency. However, to fully realize servitization's value, manufacturers must develop DSSs capable of translating the results of BI&AI or ML algorithms into economically sound decisions (Fabri et al., 2019; Kohli & Melville, 2019; Opresnik & Taisch, 2015). Such DSSs are essential for levering data-driven insights and empowering manufacturers to take informed and economically sustainable decisions (Chen et al., 2012; Phillips-Wren et al., 2021; Rouhani et al., 2016).

Research article #2: Exploiting the Value of Temporal Flexibility in Predictive Maintenance – A Real Options Approach

Research article #2 presents an approach for developing DSSs for manufacturing companies that offer PM services. Numerous studies show the economic potential of PM compared to other maintenance strategies, such as reactive maintenance. PM can reduce costs and increase resource efficiency for maintenance operations (Compare et al., 2020; Heng et al., 2009; W. Wang, 2000). However, many existing studies primarily focus on developing BI&AI models and ML algorithms for failure prediction, providing statistical key figures such as diagnostic classifiers, remaining useful lifetime, or the probability of failure (POF) as outcomes. POF offers the most accurate specification among these metrics, since the result is not approximated, such as a classification or the specification of an absolute number for the remaining useful lifetime. Thus, PM provides manufacturers with temporal flexibility in deciding when to schedule maintenance based on POF as a failure prediction indication. The cost savings derived from PM depend particularly on exploiting the temporal flexibility throughout a service contract, for instance, determining when and how often manufacturers do maintenance and to what extent unplanned breakdowns can be avoided.

Research article#2 applies ROA as an established method in ISs research for decision-making in investments characterized by temporal flexibility (Bowman & Moskowitz, 2001) and a high uncertainty (Davis, 2015; Dixit & Pindyck, 1994; Ullrich, 2013). In the context of PM, investment refers to the expenditure on machine maintenance to improve machines' conditions, as indicated by the POF. As service providers, manufacturers face the maintenance decision as an option to either do maintenance or to defer it to a later point in time (Benaroch et al., 2007; Keller et al., 2019). Against the backdrop of the maintenance decision as a deferral option that manufacturers must consider for exploiting PM's temporal flexibility, the following research question arises:

(RQ) How can a service provider decide on maintenance based on a prediction of the probability of failure using real option analysis?

To answer this research question, research article #2 provides a DSS following a two-step approach: First, the POF is calculated based on an artificial neural network (ANN) as an exemplary ML algorithm. Second, ROA is applied to take maintenance decisions based on the POF, considering the economic effects over a service contract's entire duration. The economic decision-making process involves analyzing the trade-offs between costs for conducting maintenance and costs due to unplanned breakdowns (Papakostas et al., 2010).

The developed model considers a full-service provider context, where a manufacturer as services provider schedules maintenance operations for a single machine of one customer. Under a service-level agreement (SLA), a manufacturer guarantees a specific machine's availability and covers maintenance costs, including penalties in the case of breakdowns. The SLA grants the service provider the right to do maintenance at discrete points in time during the service contract (Bowman & Moskowitz, 2001). ROA is implemented using a customized quantitative model based on a binomial tree by Cox et al. (1979), which is suitable for evaluating maintenance decisions based on failure predictions. The binomial tree represents the possible development of the POF from its current value calculated by an ANN until the service contract's end.

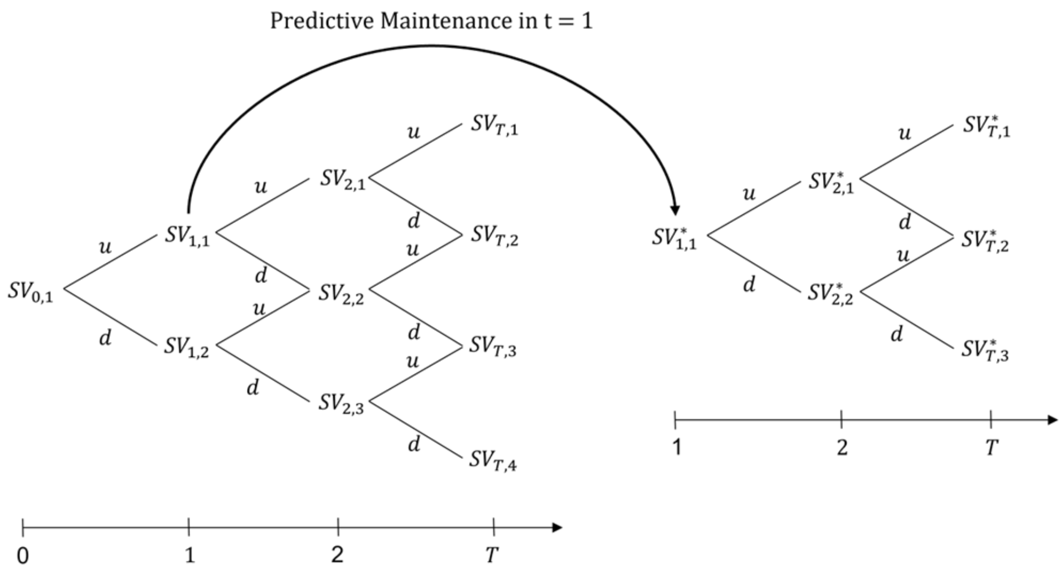

Figure 5. Exemplary binomial tree before and after maintenance in t = 1

Figure 5 shows an example where the services provider conducts PM in t = 1, thereby executing the option to do maintenance. A new option starts, encompassing the remaining term between the first option's exercise date and the service contract's end. Notably, the score value (SV) depicted in Figure 5 is a transformed value of the POF to fulfill the value range requirements of the applied binomial tree model introduced by Cox et al. (1979). Generally, node $SV_{t,\,state}$ denotes the SV at time t and the current $state$ (to distinguish between several possible nodes at the same time).

The DSS calculates two decision parameters for the maintenance decisions at each node of the binomial tree, representing possible, discrete expressions of the POF until the service contract's end. The model determines the reduced expected loss achieved by conducting maintenance and compares it to the strike price, which reflects the increase in maintenance costs if maintenance is done based on the current POF. In sum, the model evaluates the two courses of action of the manufacturer as a services provider – doing or deferring maintenance – from an economic perspective for each node of the binomial tree.

To assess the model's applicability and effectiveness, a case study involving a comprehensive simulation based on historical data from a medium-sized manufacturing company is conducted. The ROA maintenance strategy is compared to a static threshold for maintenance that considers the current POF, neglecting economic effects over the remaining duration of the SLA contract. Reactive maintenance, which involves doing maintenance only after a machine breakdown, is another benchmark. The results show that the ROA maintenance strategies based on the developed model provide lower maintenance costs than the others. On average, the developed ROA approach achieves cost savings of 18.26% compared to the static threshold approach and 26.28% compared to reactive maintenance.

Research article #2 contributes to the literature at the intersection of PM strategies, servitization, and ROA by offering a novel approach for dynamically evaluating maintenance decisions. It expands knowledge on ROA by focusing on the exercise of real options decisions instead of real options valuation, for instance, the real option's expected value (Khan et al., 2017). Prescriptive knowledge is provided by developing a DSS to exploit the value of servitization by focusing on PM as an exemplary application domain. Research article #2 contributes to the need for studies on the necessary alignment between value creation and value capture mechanisms to facilitate outcome-based services offerings (Bharadwaj et al., 2010; Chesbrough et al., 2018; Ritter & Lettl, 2018; Sjödin et al., 2020). Nonetheless, while the objective of an outcome-based service is to create value for the customer while simultaneously ensuring the profitability of the business model, the value capture mechanisms remain under-researched, since it differs fundamentally from traditional business models such as the selling of physical products or services(Desyllas & Sako, 2013). For designing a suitable value capture mechanism, it is crucial to understand the effects of applied digital technologies on data-driven services' outcomes. For instance, the PP of digital technologies such as AI must be considered when designing a PM service, which affects a machine's availability as an outcome.

Research Article #3: AI-based Industrial Full-Service Offerings: A Model for Payment Structure Selection considering Predictive Power

Research article #3 addresses the need for aligned value creation and value capture mechanisms in novel digital business models, specifically focusing on how manufacturing companies can design meaningful outcome-based services in the context of increasing servitization. In a highly service-centric setting, manufacturers as full-service providers (FSPs) retain ownership of their products (e.g., machines, devices) and sell their usage as a service that covers all associated risks. The revenue generated by FSPs by adopting new payment structures strongly correlates to a service's outcomes, i.e., meeting the service level pre-defined in the SLA (Baines et al., 2017; Kohtamäki et al., 2019). However, when a service relies on AI applications, which promise to enhance the profitability of such an FSP business, the characteristics of AI algorithms – such as the PP – must be considered when designing SLAs (Agrawal et al., 2018).

For instance, if an FSP levers PM to ensure high machine availability, a low PP of the underlying algorithm leads to lower service levels. The statistical nature of today's AI applications makes their classifications fallible, potentially leading to machine failures and, therefore, struggles with fulfilling the SLAs (Zhang et al., 2020). Further, fluctuating service levels affect an FSP's revenue, depending on the payment structure, such as subscription-based or usage-based (Halbheer et al., 2018). Thus, FSPs must consider AI applications' fallibility and the resulting PP when designing SLAs and selecting payment structures to realize AI-based service offerings' intended benefits (Cachon, 2020).

Decision-makers in the manufacturing industry must therefore (1) assess their AI applications' PP, (2) derive meaningful SLAs in alignment with their PP, and (3) thoughtfully select the net present value (NPV)-maximizing payment structure (Cachon, 2020). However, the 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:

> *(RQ1) What is the economic impact of the PP of underlying classification algorithms on the NPV of an FSP?*
>
> (RQ2) *How can FSPs select NPV-maximizing payment structures depending on the PP of underlying classification algorithms?*

To answer these questions, research article #4 employs a design science research (DSR) approach, developing a quantitative decision support model that maps AI algorithms' PP to the FSP offering's expected NPV. The model considers the chosen SLA design and the payment structure.

Developing the DSS follows the five-phase iterative DSR process of Peffers et al. (2007). The article justifies the research question in the first phase, highlighting the risks faced by decision-makers when digital services are not tailored to the characteristics of the applied AI algorithm. The second phase presents design objectives that guide the model's development. The third phase encompasses normative analytical modeling for solving the outlined decision-making problem (Keeney et al., 2003; Meredith et al., 1989). The decision support model considers the effect of the PP's effect on the SLA in an integrated way by calculating the expected NPV as a standard approach for investment valuation and decision support (Kreuzer et al., 2020). In the fourth phase and fifth phase, the decision support model is evaluated using the framework proposed by Sonnenberg and vom Brocke (2012) as an established method for the artificial and naturalistic evaluation of mathematical DSSs (Bürger et al., 2019; Kreuzer et al., 2020). For the artificial evaluation in the fourth phase, a Python prototype of the model is implemented and multiple simulations with synthetic data are conducted. For the naturalistic evaluation, the model is applied to a real-world scenario of a German manufacturing company to validate its applicability and usefulness.

In the context of the real-world application, research article #4 applies different PP scenarios to compare resulting NPVs based on different payment structures and SLA designs. The results, illustrated in Figure 6, show that higher PP (expressed by a higher AUC value) makes economic sense as long as revenues increase more rapidly than operating costs. However, excessively high PP may not be economically meaningful owing to high operating costs. The advantages of specific payment structures depend on negotiated premium payments or penalty payments and agreed service-level objectives. A robustness analysis of the model confirms the results' validity, showcasing the effects of fluctuating parameters on the NPV.

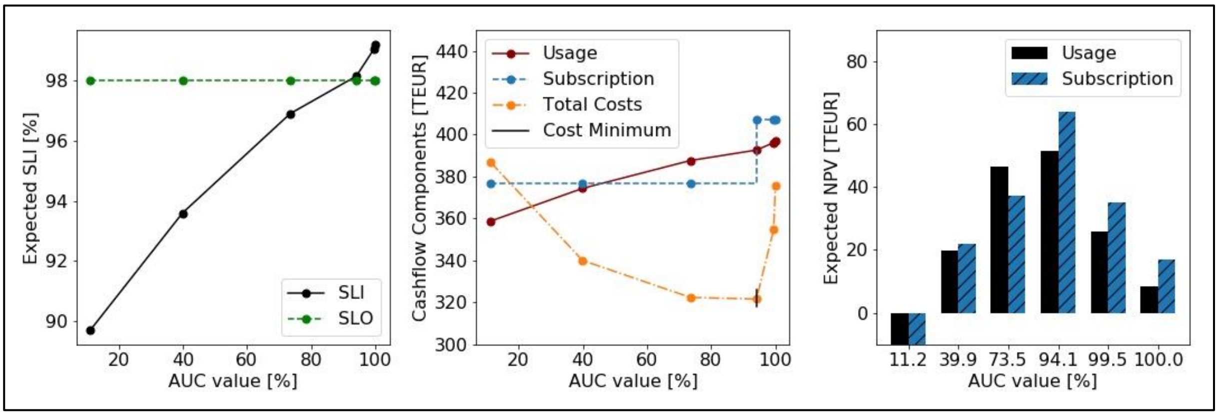

Figure 6. Ex-post application in a real-world scenario

Overall, research article #3's findings provide economically reasonable insights for decision-makers in evaluating the effects of PP and payment structures on data-driven services' expected NPV. The decision support model's applicability and added value are confirmed, contributing to prescriptive knowledge regarding the implementation of AI-based services that consider the economic implications of increasing PP in the FSP context.

3 Implement capabilities to exploit digital business' long-term value

After conceptualizing digital business models with aligned mechanisms for value creation and value capture based on digital innovation opportunities, the subsequent challenge lies in successfully implementing them. In addition to developing tangible or intangible assets such as functional ISs, manufacturers require suitable capabilities for creating and offering digital business models (Kerpedzhiev et al., 2021; Wade & Hulland, 2004).

The diverse range of possibilities for future digital value propositions available to manufacturers further complicates the challenge of *implementing capabilities to exploit digital business' long-term value*. Different value propositions characterize different archetypes of data-driven business models (DDBMs) (Hunke et al., 2022), leading to significance variations in the socio-technical capabilities required (Vial, 2019). Further, manufacturers differ in their current capabilities and resources, which are influenced by their status quo and their digital transformation maturity level (Gökalp & Martinez, 2021).

Research article #4: Data or Business First? – Manufacturers' Transformation toward Data-driven Business Models

Against this backdrop, research article #4 guides manufacturing companies in the design of digital business models by using DDBM archetypes that can be adopted (Müller & Buliga, 2019). As mentioned in section I, Hunke et al. (2022) present various archetypal DDBMs that serve as strategic orientation for the transformation by systematically characterizing different configurations of DDBMs (i.e., *data provider*, *insight provider*, *recommendation provider*, and *digital-solution provider*). The traditional business model of a *product provider* generates value solely based on physical products such as machinery and maintenance activities (Hunke et al., 2022; Y. Wang et al., 2017). In contrast, the *data provider* business model enhances a product by providing customers with processed data through programming interfaces or simple visualization (Chen et al., 2011; Hunke et al., 2022). The *insight provider* business model delivers diagnostic and supportive insights such as alerts and target benchmarking (Hunke et al., 2022; Sarker, 2021). The customization increases further with the *recommendation provider* business model, which provides customized recommendations based on predictive analytics, such as data-driven root cause analysis or automatic situational recommendations (Hunke et al., 2022; Sarker, 2021). At the highest maturity level, a *digital solution provider* business model primarily focuses on data-driven value propositions, enabling manufacturing companies to expand their reach to customers beyond the boundaries of traditional manufacturing and to enter new markets by offering services such as consulting (Hunke et al., 2022; Lehrer et al., 2018).

Given the substantial variations among the digital business model archetypes, manufacturers need to implement both business and technical capabilities that align with the specific DDBM archetype they choose to adopt (Azkan et al., 2021; Hunke et al., 2022; Rashed & Drews, 2021). For instance, manufacturers must develop new business capabilities to monetize and market digital offerings (Baltuttis et al., 2022). In addition, acquiring complementary technological capabilities for data processing is essential if one is to lever suitable tools and infrastructure (Frank et al., 2019; Weber et al., 2017). The existing research suggests that an integrated, organization-spanning perspective that encompasses both business and technology capabilities is crucial if one is to successfully develop a digital business model, as exemplified by Hausladen and Schosser (2020) for the aviation sector. However, there is a limited understanding of the specific technical and business capabilities required for designing particular digital business model archetypes in manufacturing (Favoretto et al., 2022). Research article #4 addresses the following research questions:

> *(RQ) What capabilities do manufacturers require to transform toward distinct archetypal data-driven business models?*

The study presents a MM that helps manufacturing companies transform toward DDBM archetypes, following the DSR paradigm (Gregor & Hevner, 2013; Hevner et al., 2004). MMs are valuable artifacts that guide transformation efforts and structure capabilities development in both research and practice (Becker et al., 2009; Mettler, 2011).

To successfully implement any DDBM type, manufacturers must acquire the necessary capabilities across multiple organizational layers (Rashed & Drews, 2021). In this regard, EA models are valuable tools for gleaning an integrated view of a firm and outlining reference architectures (Gampfer et al., 2018). Research article #4 utilizes the EA model by Urbach et al. (2021) since it combines the technology and the business layers. This model's socio-technical perspective is particularly suitable for the transformative processes associated with digitalization (Cleven et al., 2014).

According to Becker et al. (2009), the study follows a four-phase procedure to design and evaluate the MM. The first phase involves the justification of the problem and the definition of the requirements. Through interviews with practitioners, three key requirements for the MM are identified: The model should illustrate the target state of the transformation by integrating established business model archetypes. It should also comprehensively cover socio-technical capabilities on all EA layers and contain explicit descriptions of the identified capabilities. The second phase includes comparing existing MMs and selecting a suitable development strategy. A structured literature review reveals that no existing model meets the three identified requirements. Thus, the chosen strategy is to create a new model by incorporating valuable structures from the existing research, such as EA models and DDBM archetypes. The third phase encompasses the iterative model development and the artificial evaluation. The data-driven business model maturity model, the DDBM3, is developed based on the identified requirements, using Hunke et al.'s (2022) digital business model archetypes as maturity levels (columns). The EA model of Urbach et al. (2021) is used to structure the capabilities dimensions (rows) in five major focus areas. Based on this matrix structure, the capabilities and the associated descriptions of the capabilities are developed in an iterative process; descriptions are used from existing work or are developed based on guidance from the literature.

The fourth phase involves a naturalistic evaluation by applying the model to two real-world organizations (Sonnenberg & vom Brocke, 2012). Focus groups and semi-structured interviews are conducted to gather data and complete the evaluation.

Figure 7 illustrates the DDBM3, encompassing five focus areas as the study's key result. The first focus area, *business model*, includes four capabilities dimensions: *value proposition*, *customer interaction*, *monetization and pricing*, and *sales and channel management*. These capabilities dimensions refer to the organization's market interface and are crucial for manufacturers to define their digital business models.

The second focus area, *business processes*, revolves around specific processual capabilities that enable the creation, delivery, and capture of data-driven services. It includes four capabilities dimensions: *strategy and vision for data-based business*, *data-centric process management*, *knowledge sharing and management*, and *product life cycle management*.

The third focus area, *people and applications*, encompasses cultural aspects and soft skills represented by the capabilities dimension *recognition and mindset*, as well as hard skills, reflected by *methods* and *data analytics competencies*. Further, this focus area includes responsibilities represented by the capabilities dimensions *roles and responsibilities* and tools represented by *data analytics tooling.*

The fourth focus area, *data and information*, emphasizes mechanisms of data management and information extraction. It encompasses the capabilities dimensions *applied forms of analytics*, *data management*, *data governance and quality*, and *horizontal and vertical data integration*.

The last and fifth focus area, *infrastructure*, addresses the technological enablers that manufacturing companies need to realize digital business models. It encompasses the five capabilities dimensions *data analytics software management and operations*, *data-driven service integration and deployment*, *data architecture and scaling*, *cybersecurity and -privacy*, and *cyber-physical systems and connectivity*.

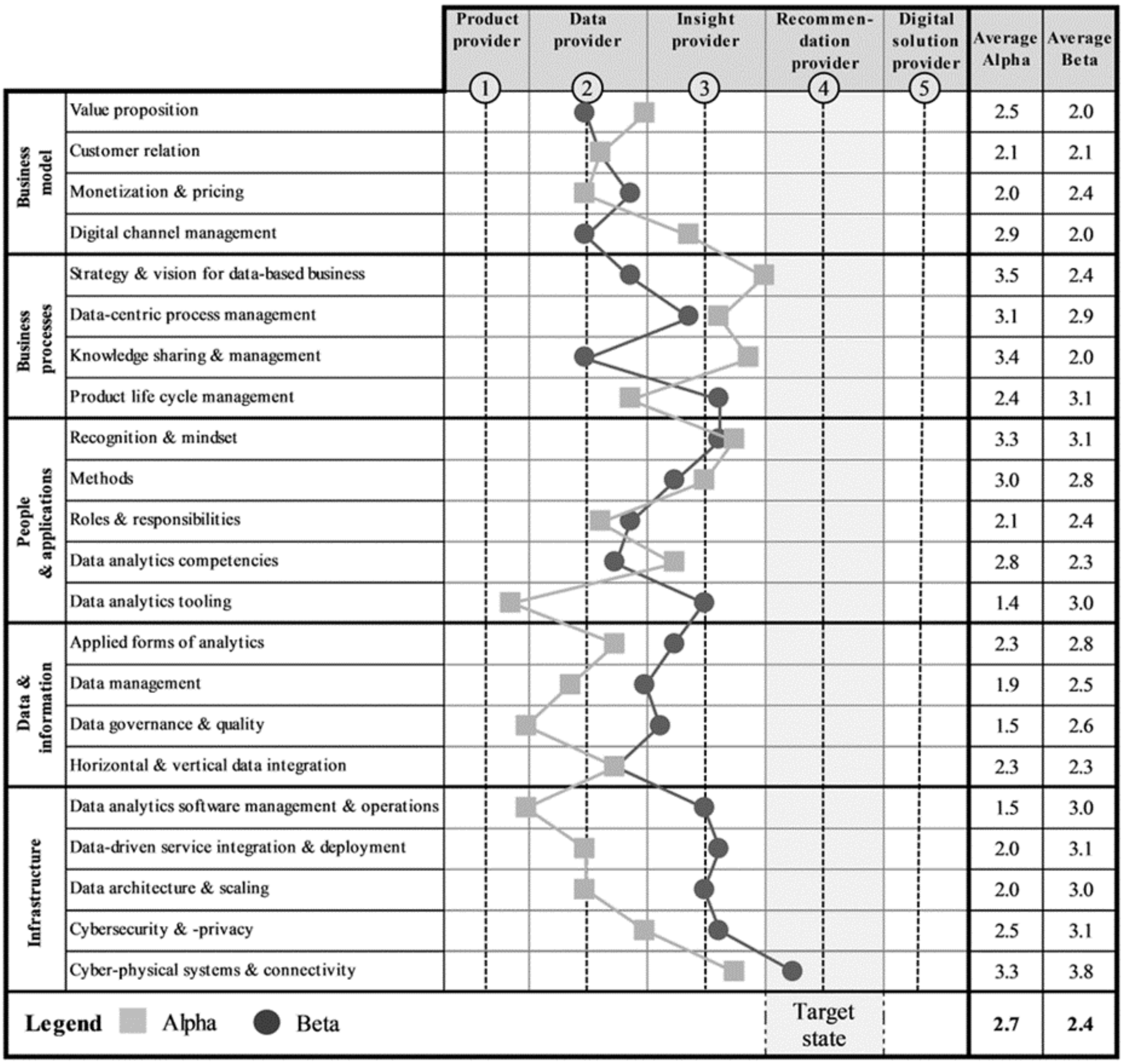

Figure 7. The data-driven business model maturity model (DDBM3)

In line with Becker et al.'s (2009) development procedure, the DDBM3 is evaluated using artificial and naturalistic approaches. The artificial evaluation is conducted by an academic focus group consisting of researchers in the digital transformation field who provide feedback to the model (Tremblay et al., 2010). The naturalistic evaluation involves applying the model with executives of two manufacturing companies, Alpha and Beta (Sonnenberg & vom Brocke, 2012). Figure 7 illustrates the results, revealing the status quo as well as the target state of the manufacturing companies. The evaluation indicates that the two firms adopted different approaches to their transformation: *data first* and *business first.*

Alpha has adopted a *business first* approach driven by customer demands for data delivery from connected machines. Thus, Alpha demonstrates higher maturity levels in most capabilities dimensions relating to the *business model* and *business process*es focus areas (except *customer relation* and *product life cycle management*); however, lower maturity levels are observed in technology-oriented dimensions in the focus areas *data and information* as well as *infrastructure.*

In contrast, Beta has followed a *data first* approach, exhibiting higher maturity levels in most capabilities dimensions relating to the *data & information* as well as *infrastructure* focus areas, shown by exemplary capabilities dimensions such as *cyber-physical systems* as well as *data analytics software management and operations*; however, Beta's capabilities are less developed in the business-related capability dimensions, such as *value proposition* and *digital channel management*.

Research article #4 utilizes the framework introduced by Hunke et al. (2022), which presents archetypes of data-driven services to structure manufacturers' transformation processes. This article makes two primary contributions: First, it introduces the DDBM3 as the central artifact that provides prescriptive knowledge regarding the capabilities required to implement specific digital business model archetypes. The evaluation shows the applicability and usefulness of the model as a diagnostic tool for practitioners to determine a firm's status quo and its target state. Second, through the naturalistic application of the DDBM3, the article demonstrates the model's integrated perspective as a comprehensive lens for analyzing transformations toward digital business models. The initial findings – specifically, identifying the *business first* and the *data first* transformation paths – offer valuable insights that can stimulate further research. The model can be utilized to examine patterns and trends in adopting digital business models in manufacturing.

The DDBM3 allows manufacturers to identify the necessary capabilities for implementing digital business models based on specific archetypes. However, the challenge of *implementing capabilities to exploit digital business' long-term value* remains regarding how firms can establish these capabilities in the long term. Further, manufacturers need guidance on effectively translating digital business model concepts into operational processes. Thus, capabilities and structures must be anchored in a company to nurture digital technologies' potentials for new digital business models and the operational processes.

As highlighted in section I, BPM offers a proven approach to address this challenge. BPM enables organizations to gain insights into processes, ensuring consistent results and the levering of improvement opportunities (Dumas et al., 2018). By establishing responsibilities, methodologies, and capabilities, BPM can be an enabler of digital transformation (Fischer et al., 2020; Friedrich et al., 2023; Grisold et al., 2022). BPM facilitates the implementation of novel business models by translating conceptualizations into operational processes (Mendling et al., 2020). BPM also fosters process transparency, enabling the identification of improvement opportunities through digital technologies (Dumas et al., 2013).

For the successful adoption of BPM, Rosemann and vom Brocke (2015) provide an established framework that outlines six core elements of BPM: strategic alignment, governance, methods, information technology, people, and culture. While governance is one of these core elements, there is a lack of a comprehensive conceptualization of BPM governance (BPM-G) setups that encompasses the roles, structures, and methods that guide BPM activities (Hammer, 2015; Spanyi, 2015). A holistic perspective on BPM-G setups is necessary to guide manufacturing companies in adopting or enhancing BPM.

Research article #5: Conceptualizing Business Process Management Governance Setups

Research article #5 endeavors to develop a taxonomy that incorporates relevant design dimensions and characteristics of BPM-G setups. While existing research focuses on analyzing individual organizations' approaches to introducing new roles, structures, methods, and implementation drivers and barriers (e.g., Alibabaei, 2021; Santana et al., 2011), a holistic conceptualization of BPM-G setups remains lacking. Despite its strategic importance, it remains unclear which dimensions constitute BPM-G setups, which characteristics can be chosen and combined, and which rationales organizations apply when designing their BPM-G setup. It is crucial for both the academic community and practitioners to address this gap. For researchers, a taxonomy facilitates systematic description and analysis of BPM-G setups, enabling contextualization of research efforts as well as the development of more robust theories concerning specific setups' impacts on business performance (Gregor, 2006; Gregor & Hevner, 2013). For practitioners, a clear conceptualization of BPM-G supports informed decision-making, particularly when adopting BPM at the enterprise level. Thus, research article #5 deals with the following research question:

(RQ) How can BPM-G setups be conceptualized?

By developing a taxonomy of BPM-G setups, the study aims to comprehensively understand the dimensions, characteristics, and underlying rationales associated with BPM-G setups. This taxonomy will enable practitioners to describe, discuss, and compare different BPM-G setups, supporting the alignment of BPM adoption to organizational goals. It also guides practitioners in the initial stages of BPM adoption and long-term planning, aiding in the continual improvement and strategic alignment of BPM at the enterprise level.

The taxonomy development approach is based on Nickerson et al. (2013) and Kundisch et al. (2021), since taxonomies are an established method for systematically structuring and categorizing knowledge in the IS and the BPM research. As first result, the taxonomy development process reveals three organizational tensions (Gaim et al., 2018) that continually occur in the interviews, as practitioners consider them when designing their BPM-G setup: *centralization vs. decentralization (Siggelkow & Levinthal, 2003)*, *exploration vs. exploitation* (Smith & Tushman, 2005), and *standardization vs. flexibilization* (Howard-Grenville, 2005).

The resulting taxonomy of BPM-G setups, presented in Table 1, serves as the central artifact of research article #5. It is structured along the three organizational tensions, representing distinct layers. Further, the taxonomy has 10 dimensions (6 non-exclusive and 4 exclusive) and 39 characteristics, providing a comprehensive framework for structuring and categorizing BPM-G setups.

Table 1. The taxonomy of BPM-G setups

Tension	Dimension	E/N	Characteristics				
Centralization vs. decentralization	Organizational anchoring	N	BPM team in a dedicated department	BPM team in non-dedicated department(s)	BPM community of practice	Individual BPM practitioners	
	BPM ownership	N	Senior management	BPM team	BPM community of practice	Not defined	
	Financial resources	N	Global BPM budget	Project-based BPM budget	Process-based BPM budget	Not defined	
	Leading activities	N	Design & modeling	Monitoring & control	Improvement & innovation	Program & project management	None
	Supporting activities	N	Design & modeling	Monitoring & control	Improvement & innovation	Program & project management	None
Exploitation vs. exploration	Institutionalization of ambidexterity	E	Separated	Integrated	None		
Standardization vs. flexibilization	Process ownership	E	Pre-defined for all processes	Pre-defined per process (type)	Flexible		
	Data ownership	E	Pre-defined for all processes	Pre-defined per process (type)	Flexible	Not defined	
	Role allocation	N	Per business department(s)	Per BPM activity	Per end-to-end process	Flexible	
	Standards & methods	E	Pre-defined for all processes	Pre-defined per process (type)	Flexible		
	E = exclusive; N = non-exclusive						

The taxonomy's *centralization vs. decentralization* layer has five design dimensions: The dimension *organizational anchoring* focuses on the primary unit or team responsible for BPM-G in an organization. It can be a dedicated BPM team in a centralized unit such as a BPM Center of Excellence (Rosemann, 2015) or a non-dedicated department such as information technology (IT) or human resources (HR) (Harmon, 2016). Alternatively, decentralization options include establishing a BPM community of practice or promoting individual BPM practitioners who operate independently. The dimension *BPM ownership* pertains to the organizational unit or role with authority and guidance over BPM activities (de Boer et al., 2015). This ownership can be held by senior management or the dedicated BPM team. It can also be shared among a BPM community of practice or even absent. The allocation of *financial resources* for BPM is another dimension addressing the *centralization vs. decentralization* tension (Kirchmer et al., 2013; Lehnert et al., 2016). It can involve a global BPM budget, where the BPM team can access a centralized budget. Alternatively, organizations may provide project-based budgets for strategic BPM initiatives or may allocate budgets to specific processes or process types. Some organizations may not have a dedicated BPM budget, relying on other financial resources from relevant business departments. The last two dimensions in this layer focus on the responsibilities of BPM-G in the activities of the BPM lifecycle (vom Brocke & Rosemann, 2015); these activities include process design and modeling, monitoring and control, improvement and innovation, and program and project management. While important, implementation and execution, are excluded, since they are primarily managed at the process level by process owners. The taxonomy distinguishes between *leading activities* (where the BPM team takes operational responsibility) and *supporting activities* (where the BPM team assists but is not solely responsible).

In the *exploitation vs. exploration* layer, organizations can incorporate ambidextrous activities in their BPM. Ambidexterity in BPM (Grisold et al., 2022) refers to the strategic pursuit of both exploitative BPM, which involves improving existing processes, and explorative BPM, which entails innovating and exploring new opportunities for process improvement (Grisold et al., 2019; Rosemann, 2014). The dimension *institutionalization of ambidexterity* examines how organizations implement such ambidexterity in their BPM practices. The taxonomy shows that organizations can implement ambidexterity in BPM through dedicated teams focusing separately on exploitation or exploration activities. Alternatively, a single team can be responsible for both exploitation and exploration within BPM. Further, some organizations do not explicitly consider ambidexterity as a deliberate aspect of their BPM practices.

The third layer of the taxonomy focuses on the organizational tension *standardization vs. flexibilization*, which includes process ownership, data ownership, role allocation, and implementing standards and methods. Organizations have different approaches to *process ownership* (Danilova, 2019). They may assign process ownership to the unit responsible for all processes, or they may standardize it for specific process types. For instance, stakeholders responsible for a particular customer group hold ownership for relevant customer processes. Alternatively, organizations can maintain flexibility in process ownership assignments. *Data ownership*, considering the growing importance of data in BPM, refers to the ownership of data extracted during process execution, such as process log files (Kerpedzhiev et al., 2021). Organizations can predefine data ownership for all processes, predefine it per process type, or leave it flexible without defined ownership. *Role allocation* examines how organizations assign roles for BPM activities (Valenca et al., 2013). Roles can be allocated per business department or focused on specific departments dedicated to a particular BPM activity. Alternatively, roles can be allocated per end-to-end processes or assigned flexibly based on a process type or a business unit. Implementing *standards and methods* is another dimension (Kerpedzhiev et al., 2021). Organizations can predefine standards and methods for all processes or per process type, offering a portfolio of methods and tools for stakeholders involved in BPM activities. Alternatively, organizations may choose to not implement specific standards and methods, thereby allowing stakeholders flexibility in their choices of methods.

The taxonomy is evaluated in two steps. First, it is applied to classify 14 firms' BPM-G setups, with feedback collected from BPM practitioners to validate and adjust the classification. Second, the taxonomy is applied to three illustrative cases (Beverungen, Kundisch, & Wünderlich, 2021; Limaj & Bernroider, 2022), with in-depth interviews conducted with BPM practitioners from each firm.

The evaluation demonstrates the taxonomy's usefulness and applicability. It serves as a tool for understanding and describing BPM-G setups and for facilitating discussions on the adoption of BPM. Practitioners found the taxonomy valuable for describing their current BPM-G setups, reflecting on the underlying rationale and designing desired target states. The evaluation reveals that firms address tensions differently based on their specific organizational context. The cases showcase the variability of BPM-G setups in practice and the diverse rationales behind selecting a specific setup in response to organizational tensions. Incorporating perspectives from multiple organizations enriched the insights provided by the taxonomy, enhancing its credibility and supporting discussions within firms. Overall, the evaluation confirms the taxonomy's utility in understanding BPM-G setups and offering guidance to practitioners throughout their BPM journey.

The study significantly contributes to the descriptive knowledge of BPM-G setups and their intersections with organizational design. Developing a comprehensive taxonomy offers a high-level abstraction and conceptualization that enables the systematic description and analysis of BPM-G setups. The taxonomy's generic nature and the ease of updates (Limaj & Bernroider, 2022) make it a valuable tool for researchers to situate their studies and grasp the evolving nature of BPM-G setups. The study emphasizes the importance of adopting a context-aware approach in designing BPM-G setups, considering factors such as business strategy, BPM's purpose, and industry-specific requirements (vom Brocke et al., 2021; vom Brocke et al., 2016). Further, the research underscores the interplays between BPM and organizational design, particularly BPM-G setups and organizational tensions. The taxonomy's dimensions are structured along three organizational tensions, presenting potential solutions for organizations to address competing demands (Gaim et al., 2018). However, further investigation is needed to explore the relationship between BPM-G and organizational tensions and delve into the convergence between BPM and organizational design.

III Summary and Future Research

1 Summary

In the context of advanced digitalization, manufacturing companies seek to design novel digital business models (O. Müller et al., 2016; Nambisan et al., 2017). Drawing inspiration from digital-born firms, manufacturers aim to lever digital technologies to establish novel revenue streams, enhance individualized customer relationships and differentiate themselves in a highly competitive market (Opresnik & Taisch, 2015). A particular urgency accompanies these ambitions since international market pressures are amplified by supply shortages and escalating prices resulting from external dynamics and multiple crises (Ardolino et al., 2022). However, the socio-technological phenomenon of digital transformation poses significant challenges for the manufacturing industry, which is a crucial sector in the global economy. This doctoral thesis contributes novel knowledge to help manufacturers in navigate digital transformation by redefining their value proposition (Vial, 2019; Wessel et al., 2021).

Adopting a socio-technical perspective, this thesis outlines a comprehensive pathway for addressing the three primary challenges of initiating, developing, and implementing digital business models across organizational layers. By bridging the gap between conceptualizing strategic target states and providing guidance for the design of digital business models, the thesis supports manufacturing companies in their digital transformation. The work extends descriptive and prescriptive knowledge at the intersection of the information systems domain, the business model innovation research, and the servitization literature (Kohtamäki et al., 2020; Legner et al., 2017; Sjödin et al., 2020). Lastly, the thesis responds to calls for research by delving into the transformation of manufacturing companies in the business-to-business context (Sjödin et al., 2020).

Addressing the challenge of *initiating the exploration of digital opportunities*, section II.1 introduces research article #1, which presents a comprehensive four-phase approach for identifying and levering digital opportunities. The approach was employed in a case study featuring WashTec, a leading car wash system manufacturer, as it explored novel digital business beyond its existing product and service offerings. Using action design research methodology (Mullarkey & Hevner, 2019), the study demonstrates the effectiveness of the four-phase approach (*Activation*, *Inspiration*, *Evaluation*, and *Monetization)* through the strategic, business, and transformative outcomes for WashTec. Further, the WashTec case serves as a blueprint for incumbents in the manufacturing industry seeking to explore novel digital business models by offering valuable insights and recommendations. Thus, this work contributes descriptive knowledge by highlighting the challenges, procedures, and outcomes of WashTec's exploration journey. Further, the developed four-phase approach and the associated recommendations contribute to prescriptive knowledge by expanding knowledge and tooling on developing digital business models (Teece, 2010).

Addressing the challenge of *developing aligned value creation and value capture mechanisms,* section II.2 provides two decision support systems that help manufacturing companies develop profitable and sustainable digital business models. Research article #2 focuses on a decision support system designed for predictive maintenance services using real options analysis. In the context of servitization, where ensuring machine availability is crucial, the decision support system incorporates real options analysis to optimize maintenance decisions considering the economic effects on a service contract's duration. Research article #2 expands prescriptive knowledge on real options analysis by focusing on exercising real options decisions in predictive maintenance (Khan et al., 2017). It also offers prescriptive knowledge on developing decision support systems to exploit the value of servitization providing predictive maintenance as an exemplary application domain. Further, research article #3 expands prescriptive knowledge on the alignment of value creation and value capture mechanisms (Chesbrough et al., 2018; Ritter & Lettl, 2018) by developing a model for evaluating the economic effects of an algorithm's prediction power on a digital business model's revenue. In service offerings based on artificial intelligence applications, the underlying algorithms' low predictive power impact on the service level and the resulting revenue (Kohtamäki et al., 2019). The study provides a decision support system that assesses the effects of predictive power and the selected payment structure on a data-driven service offering's expected net present value. The results of the study guide manufacturers as providers of digital services, such as predictive maintenance, in deciding between usage-based or subscription-based payment structures.

In addressing the challenge of *implementing capabilities to exploit digital business' long-term value*, section II.3 offers detailed perspectives on how manufacturing companies can identify and implement the capabilities that are necessary for realizing successful digital business models. Research article #4 provides a maturity model for the capabilities necessary to implement specific digital business model archetypes. The study levers existing descriptive knowledge on archetypes (Hunke et al., 2022) and enterprise architecture (Urbach et al., 2021) to provide prescriptive knowledge on how archetypical business models can be attained. The model's integrated perspective can serve as a comprehensive lens for analyzing manufacturers' transformation toward digital business models. Further, considering the role of business process management in facilitating the allocation of resources and capabilities for a successful digital transformation (Fischer et al., 2020; Grisold et al., 2022), research article #5 introduces a taxonomy of governance setups for business process management. This taxonomy is a powerful tool for better understanding potential design options when implementing or adjusting business process management. The study significantly contributes to the descriptive knowledge of governance setups for business process management and their intersections with organizational design, since the taxonomy presents potential solutions for addressing organizational tensions.

2 Future Research

This doctoral thesis and its findings have limitations. While the individual articles address specific limitations (see Appendices V.3 to V.7), this section presents an aggregated perspective, identifying possible avenues for further research surrounding the design of digital business models for the manufacturing industry.

First, the research in this thesis integrates existing knowledge to contribute novel artifacts for both research and practice. Drawing on the paradigms of action design research and design science research (Baskerville, 1999; Gregor & Hevner, 2013; Mullarkey & Hevner, 2019), the underlying problem statements, design objectives, and the usefulness of the developed artifacts are assessed through evaluations with both practitioners and academics. However, notably, the scope of research article #1, which relies on a case study approach, is limited to its application in a single firm. Thus, further research is needed to validate the applicability of the developed four-phase approach for exploring digital business models across a broader range of firms. Further, the instantiations of the models resulting from research articles #2 and #3 rely on data and inputs from individual manufacturing companies. While these initial applications have yielded promising results, it is crucial to validate these models' usefulness by gathering data from additional organizations. While the artifacts of research articles #4 and #5 are developed and evaluated based on data from multiple organizations, researchers may nonetheless also study a larger sample of organizations to challenge the findings' comprehensiveness. Scholars could utilize the maturity model in research article #4 to explore other firms' transformation paths and could challenge the first insights into manufacturers' *data first* and *business first* transformation strategies. Similarly, augmenting the sample size used in developing and evaluating the taxonomy of governance setups for business process management in research article #5 would increase the results' generalizability (Lee & Baskerville, 2003).

Second, the quantitative decision support models developed in research articles #2 and #3 consider multiple input parameters as deterministic or expected values. However, in reality, parameters such as machines' standstill costs owing to the misclassification of algorithms for predictive maintenance strategies can vary. The aspiration for the modeling was to capture the relevant parameters while avoiding unnecessary complexity, enabling the applicability of the resulting decision support systems from the perspective of manufacturing companies. However, researchers could focus on stochastic modeling of additional parameters to better represent reality. For instance, in research article #2, the real options analysis based on discrete points in time could be replaced by a continuous time-based model, allowing for an extended evaluation.

Third, in addressing the three primary challenges faced by manufacturers when designing digital business models, this dissertation provides descriptive and prescriptive knowledge to tackle selected issues. However, there are undoubtedly additional challenges in the realms of information systems, business model development, and digital innovation that warrant further investigation from research and practical perspectives (Vial, 2019; Wessel et al., 2021). Particularly concerning manufacturers' comprehensive digital transformation, extending beyond a business model's boundaries, numerous research questions arise that necessitate interdisciplinary discourse (Kraus et al., 2020; Paschou et al., 2020; Verhoef et al., 2021).

Looking to the future, in my view, the design of digital business models, particularly in the manufacturing industry, will ultimately become indispensable for the success of individual companies operating in a fiercely competitive environment. It is my aspiration that this thesis will support researchers and practitioners by providing novel knowledge, insights, and perspectives regarding the design of digital business models for manufacturing companies.

IV Publication Bibliography

Abrell, T., Pihlajamaa, M., Kanto, L., vom Brocke, J., & Uebernickel, F. (2016). The role of users and customers in digital innovation: Insights from B2B manufacturing firms. *Information & Management*, *53*(3), 324–335. https://doi.org/10.1016/j.im.2015.12.005

Agrawal, A., Gans, J., & Goldfarb, A. (2018). *Prediction machines: The simple economics of artificial intelligence*. Harvard Business Review Press.

Ahmad, T., & van Looy, A. (2020). Business Process Management and Digital Innovations: A Systematic Literature Review. *Sustainability*, *12*(17), 6827. https://doi.org/10.3390/su12176827

Alibabaei, A. (2021). On the Role of BPM Governance at "System Group". The BPM Journey of an Iranian Software Solution Provider. In J. vom Brocke, J. Mendling, & M. Rosemann (Eds.), *Business Process Management Cases Vol. 2: Digital Transformation - Strategy, Processes and Execution* (Vol. 4, pp. 207–220). Springer-Verlag GmbH, DE.

Ardolino, M., Bacchetti, A., & Ivanov, D. (2022). Analysis of the COVID-19 pandemic's impacts on manufacturing: a systematic literature review and future research agenda. *Operations Management Research*, *15*(1-2), 551–566. https://doi.org/10.1007/s12063-021-00225-9

Ardolino, M., Rapaccini, M [Mario], Saccani, N [Nicola], Gaiardelli, P., Crespi, G., & Ruggeri, C. (2018). The role of digital technologies for the service transformation of industrial companies. *International Journal of Production Research*, *56*(6), 2116–2132. https://doi.org/10.1080/00207543.2017.1324224

Arnold, C., Kiel, D., & Voigt Kai-Ingo (2016). How the industrial internet of things changes business models in different manufacturing industries. *International Journal of Innovation Management*, *20*(08), 1640015.

Athanasopoulou, A., & Reuver, M. de (2020). How do business model tools facilitate business model exploration? Evidence from action research. *Electronic Markets*, *30*(3), 495–508. https://doi.org/10.1007/s12525-020-00418-3

Azkan, C., Iggena, L., Möller, F., & Otto, B. (2021). Towards Design Principles for Data-Driven Services in Industrial Environments. In T. Bui (Ed.), *Proceedings of the Annual Hawaii International Conference on System Sciences, Proceedings of the 54th Hawaii International Conference on System Sciences*. Hawaii International Conference on System Sciences. https://doi.org/10.24251/HICSS.2021.217

Baden-Fuller, C., & Morgan, M. S. (2010). Business Models as Models. *Long Range Planning*, *43*(2-3), 156–171. https://doi.org/10.1016/j.lrp.2010.02.005

Baia, E., Ferreira, J. J., & Rodrigues, R. (2020). Value and rareness of resources and capabilities as sources of competitive advantage and superior performance. *Knowledge Management Research & Practice*, *18*(3), 249–262. https://doi.org/10.1080/14778238.2019.1599308

Baines, T., Lightfoot, H. W., Benedettini, O., & Kay, J. M. (2009). The servitization of manufacturing. *Journal of Manufacturing Technology Management*, *20*(5), 547–567. https://doi.org/10.1108/17410380910960984

Baines, T., Ziaee Bigdeli, A., Bustinza, O. F., Shi, V. G., Baldwin, J., & Ridgway, K. (2017). Servitization: revisiting the state-of-the-art and research priorities. *International Journal of Operations & Production Management*, *37*(2), 256–278. https://doi.org/10.1108/IJOPM-06-2015-0312

Baltuttis, D., Häckel, B., Jonas, C. M., Oberländer, A. M., Röglinger, M., & Seyfried, J. (2022). Conceptualizing and Assessing the Value of Internet of Things Solutions. *Journal of Business Research*, *140*, 245–263. https://doi.org/10.1016/j.jbusres.2021.10.063

Baskerville, R. L. (1999). Investigating Information Systems with Action Research. *Communications of the Association for Information Systems*, *2*. https://doi.org/10.17705/1CAIS.00219

Becker, J., Knackstedt, R., & Pöppelbuß, J. (2009). Developing Maturity Models for IT Management. *Business & Information Systems Engineering*, *1*(3), 213–222. https://doi.org/10.1007/s12599-009-0044-5

Benaroch, M., Jeffery, M., Kauffman, R. J., & Shah, S. (2007). Option-Based Risk Management: A Field Study of Sequential Information Technology Investment Decisions. *Journal of Management Information Systems*, *24*(2), 103–140. https://doi.org/10.2753/MIS0742-1222240205

Benner, M. J., & Tushman, M. L. (2003). Exploitation, Exploration, and Process Management: The Productivity Dilemma Revisited. *The Academy of Management Review*, *28*(2), 238.

Bergman, R., Abbas, A. E., Jung, S., Werker, C., & Reuver, M. de (2022). Business model archetypes for data marketplaces in the automotive industry: Contrasting business models of data marketplaces with varying ownership and orientation structures. *Electronic Markets*, *32*(2), 747–765.

Bertolini, M., Mezzogori, D., Neroni, M., & Zammori, F. (2021). Machine Learning for industrial applications: A comprehensive literature review. *Expert Systems with Applications*, *175*, 114820. https://doi.org/10.1016/j.eswa.2021.114820

Beverungen, D., Buijs, J., Becker, J., Di Ciccio, C., van der Aalst, W. M. P., Bartelheimer, C., vom Brocke, J., Comuzzi, M., Kraume, K., Leopold, H., Matzner, M., Mendling, J., Ogonek, N., Post, T., Resinas, M., Revoredo, K., del-Río-Ortega, A., La Rosa, M., Santoro, F. M., . . . Wolf, V. (2021). Seven Paradoxes of Business Process Management in a Hyper-Connected World. *Business & Information Systems Engineering*, *63*(2), 145–156. https://doi.org/10.1007/s12599-020-00646-z

Beverungen, D., Kundisch, D., & Wünderlich, N. (2021). Transforming into a Platform Provider: Strategic Options for Industrial Smart Service Providers. *Journal of Service Management*, *32*(4), 507–532. https://doi.org/10.1108/JOSM-03-2020-0066

Bharadwaj, S. S., Saxena, K. B. C., & Halemane, M. D. (2010). Building a successful relationship in business process outsourcing: an exploratory study. *European Journal of Information Systems*, *19*(2), 168–180. https://doi.org/10.1057/ejis.2010.8

Bocken, N. M., Harsch, A., & Weissbrod, I. (2022). Circular business models for the fastmoving consumer goods industry: Desirability, feasibility, and viability. *Sustainable Production and Consumption*, *30*, 799–814. https://doi.org/10.1016/j.spc.2022.01.012

Bowman, E. H., & Moskowitz, G. T. (2001). Real Options Analysis and Strategic Decision Making. *Organization Science*, *12*(6), 772–777. https://doi.org/10.1287/orsc.12.6.772.10080

Buhl, H. U., Röglinger, M., Moser, F., & Heidemann, J. (2013). Big Data. *Business & Information Systems Engineering*, *5*(2), 65–69. https://doi.org/10.1007/s12599-013-0249-5

Bürger, O., Häckel, B., Karnebogen, P., & Töppel, J. (2019). Estimating the impact of IT security incidents in digitized production environments. *Decision Support Systems*, 113–144. https://doi.org/10.1016/j.dss.2019.113144

Cachon, G. P. (2020). A Research Framework for Business Models: What Is Common Among Fast Fashion, E-Tailing, and Ride Sharing? *Management Science*, *66*(3), 1172–1192. https://doi.org/10.1287/mnsc.2018.3275

Carvalho, T. P., Soares, F. A. A. M. N., Vita, R., Da Francisco, R. P., Basto, J. P., & Alcalá, S. G. S. (2019). A systematic literature review of machine learning methods applied to predictive maintenance. *Computers & Industrial Engineering*, *137*, 106024. https://doi.org/10.1016/j.cie.2019.106024

Chasin, F., Kowalkiewicz, M., & Gollhardt, T. (2022). How Watkins Steel Went from Traditional Steel Fabrication to Digital Service Provision. *MIS Quarterly Executive.* Advance online publication. https://doi.org/10.17705/2msqe.00066

Chatain, O. (2011). Value creation, competition, and performance in buyer-supplier relationships. *Strategic Management Journal*, *32*(1), 76–102. https://doi.org/10.1002/smj.864

Chen, Chiang, & Storey (2012). Business Intelligence and Analytics: From Big Data to Big Impact. *MIS Quarterly*, *36*(4), 1165. https://doi.org/10.2307/41703503

Chen, Y., Kreulen, J., Campbell, M., & Abrams, C. (2011). Analytics Ecosystem Transformation: A Force for Business Model Innovation. In *2011 Annual SRII Global Conference.* IEEE. https://doi.org/10.1109/srii.2011.12

Chesbrough, H. (2002). The role of the business model in capturing value from innovation: evidence from Xerox Corporation's technology spin-off companies. *Industrial and Corporate Change*, *11*(3), 529–555. https://doi.org/10.1093/icc/11.3.529

Chesbrough, H., Lettl, C., & Ritter, T. (2018). Value Creation and Value Capture in Open Innovation. *Journal of Product Innovation Management*, *35*(6), 930–938. https://doi.org/10.1111/jpim.12471

Christensen, C. M. (1997). *The Innovator's Dilemma: When New Technologies Cause Great firms to Fail.: The management of Innovation and Change Series*. Harvard Business School Press.

Cleven, A. K., Winter, R., Wortmann, F., & Mettler, T. (2014). Process Management in Hospitals: an Empirically Grounded Maturity Model. *Business Research*, *7*(2), 191–216. https://doi.org/10.1007/s40685-014-0012-x

Compare, M., Baraldi, P., & Zio, E. (2020). Challenges to IoT-Enabled Predictive Maintenance for Industry 4.0. *IEEE Internet of Things Journal*, *7*(5), 4585–4597. https://doi.org/10.1109/JIOT.2019.2957029

Constantiou, I. D., & Kallinikos, J. (2015). New Games, New Rules: Big Data and the Changing Context of Strategy. *Journal of Information Technology*, *30*(1), 44–57. https://doi.org/10.1057/jit.2014.17

Cooper, R. G., Edgett, S. J., & Kleinschmidt, E. J. (2002). Optimizing the Stage-Gate Process: What Best-Practice Companies Do—I. *Research-Technology Management*, *45*(5), 21–27. https://doi.org/10.1080/08956308.2002.11671518

Cox, J. C., Ross, S. A., & Rubinstein, M. (1979). Option pricing: A simplified approach. *Journal of Financial Economics*, *7*(3), 229–263.

Dai, H.-N., Wang, H., Xu, G., Wan, J., & Imran, M. (2020). Big data analytics for manufacturing internet of things: opportunities, challenges and enabling technologies. *Enterprise Information Systems*, *14*(9-10), 1279–1303. https://doi.org/10.1080/17517575.2019.1633689

Davenport, T. H., Barth, P., Bean, R., & others (2012). How'big data'is different.

Davis, A. R. (2015). A Conceptual Framework for Understanding Path Dependency and Technology Option Evaluation when Valuing IT Opportunities. *International Journal of Business and Social Science*, *6*(1), 34–42.

de Boer, F. G., Müller, C. J., & ten Caten, C. S. (2015). Assessment model for organizational business process maturity with a focus on BPM governance practices. *BPMJ*, *21*(4), 908–927.

Dennehy, D., Kasraian, L., O'Raghallaigh, P., Conboy, K., Sammon, D., & Lynch, P. (2019). A Lean Start-up approach for developing minimum viable products in an established company. *Journal of Decision Systems*, *28*(3), 224–232. https://doi.org/10.1080/12460125.2019.1642081

Desyllas, P., & Sako, M. (2013). Profiting from business model innovation: Evidence from Pay-As-You-Drive auto insurance. *Research Policy*, *42*(1), 101–116. https://doi.org/10.1016/j.respol.2012.05.008

Dixit, A. K., & Pindyck, R. S. (1994). *Investment under uncertainty*. Princeton Univ. Press.

Dumas, M., La Rosa, M., Mendling, J., & Reijers, H. A. (2013). Introduction to Business Process Management. In M. Dumas, M. La Rosa, J. Mendling, & H. A. Reijers (Eds.), *Fundamentals of Business Process Management* (Vol. 31, pp. 1–31). Springer Berlin Heidelberg.

Dumas, M., La Rosa, M., Mendling, J., & Reijers, H. A. (2018). *Fundamentals of Business Process Management* (2nd ed.). Springer Berlin Heidelberg.

Dyer, J. H., Singh, H., & Hesterly, W. S. (2018). The relational view revisited: A dynamic perspective on value creation and value capture. *Strategic Management Journal*, *39*(12), 3140–3162. https://doi.org/10.1002/smj.2785

Eisenmann, T. R., Ries, E., & Dillard, S. (2012). *Hypothesis-Driven Entrepreneurship: The Lean Startup.*

Fabri, L., Björn, H., Anna Maria, O., Jannick, T., & Patrick, Z. (2019). Economic Perspective on Algorithm Selection for Predictive Maintenance. In *27th European Conference on Information Systems (ECIS)*. https://eref.uni-bayreuth.de/49886/

Favoretto, C., Mendes, G. H., Oliveira, M. G., Cauchick-Miguel, P. A., & Coreynen, W. (2022). From Servitization to Digital Servitization: How Digitalization Transforms Companies' Transition Towards Services. *Industrial Marketing Management*, *102*, 104–121. https://doi.org/10.1016/j.indmarman.2022.01.003

Fischer, M., Imgrund, F., Janiesch, C., & Winkelmann, A. (2020). Strategy archetypes for digital transformation: Defining meta objectives using business process management. *Information & Management*, *57*(5), 103262. https://doi.org/10.1016/j.im.2019.103262

Foss, N. J., & Saebi, T. (2017). Fifteen years of research on business model innovation: How far have we come, and where should we go? *Journal of Management*, *43*(1), 200–227.

Frank, A. G., Dalenogare, L. S., & Ayala, N. F. (2019). Industry 4.0 Technologies: Implementation Patterns in Manufacturing Companies. *International Journal of Production Economics*, *210*, 15–26. https://doi.org/10.1016/j.ijpe.2019.01.004

Friedrich, F., Kreuzer, T., & Kuch, F. (2023). A match made in heaven? Empowering effects of business process management and digital innovation capabilities.

Gaim, M., Wåhlin, N., e Cunha, M. P., & Clegg, S. (2018). Analyzing competing demands in organizations: a systematic comparison. *Journal of Organization Design*, *7*(1).

Gampfer, F., Jürgens, A., Müller, M., & Buchkremer, R. (2018). Past, Current and Future Trends in Enterprise Architecture—A View Beyond the Horizon. *Computers in Industry*, *100*, 70–84. https://doi.org/10.1016/j.compind.2018.03.006

Gökalp, E., & Martinez, V. (2021). Digital transformation capability maturity model enabling the assessment of industrial manufacturers. *Computers in Industry*, *132*, 103522. https://doi.org/10.1016/j.compind.2021.103522

Gregor (2006). The Nature of Theory in Information Systems. *MIS Quarterly*, *30*(3), 611.

Gregor, S., & Hevner, A. R. (2013). Positioning and Presenting Design Science Research for Maximum Impact. *MIS Quarterly, 37*(2), 337–355. https://doi.org/10.25300/MISQ/2013/37.2.01

Grisold, T., Gross, S., Röglinger, M., Stelzl, K., & vom Brocke, J. (2019). Exploring Explorative BPM - Setting the Ground for Future Research. In T. Hildebrandt, B. F. van Dongen, M. Röglinger, & J. Mendling (Eds.), *Lecture Notes in Computer Science. Business Process Management* (Vol. 11675, pp. 23–31). Springer International Publishing.

Grisold, T., Groß, S., Stelzl, K., vom Brocke, J., Mendling, J., Röglinger, M., & Rosemann, M. (2022). The Five Diamond Method for Explorative Business Process Management. *Business & Information Systems Engineering*, *64*(2), 149–166.

Grisold, T., vom Brocke, J., Gross, S., Mendling, J., Röglinger, M., & Stelzl, K. (2021). Digital Innovation and Business Process Management: Opportunities and Challenges as Perceived by Practitioners. *Communications of the Association for Information Systems*, *49*(1), 556–571. https://doi.org/10.17705/1cais.04927

Grubic, T. (2018). Remote monitoring technology and servitization: Exploring the relationship. *Computers in Industry*, *100*, 148–158. https://doi.org/10.1016/j.compind.2018.05.002

Haftor, D. M., & Climent, C. R. (2023). Five dimensions of business model innovation: A multi-case exploration of industrial incumbent firm's business model transformations. *Journal of Business Research*, *154*, 113352. https://doi.org/10.1016/j.jbusres.2022.113352

Halbheer, D., Gärtner, D. L., Gerstner, E., & Koenigsberg, O. (2018). Optimizing service failure and damage control. *International Journal of Research in Marketing*, *35*(1), 100–115. https://doi.org/10.1016/j.ijresmar.2017.11.001

Hammer, M. (2015). What is Business Process Management? In J. vom Brocke & M. Rosemann (Eds.), *International Handbooks on Information Systems. Handbook on Business Process Management 1: Introduction, Methods, and Information Systems* (2nd ed., pp. 3–16). Springer Berlin Heidelberg.

Harmon, P. (2016). *The State of Business Process Management 2016.* Business Process Trends. https://www.bptrends.com/bpt/wp-content/uploads/2015-BPT-Survey-Report.pdf

Hartmann, P. M., Zaki, M., Feldmann, N., & Neely, A. (2016). Capturing value from big data – a taxonomy of data-driven business models used by start-up firms. *International Journal of Operations & Production Management*, *36*(10), 1382–1406. https://doi.org/10.1108/IJOPM-02-2014-0098

Hausladen, I., & Schosser, M. (2020). Towards a maturity model for big data analytics in airline network planning. *Journal of Air Transport Management*, *82*, 101721. https://doi.org/10.1016/j.jairtraman.2019.101721

Heng, A., Zhang, S., Tan, A. C., & Mathew, J. (2009). Rotating machinery prognostics: State of the art, challenges and opportunities. *Mechanical Systems and Signal Processing*, *23*(3), 724–739. https://doi.org/10.1016/j.ymssp.2008.06.009

Heuchert, M., Verhoeven, Y., Cordes, A.-K., & Becker, J. (2020). Smart Service Systems in Manufacturing: An Investigation of Theory and Practice. In *Proceedings of the Annual Hawaii International Conference on System Sciences.* Hawaii International Conference on System Sciences. https://doi.org/10.24251/hicss.2020.208

Hevner, A. R., March, S. T., Park, J., & Ram, S. (2004). Design Science in Information Systems Research. *MIS Quarterly*, Article Vol. 28 No. 1, 75–105.

Hou, J., & Neely, A. (2018). Investigating risks of outcome-based service contracts from a provider's perspective. *International Journal of Production Research*, *56*(6), 2103–2115. https://doi.org/10.1080/00207543.2017.1319089

Howard-Grenville, J. A. (2005). The Persistence of Flexible Organizational Routines: The Role of Agency and Organizational Context. *Organization Science*, *16*(6), 618–636.

Huber, S., & Spinler, S. (2014). Pricing of Full-Service Repair Contracts with Learning, Optimized Maintenance, and Information Asymmetry. *Decision Sciences*, *45*(4), 791–815. https://doi.org/10.1111/deci.12098

Hunke, F., Heinz, D., & Satzger, G. (2022). Creating customer value from data: foundations and archetypes of analytics-based services. *Electronic Markets*, 1–19.

Hutchison, D., Kanade, T., Kittler, J., Kleinberg, J. M., Mattern, F., Mitchell, J. C., Naor, M., Nierstrasz, O., Pandu Rangan, C., Steffen, B., Sudan, M., Terzopoulos, D., Tygar, D., Vardi, M. Y., Weikum, G., Gama, J., Camacho, R., Brazdil, P. B., Jorge, A. M., & Torgo, L. (Eds.). (2005). *Lecture Notes in Computer Science*. *Machine Learning: ECML 2005*. Springer Berlin Heidelberg. https://doi.org/10.1007/11564096

Johnson, M. W., Christensen, C. M., Kagermann, H., & others (2008). Reinventing your business model. *Harvard Business Review*, *86*(12), 50–59.

Kastalli, I. V., van Looy, B., & Neely, A. (2013). Steering Manufacturing Firms towards Service Business Model Innovation. *California Management Review*, *56*(1), 100–123. https://doi.org/10.1525/cmr.2013.56.1.100

Keeney, R. L., Raiffa, H., & Meyer, R. F. (2003). *Decisions with multiple objectives: Preferences and value tradeoffs* (Digital printing). University Press.

Keller, R., Häfner, L., Sachs, T., & Fridgen, G. (2019). Scheduling Flexible Demand in Cloud Computing Spot Markets. *Business & Information Systems Engineering*, *26*(4), 477. https://doi.org/10.1007/s12599-019-00592-5

Kerpedzhiev, G. D., König, U. M., Röglinger, M., & Rosemann, M. (2021). An Exploration into Future Business Process Management Capabilities in View of Digitalization: Results from a Delphi Study. *BISE*, *63*(2), 83–96.

Khan, S., Zhao, K., Kumar, R., & Stylianou, A. (2017). Examining Real Options Exercise Decisions in Information Technology Investments. *Journal of the Association for Information Systems*, *18*(5), 372–402. https://doi.org/10.17705/1jais.00459

Kirchmer, M., zur Muehlen, M., Rosemann, M., Lehmann, S., & Laengle, S. (2013). *Research Study: BPM Governance in Practice*. Accenture Whitepapers. https://www.researchgate.net/publication/259755325_Research_Study_-_BPM_Governance_in_Practice

Knote, R., Janson, A., Söllner, M., & Leimeister, J. M. (2020). *Value Co-Creation in Smart Services: A Functional Affordances Perspective on Smart Personal Assistants.* https://doi.org/10.2139/ssrn.3923706

Kohli, R., & Melville, N. P. (2019). Digital innovation: A review and synthesis. *Information Systems Journal*, *29*(1), 200–223. https://doi.org/10.1111/isj.12193

Kohtamäki, M., Parida, V., Oghazi, P., Gebauer, H., & Baines, T. (2019). Digital servitization business models in ecosystems: A theory of the firm. *Journal of Business Research*, *104*, 380–392. https://doi.org/10.1016/j.jbusres.2019.06.027

Kohtamäki, M., Parida, V., Patel, P. C., & Gebauer, H. (2020). The relationship between digitalization and servitization: The role of servitization in capturing the financial potential of digitalization. *Technological Forecasting and Social Change*, *151*, 119804. https://doi.org/10.1016/j.techfore.2019.119804

Kotarba, M. (2018). Digital Transformation of Business Models. *Foundations of Management*, *10*(1), 123–142. https://doi.org/10.2478/fman-2018-0011

Kowalkowski, C., Windahl, C., Kindström, D., & Gebauer, H. (2015). What service transition? Rethinking established assumptions about manufacturers' service-led growth strategies. *Industrial Marketing Management*, *45*, 59–69. https://doi.org/10.1016/j.indmarman.2015.02.016

Kraus, M., Feuerriegel, S., & Oztekin, A. (2020). Deep learning in business analytics and operations research: Models, applications and managerial implications. *European Journal of Operational Research*, *281*(3), 628–641. https://doi.org/10.1016/j.ejor.2019.09.018

Kreuzer, T., Röglinger, M., & Rupprecht, L. (2020). Customer-centric prioritization of process improvement projects. *Decision Support Systems*, *133*, 113286. https://doi.org/10.1016/j.dss.2020.113286

Krogh, G. von (2018). Artificial Intelligence in Organizations: New Opportunities for Phenomenon-Based Theorizing. *Academy of Management Discoveries*, *4*(4), 404–409. https://doi.org/10.5465/amd.2018.0084

Kundisch, D., Muntermann, J., Oberländer, A. M., Rau, D., Röglinger, M., Schoormann, T., & Szopinski, D. (2021). An Update for Taxonomy Designers: Methodological Guidance from Information Systems Research. *Business & Information Systems Engineering*.

Lee, A. S., & Baskerville, R. L. (2003). Generalizing Generalizability in Information Systems Research. *Information Systems Research*, *14*(3), 221–243.

Legner, C., Eymann, T., Hess, T., Matt, C., Böhmann, T., Drews, P., Mädche, A., Urbach, N., & Ahlemann, F. (2017). Digitalization: Opportunity and Challenge for the Business and Information Systems Engineering Community. *Business & Information Systems Engineering*, *59*(4), 301–308. https://doi.org/10.1007/s12599-017-0484-2

Lehnert, M., Linhart, A., & Röglinger, M. (2016). Value-based process project portfolio management: integrated planning of BPM capability development and process improvement. *Business Research*, *9*(2), 377–419.

Lehrer, C., Wieneke, A., vom Brocke, J., Jung, R., & Seidel, S. (2018). How Big Data Analytics Enables Service Innovation: Materiality, Affordance, and the Individualization of Service. *Journal of Management Information Systems*, *35*(2), 424–460. https://doi.org/10.1080/07421222.2018.1451953

Limaj, E., & Bernroider, E. W. (2022). A taxonomy of scaling agility. *The Journal of Strategic Information Systems*, *31*(3), 101721. https://www.sciencedirect.com/science/article/pii/s0963868722000178

Loebbecke, C., & Picot, A. (2015). Reflections on societal and business model transformation arising from digitization and big data analytics: A research agenda. *The Journal of Strategic Information Systems*, *24*(3), 149–157. https://doi.org/10.1016/j.jsis.2015.08.002

Mendling, J., Pentland, B. T., & Recker, J. (2020). Building a complementary agenda for business process management and digital innovation. *European Journal of Information Systems*, *29*(3), 208–219. https://doi.org/10.1080/0960085X.2020.1755207

Meredith, J. R., Raturi, A., Amoako-Gyampah, K., & Kaplan, B. (1989). Alternative research paradigms in operations. *Journal of Operations Management*, *8*(4), 297–326. https://doi.org/10.1016/0272-6963(89)90033-8

Mettler, T. (2011). Maturity Assessment Models: a Design Science Research Approach. *International Journal of Society Systems Science*, *3*(1/2), Article 38934, 81. https://doi.org/10.1504/IJSSS.2011.038934

Mobley, R. K. (2002). *An introduction to predictive maintenance*. Elsevier.

Mullarkey, M. T., & Hevner, A. R. (2019). An elaborated action design research process model. *European Journal of Information Systems*, *28*(1), 6–20. https://doi.org/10.1080/0960085X.2018.1451811

Müller, J., & Buliga, O. (2019). Archetypes for data-driven business models for manufacturing companies in Industry 4.0.

Müller, O., Junglas, I., vom Brocke, J., & Debortoli, S. (2016). Utilizing big data analytics for information systems research: Challenges, promises and guidelines. *European Journal of Information Systems*, *25*(4), 289–302. https://doi.org/10.1057/ejis.2016.2

Nambisan, S., K. Lyytinen, A. Majchrzak, & M. Song (2017). Digital innovation management: reinventing innovation management research in a digital world. *Management Information Systems Quarterly*, *41*, 223–238.

Nickerson, R. C., Varshney, U., & Muntermann, J. (2013). A method for taxonomy development and its application in information systems. *European Journal of Information Systems*, *22*(3), 336–359.

Oberländer, A. M., Röglinger, M., & Rosemann, M. (2021). Digital opportunities for incumbents – A resource-centric perspective. *The Journal of Strategic Information Systems*, *30*(3), 101670. https://doi.org/10.1016/j.jsis.2021.101670

Opresnik, D., & Taisch, M. (2015). The value of Big Data in servitization. *International Journal of Production Economics*, *165*, 174–184. https://doi.org/10.1016/j.ijpe.2014.12.036

Osterwalder, A., & Pigneur, Y. (2013). *Business model generation: A handbook for visionaries, game changers, and challengers*. Wiley & Sons.

Osterwalder, A., Pigneur, Y., Bernarda, G., & Smith, A. (2015). *Value Proposition Design: How to Create Products and Services Customers Want* (1., Auflage). John Wiley & Sons.

Pagani, M. (2013). Digital Business Strategy and Value Creation: Framing the Dynamic Cycle of Control Points. *MIS Quarterly*(37), Article 2, 617–632.

Paiola, M., & Gebauer, H. (2020). Internet of things technologies, digital servitization and business model innovation in BtoB manufacturing firms. *Industrial Marketing Management*, *89*, 245–264. https://doi.org/10.1016/j.indmarman.2020.03.009

Papakostas, N., Papachatzakis, P., Xanthakis, V., Mourtzis, D., & Chryssolouris, G. (2010). An approach to operational aircraft maintenance planning. *Decision Support Systems*, *48*(4), 604–612. https://doi.org/10.1016/j.dss.2009.11.010

Paschou, T., Rapaccini, M [M.], Adrodegari, F., & Saccani, N [N.] (2020). Digital servitization in manufacturing: A systematic literature review and research agenda. *Industrial Marketing Management*, *89*, 278–292. https://doi.org/10.1016/j.indmarman.2020.02.012

Phillips-Wren, G., Daly, M., & Burstein, F. (2021). Reconciling business intelligence, analytics and decision support systems: More data, deeper insight. *Decision Support Systems*, *146*, 113560. https://doi.org/10.1016/j.dss.2021.113560

Pieroni, M. P. P., McAloone, T. C., & Pigosso, D. C. A. (2020). From theory to practice: systematising and testing business model archetypes for circular economy. *Resources, Conservation and Recycling*, *162*, 105029.

Priyono, A., Moin, A., & Putri, V. N. A. O. (2020). Identifying Digital Transformation Paths in the Business Model of SMEs during the COVID-19 Pandemic. *Journal of Open Innovation: Technology, Market, and Complexity*, *6*(4), 104. https://doi.org/10.3390/joitmc6040104

Ranjan, J., & Foropon, C. (2021). Big Data Analytics in Building the Competitive Intelligence of Organizations. *International Journal of Information Management*, *56*, 102231. https://doi.org/10.1016/j.ijinfomgt.2020.102231

Rashed, F., & Drews, P. (2021). How Does Enterprise Architecture Support the Design and Realization of Data-Driven Business Models? An Empirical Study. In F. Ahlemann, R. Schütte, & S. Stieglitz (Eds.), *Lecture Notes in Information Systems and Organisation. Innovation Through Information Systems* (Vol. 48, pp. 662–677). Springer International Publishing. https://doi.org/10.1007/978-3-030-86800-0_45

Ritter, T., & Lettl, C. (2018). The wider implications of business-model research. *Long Range Planning*, *51*(1), 1–8. https://doi.org/10.1016/j.lrp.2017.07.005

Rosemann, M. (2014). Proposals for Future BPM Research Directions. In C. Ouyang & J.-Y. Jung (Eds.), *Lecture Notes in Business Information Processing: Vol. 181. Asia Pacific Business Process Management: Second Asia Pacific Conference, AP-BPM 2014 Brisbane, QLD, Australia, July 3-4, 2014; Proceedings* (Vol. 181, pp. 1–15). Springer International Publishing.

Rosemann, M. (2015). The Service Portfolio of a BPM Center of Excellence. In J. vom Brocke & M. Rosemann (Eds.), *International Handbooks on Information Systems. Handbook on Business Process Management 2: Strategic Alignment, Governance, People and Culture* (2nd ed., pp. 381–398). Springer Berlin Heidelberg.

Rosemann, M., & vom Brocke, J. (2015). The Six Core Elements of Business Process Management. In *Handbook on Business Process Management 1* (pp. 105–122). Springer, Berlin, Heidelberg. https://doi.org/10.1007/978-3-642-45100-3_5

Rouhani, S., Ashrafi, A., Zare Ravasan, A., & Afshari, S. (2016). The impact model of business intelligence on decision support and organizational benefits. *Journal of Enterprise Information Management*, *29*(1), 19–50. https://doi.org/10.1108/JEIM-12-2014-0126

Rymaszewska, A., Helo, P., & Gunasekaran, A. (2017). IoT powered servitization of manufacturing – an exploratory case study. *International Journal of Production Economics*, *192*, 92–105. https://doi.org/10.1016/j.ijpe.2017.02.016

Santana, A. F. L., Alves, C. F., Santos, H. R. M., & de Lima Cavalcanti Felix, A. (2011). BPM Governance: An Exploratory Study in Public Organizations. In T. Halpin, S. Nurcan, J. Krogstie, P. Soffer, E. Proper, R. Schmidt, & I. Bider (Eds.), *Lecture Notes in Business Information Processing: Vol. 81. Enterprise, Business-Process and Information Systems Modeling: BPMDS EMMSAD 2011 2011* (Vol. 81, pp. 46–60). Springer Berlin Heidelberg.

Sarker, I. H. (2021). Data Science and Analytics: An Overview from Data-Driven Smart Computing, Decision-Making and Applications Perspective. *SN Computer Science*, *2*(5), 377. https://doi.org/10.1007/s42979-021-00765-8

Schuh, G., Frank, J., Holst, L., Müller, D., Leiting, T., & Bruhns, L. (2021). Digitalization as an Enabler of Subscription Business Models in the Manufacturing Industry. In *Digital Business Models in Industrial Ecosystems* (pp. 49–70). Springer, Cham. https://doi.org/10.1007/978-3-030-82003-9_4

Siggelkow, N., & Levinthal, D. A. (2003). Temporarily Divide to Conquer: Centralized, Decentralized, and Reintegrated Organizational Approaches to Exploration and Adaptation. *OrgSci*, *14*(6), 650–669.

Sjödin, D., Parida, V., Jovanovic, M., & Visnjic, I. (2020). Value Creation and Value Capture Alignment in Business Model Innovation: A Process View on Outcome-Based Business

Models. *Journal of Product Innovation Management*, *37*(2), 158–183. https://doi.org/10.1111/jpim.12516

Smith, W. K., & Tushman, M. L. (2005). Managing Strategic Contradictions: A Top Management Model for Managing Innovation Streams. *Organization Science*, *16*(5), 522–536.

Sonnenberg, C., & vom Brocke, J. (2012). Evaluation Patterns for Design Science Research Artefacts. In M. Helfert & B. Donnellan (Eds.), *Communications in Computer and Information Science: Vol. 286. Practical aspects of design science: European Design Science Symposium, EDSS 2011, Leixlip, Ireland, October 14, 2011 ; revised selected papers* (Vol. 286, pp. 71–83). Springer. https://doi.org/10.1007/978-3-642-33681-2_7

Spanyi, A. (2015). The Governance of Business Process Management. In J. vom Brocke & M. Rosemann (Eds.), *International Handbooks on Information Systems. Handbook on Business Process Management 2: Strategic Alignment, Governance, People and Culture* (2nd ed., pp. 333–349). Springer Berlin Heidelberg.

Stacey, R. D. (1996). *Complexity and creativity in organizations*. https://psycnet.apa.org/record/1996-98270-000

Struyf, B., Galvani, S., Matthyssens, P., & Bocconcelli, R. (2021). Toward a multilevel perspective on digital servitization. *International Journal of Operations & Production Management*, *41*(5), 668–693. https://doi.org/10.1108/ijopm-08-2020-0538

Teece, D. J. (2010). Business Models, Business Strategy and Innovation. *Long Range Planning*, *43*(2-3), 172–194. https://doi.org/10.1016/j.lrp.2009.07.003

Teubner, R. A. (2013). Information Systems Strategy. *Business & Information Systems Engineering*, *5*(4), 243–257. https://doi.org/10.1007/s12599-013-0279-z

Thomas, V. J., & Maine, E. (2019). Market entry strategies for electric vehicle start-ups in the automotive industry – Lessons from Tesla Motors. *Journal of Cleaner Production*, *235*, 653–663. https://doi.org/10.1016/j.jclepro.2019.06.284

Tremblay, M. C., Hevner, A. R., & Berndt, D. J. (2010). Focus Groups for Artifact Refinement and Evaluation in Design Research. *Communications of the Association for Information Systems*, *26*. https://doi.org/10.17705/1CAIS.02627

Tuli, K. R., Kohli, A. K., & Bharadwaj, S. G. (2007). Rethinking Customer Solutions: From Product Bundles to Relational Processes. *Journal of Marketing*, *71*(3), 1–17. https://doi.org/10.1509/jmkg.71.3.1

Ullrich, C. (2013). Valuation of IT Investments Using Real Options Theory. *Business & Information Systems Engineering*, *5*(5), 331–341. https://doi.org/10.1007/s12599-013-0286-0

Urbach, N., Röglinger, M., Kautz, K., Alias, R. A., Saunders, C., & Wiener, M. (2021). *Digitalization Cases Vol. 2: Mastering Digital Transformation for Global Business*. Springer.

Usai, A., Fiano, F., Messeni Petruzzelli, A., Paoloni, P., Farina Briamonte, M., & Orlando, B. (2021). Unveiling the impact of the adoption of digital technologies on firms' innovation performance. *Journal of Business Research, 133,* 327–336. https://doi.org/10.1016/j.jbusres.2021.04.035

Valenca, G., Alves, C. F., Santana, A. F. L., de Oliveira, J. A. P., & Santos, H. R. M. (2013). Understanding The Adoption Of BPM Governance In Brazilian Public Sector. In *ECIS 2013 Completed Research* (Vol. 56). https://aisel.aisnet.org/ecis2013_cr/56

van Giffen, B., & Ludwig, H. (2023). How Siemens Democratized Artificial Intelligence. *MIS Quarterly Executive*, *22*(1), 3.

VDMA. (2022, April 1). *Mechanical Engineering - Figures and Charts 2022*. https://www.vdma.org/documents/34570/6128644/Maschinenbau%20in%20Zahl%20und%20Bild%202022.pdf/43a31467-dc91-1bd9-41ee-97413c4e769d

Vega, A., & Chiasson, M. (2019). A comprehensive framework to research digital innovation: The joint use of the systems of innovation and critical realism. *The Journal of Strategic Information Systems*, *28*(3), 242–256. https://doi.org/10.1016/j.jsis.2019.06.001

Verhoef, P. C., Broekhuizen, T., Bart, Y., Bhattacharya, A., Qi Dong, J., Fabian, N., & Haenlein, M. (2021). Digital transformation: A multidisciplinary reflection and research agenda. *Journal of Business Research*, *122*, 889–901. https://doi.org/10.1016/j.jbusres.2019.09.022

Vial, G. (2019). Understanding digital transformation: A review and a research agenda. *The Journal of Strategic Information Systems*, *28*(2), 118–144. https://doi.org/10.1016/j.jsis.2019.01.003

vom Brocke, J., Baier, M.-S., Schmiedel, T., Stelzl, K., Röglinger, M., & Wehking, C. (2021). Context-Aware Business Process Management: Method Assessment and Selection. *BISE*, *63*(5), 533–550.

vom Brocke, J., & Rosemann, M. (Eds.). (2015). *International Handbooks on Information Systems*. *Handbook on Business Process Management 2: Strategic Alignment, Governance, People and Culture* (2nd ed.). Springer Berlin Heidelberg.

vom Brocke, J., Zelt, S., & Schmiedel, T. (2016). On the role of context in business process management. *International Journal of Information Management*, *36*(3), 486–495.

Wade, & Hulland (2004). Review: The Resource-Based View and Information Systems Research: Review, Extension, and Suggestions for Future Research. *MIS Quarterly*, *28*(1), 107. https://doi.org/10.2307/25148626

Wang, R., Dada, M., & Sahin, O. (2019). Pricing Ancillary Service Subscriptions. *Management Science*, *65*(10), 4712–4732. https://doi.org/10.1287/mnsc.2018.3168

Wang, W. (2000). A model to determine the optimal critical level and the monitoring intervals in condition-based maintenance. *International Journal of Production Research*, *38*(6), 1425–1436. https://doi.org/10.1080/002075400188933

Wang, Y., Ma, H.-S., Yang, J.-H., & Wang, K.-S. (2017). Industry 4.0: A way from mass customization to mass personalization production. *Advances in Manufacturing*, *5*(4), 311–320. https://doi.org/10.1007/s40436-017-0204-7

Weber, C., Königsberger, J., Kassner, L., & Mitschang, B. (2017). M2DDM – A Maturity Model for Data-Driven Manufacturing. *Procedia CIRP*, *63*, 173–178. https://doi.org/10.1016/j.procir.2017.03.309

Wessel, L., Baiyere, A., Ologeanu-Taddei, R., Cha, J., & Blegind Jensen, T. (2021). Unpacking the Difference Between Digital Transformation and IT-Enabled Organizational Transformation. *Journal of the Association for Information Systems*, *22*(1), 102–129. https://doi.org/10.17705/1jais.00655

Wu, X., Zhu, X., Wu, G.-Q., & Ding, W. (2014). Data mining with big data. *IEEE Transactions on Knowledge and Data Engineering*, *26*(1), 97–107. https://doi.org/10.1109/TKDE.2013.109

Yoo, Y., Henfridsson, O., & Lyytinen, K. (2010). Research Commentary —The New Organizing Logic of Digital Innovation: An Agenda for Information Systems Research. *Information Systems Research*, *21*(4), 724–735. https://doi.org/10.1287/isre.1100.0322

Zhang, Z., Nandhakumar, J., Hummel, J. T., & Waardenburg, L. (2020). Addressing the Key Challenges of Developing Machine Learning AI Systems for Knowledge-Intensive Work. *MIS Quarterly Executive*, 221–238. https://doi.org/10.17705/2msqe.00035

Zheng, P., Lin, T.-J., Chen, C.-H., & Xu, X. (2018). A systematic design approach for service innovation of smart product-service systems. *Journal of Cleaner Production*, *201*, 657–667. https://doi.org/10.1016/j.jclepro.2018.08.101

Zonta, T., da Costa, C. A., da Rosa Righi, R., Lima, M. J. de, da Trindade, E. S., & Li, G. P. (2020). Predictive maintenance in the Industry 4.0: A systematic literature review. *Computers & Industrial Engineering*, *150*, 106889. https://doi.org/10.1016/j.cie.2020.106889

V Appendix

1 Index of Research Articles

Research Article #1: How WashTec Explored Digital Business Models

Ritter, Christian; Oberländer Anna Maria; Stahl Bastian; Häckel, Björn; Klees, Carsten; Koeppe, Ralf; Röglinger, Maximilian. How WashTec Explored Digital Business Models. Accepted for publication at *MIS Quarterly Executive*

(VHB-Jourqual 3: Category B)

Research Article #2: Exploit the Value of Temporal Flexibility in Predictive Maintenance – A Real Options Approach

Häckel, Björn; Häfner, Lukas; Ritter, Christian; Töppel, Jannick; Willburger, Lukas. Exploit the Value of Temporal Flexibility in Predictive Maintenance. *Working Paper*

Research Article #3: 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 | Part of the Senior Scholars' List of Premier Journals)

Research Article #4: Data or Business First? – Manufacturers´ Transformation toward Data-driven Business Models

Stahl, Bastian; Häckel, Björn; Leuthe, Daniel; Ritter, Christian. Data or Business First- Manufacturer´s Transformation toward Data-driven Business Models. *Schmalenbach Journal of Business Research (SBUR)* (2023).

(VHB-Jourqual 3: Category B)

Research Article #5: Conceptualizing Business Process Management Governance Setups

Friedrich, Franziska; Kreuzer, Thomas; Ritter, Christian; Röglinger, Maximilian. Conceptualizing Business Process Management Governance Setups. Submitted to *Information & Management*.

(VHB-Jourqual 3: Category B)

2 Individual Contribution to the Research Articles

This cumulative dissertation encompasses five research articles representing the primary body of work. These articles were collaborative efforts involving multiple co-authors. This section details the respective research settings and highlights my individual contributions to each article.

Research article #1: This research article was developed by seven co-authors (Christian Ritter, Anna Maria Oberländer, Bastian Stahl, Björn Häckel, Carsten Klees, Ralf Koeppe, Maximilian Röglinger). As the leading author of this research article, I played a pivotal role in the project with WashTec, developed and conceptualized the research idea, and contributed significantly to the design of the research methodology. Further, I took the lead in model development, evaluation, and writing all sections of the manuscript. Additionally, I was in charge of conducting the article's refinement through several revisions. 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 #2: In collaboration with Björn Häckel, Lukas Häfner, Jannick Töppel, and Lukas Willburger, I co-authored this research article. Together, we jointly developed the decision support model for exploiting the value of predictive maintenance services using real options analysis. I was involved in all stages of the research process, from crafting the initial research idea and manuscript to participating in multiple rounds of textual refinement. Further, I took responsibility for implementing the decision support model in R and conducting a case study on a German manufacturing company to demonstrate its effectiveness. All co-authors contributed equally to the article's content.

Research article #3: With Björn Häckel and Philip Karnebogen as co-authors, I collaborated on this research article. Our joint effort led to the development of a decision support model for selecting suitable payment structures for AI-based industrial full-service offerings. I actively contributed throughout the research process, from conceiving the initial research idea and manuscript to participating in multiple rounds of textual refinement throughout various revisions. Further, I played a key role in conducting a multistage evaluation involving interviews with industry experts, reviewing a software implementation in Python of the developed decision-support model, and showcasing it in a case study at a German manufacturing company. All co-authors contributed equally to the article's content.

Research article #4: Collaborating with Bastian Stahl, Björn Häckel, and Daniel Leuthe, I co-authored this research article. Together, we developed the maturity model for capabilities required for different data-driven business model archetypes. My contributions included shaping the research idea, defining the research method, and conducting several interviews with industry experts to evaluate the resulting artifact. I engaged in the initial draft of the paper and its further textual elaboration throughout the revisions. Bastian Stahl is the lead author of this paper.

Research article #5: This research article was co-authored by Franziska Friedrich, Thomas Kreuzer, Christian Ritter, and Maximilian Röglinger. Our collaborative effort resulted in developing the research idea, methodology, and taxonomy of governance setups for business process management. Further, I engaged in the initial draft of the paper, the paper's textual refinement, and in conducting interviews with industry experts to develop and evaluate the taxonomy. All co-authors contributed equally to the article's content.

3 Research Article #1

How WashTec Explored Digital Business Models

Authors: Ritter, Christian; Oberländer Anna Maria; Stahl Bastian; Häckel, Björn; Klees, Carsten; Koeppe, Ralf; Röglinger, Maximilian

Accepted for publication at MIS Quarterly Executive.

Abstract: Many incumbent companies excel in digitally enhancing their existing business models (exploiting) but struggle to develop new digital business models (exploring). We describe how WashTec, a global leader in the car wash industry, successfully explored three digital business models using a four-phase exploration approach. The WashTec case offers incumbents a blueprint and gives rise to five recommendations for exploring new digital business models.

Keywords: Exploration, Digital Business Models, Strategy, Digitalization, Innovation.

4 Research Article #2

Exploit the Value of Temporal Flexibility in Predictive Maintenance – A Real Options Approach

Authors: Häckel, Björn; Häfner, Lukas; Ritter, Christian; Töppel, Jannick; Willburger, Lukas.

Working Paper

Extended Abstract:

The digitalization of industries enables manufacturing companies to offer data-driven value propositions to customers by analyzing data from production processes. In this context, predictive maintenance (PM) is an essential strategy for service providers to flexibly decide on maintenance actions and optimize the frequency and timing of maintenance operations. In this study, we propose a decision support system (DSS) that harnesses real options analysis (ROA) to exploit the economic value of temporal flexibility in maintenance scheduling based on predicted failure probabilities.

We apply ROA as an established method in information systems for decision-making in investments characterized by temporal flexibility (Bowman & Moskowitz, 2001) and high uncertainty (Davis, 2015; Dixit & Pindyck, 1994; Ullrich, 2013). In the context of PM, investment refers to the expenditure on machine maintenance to improve its condition, as indicated by the probability of failure (POF). As service providers, manufacturers face the maintenance decision as an option to either execute maintenance or defer it to a later point in time (Benaroch et al., 2007; Keller et al., 2019).

To decide about the execution of the deferral option, the study provides a DSS following a two-step approach: First, the POF is calculated based on an artificial neural network (ANN) as an exemplary machine learning algorithm. Second, ROA is applied to make maintenance decisions based on the POF, considering the economic implications over the entire duration of a service contract. This decision-making process involves analyzing the trade-off between costs for conducting maintenance and potential costs arising from unplanned breakdowns (Papakostas et al., 2010).

The proposed DSS is designed to operate within a full-service provider context, where a manufacturer as service provider schedules maintenance operations for a customer's machine. Under a service level agreement, the manufacturer guarantees a specific machine availability and covers maintenance costs, including penalties in the case of breakdown. The service level agreement grants the service provider the right to perform maintenance at discrete points in time during the service contract. To evaluate the maintenance decision and, therefore, the execution of the resulting deferral option, ROA is implemented using a customized quantitative model based on a binomial tree by Cox et al. (1979). The binomial tree model represents the possible development of the POF from its current value calculated by an ANN until the end of the service contract.

Our findings highlight the superiority of a dynamic threshold approach for deciding if and when to schedule maintenance is more effective than a static threshold, as the economic incentives to take the risk of a machine breakdown depend on the current failure prediction and the remaining duration of a service contract. By using real-world data, our decision support algorithm demonstrates maintenance cost savings of up to 26% compared to reactive maintenance and up to 18% compared to a static threshold approach. These results underscore the potential of real options analysis in decision-making and emphasize the significance of predictive maintenance strategies for service providers.

The research contributes to the literature at the intersection of PM strategies, servitization, and ROA by offering a novel approach for dynamically evaluating maintenance decisions. It expands knowledge on ROA by focusing on the exercise of real options decisions rather than real options valuation, e.g., the expected value of the real option (Khan et al., 2017). Furthermore, this study provides prescriptive knowledge on the development of a DSS to exploit the value of servitization with a focus on PM as an exemplary application domain. Lastly, this research addresses the need for studies exploring the alignment between value creation and value capture to facilitate outcome-based service offerings in the manufacturing industry (Bharadwaj et al., 2010; Chesbrough et al., 2018; Ritter & Lettl, 2018; Sjödin et al., 2020).

Keywords: Predictive Maintenance, Decision Support, Real Options Approach.

References:

Benaroch, M., Jeffery, M., Kauffman, R. J., & Shah, S. (2007). Option-Based Risk Management: A Field Study of Sequential Information Technology Investment Decisions. *Journal of Management Information Systems*, *24*(2), 103–140. https://doi.org/10.2753/MIS0742-1222240205

Bowman, E. H., & Moskowitz, G. T. (2001). Real Options Analysis and Strategic Decision Making. *Organization Science*, *12*(6), 772–777. https://doi.org/10.1287/orsc.12.6.772.10080

Chesbrough, H., Lettl, C., & Ritter, T. (2018). Value Creation and Value Capture in Open Innovation. *Journal of Product Innovation Management*, *35*(6), 930–938. https://doi.org/10.1111/jpim.12471

Cox, J. C., Ross, S. A., & Rubinstein, M. (1979). Option pricing: A simplified approach. *Journal of Financial Economics*, *7*(3), 229–263.

Davis, A. R. (2015). A Conceptual Framework for Understanding Path Dependency and Technology Option Evaluation when Valuing IT Opportunities. *International Journal of Business and Social Science*, *6*(1), 34–42.

Keller, R., Häfner, L., Sachs, T., & Fridgen, G. (2019). Scheduling Flexible Demand in Cloud Computing Spot Markets. *Business & Information Systems Engineering*, *26*(4), 477. https://doi.org/10.1007/s12599-019-00592-5

Khan, S., Zhao, K., Kumar, R., & Stylianou, A. (2017). Examining Real Options Exercise Decisions in Information Technology Investments. *Journal of the Association for Information Systems*, *18*(5), 372–402. https://doi.org/10.17705/1jais.00459

Papakostas, N., Papachatzakis, P., Xanthakis, V., Mourtzis, D., & Chryssolouris, G. (2010). An approach to operational aircraft maintenance planning. *Decision Support Systems*, *48*(4), 604–612. https://doi.org/10.1016/j.dss.2009.11.010

Sjödin, D., Parida, V., Jovanovic, M., & Visnjic, I. (2020). Value Creation and Value Capture Alignment in Business Model Innovation: A Process View on Outcome-Based Business Models. *Journal of Product Innovation Management*, *37*(2), 158–183. https://doi.org/10.1111/jpim.12516

Ullrich, C. (2013). Valuation of IT Investments Using Real Options Theory. *Business & Information Systems Engineering*, *5*(5), 331–341. https://doi.org/10.1007/s12599-013-0286-0

5 Research Article #3

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

6 Research Article #4

Data or Business First? – Manufacturers´ Transformation toward Data-driven Business Models

Authors: Stahl Bastian; Häckel, Björn; Leuthe, Daniel; Ritter, Christian

Published in: *Schmalenbach Journal of Business Research (SBUR) (2023).*

Abstract: Driven by digital technologies, manufacturers aim to tap into data-driven business models, in which value is generated from data as a complement to physical products. However, this transformation can be complex, as different archetypes of data-driven business models require substantially different business and technical capabilities. While there are manifold contributions to research on technical capability development, an integrated and aligned perspective on both business and technology capabilities for distinct data-driven business model archetypes is needed. This perspective promises to enhance research's understanding of this transformation and offers guidance for practitioners. As maturity models have proven to be valuable tools in capability development, we follow a design science approach to develop a maturity model for the transformation toward archetypal data-driven business models. To provide an integrated perspective on business and technology capabilities, the maturity model leverages a layered enterprise architecture model. By applying and evaluating in use at two manufacturers, we find two different transformation approaches, namely 'data first' and 'business first'. The resulting insights highlight the model's integrative perspective's value for research to improve the understanding of this transformation. For practitioners, the maturity model allows a status quo assessment and derives fields of action to develop the capabilities required for the aspired data-driven business model.

Keywords: Exploration, Digital Business Models, Strategy, Digitalization, Innovation.

7 Research Article #5

Conceptualizing Business Process Management Governance Setups

Authors: Friedrich Franziska; Kreuzer, Thomas; Ritter, Christian; Röglinger, Maximilian.

Submitted to Information & Management.

Extended Abstract:

Business Process Management (BPM) is a pivotal driver of operational excellence in the digital age (Klun & Trkman, 2018). An appropriate BPM Governance (BPM-G) setup is essential to establish boundaries and ensure continuity for all BPM activities (Spanyi, 2015). Despite its strategic importance, a comprehensive conceptualization of BPM-G setups remains elusive, leading to challenges in understanding their multidimensional nature. Existing research predominantly focuses on individual organizations' approaches (Alibabaei, 2021; Rosemann, 2015; Santana et al., 2011), leaving uncertainties about the constituent dimensions, characteristics, and rationales behind the design of BPM-G setups.

In this study, we develop a taxonomy of BPM-G setups based on Nickerson et al. (2013) and Kundisch et al. (2021), as taxonomies are an established methodology for systematically categorizing knowledge in the information systems and BPM research (Kundisch et al., 2021; vom Brocke & Mendling, 2018). The conceptualization of BPM-G setups incorporates relevant design dimensions and characteristics, drawing on justificatory knowledge of BPM-G and organizational design, as well as empirical data collected from diverse organizations.

The resulting taxonomy is structured along three organizational tensions, as the interviews with experts revealed that practitioners consider these tensions (Gaim et al., 2018), when designing their BPM-G setup: *Centralization vs. decentralization* (Siggelkow & Levinthal, 2003), *exploration vs. exploitation* (Smith & Tushman, 2005), and *standardization vs. flexibilization* (Howard-Grenville, 2005). The taxonomy's applicability is evaluated by classifying the BPM-G setups of 14 organizations. Further, we apply the taxonomy in three illustrative cases of organizations to determine the current states, the target states of the BPM-G setups, and the underlying rationales for the design decisions. The evaluation demonstrates the taxonomy's utility, providing valuable insights for understanding, describing, and discussing different BPM-G setups. Additionally, it guides practitioners in the initial stages of BPM adoption and long-term planning, aiding in the continuous improvement and strategic alignment of BPM at the enterprise level. Further, the cases highlight the diversity of BPM-G setups and the varying rationales behind their selection in response to organizational tensions.

The research contributes to the descriptive knowledge of BPM-G setups and their intersections with organizational design. The taxonomy's high-level abstraction enables systematic description and analysis of BPM-G setups, making it a valuable tool for researchers to comprehend the evolving nature of BPM-G setups (Limaj & Bernroider, 2022). Moreover, the study emphasizes the importance of context awareness in designing BPM-G setups, considering factors such as business strategy, the purpose of BPM, and industry-specific requirements (vom Brocke et al., 2021; vom Brocke et al., 2016). The research also highlights the interplay between BPM and organizational design, especially concerning BPM-G setups and organizational tensions. The taxonomy's dimensions are structured along three organizational tensions, presenting potential solutions for organizations to address competing demands (Gaim et al., 2018). However, further investigation is warranted to explore the relationship between BPM-G and organizational tensions and delve into the convergence between BPM and organizational design.

Keywords: Business Process Management, Taxonomy Development, Organizational Design, Organizational Tensions

References:

Alibabaei, A. (2021). On the Role of BPM Governance at "System Group". The BPM Journey of an Iranian Software Solution Provider. In J. vom Brocke, J. Mendling, & M. Rosemann (Eds.), *Business Process Management Cases Vol. 2: Digital Transformation - Strategy, Processes and Execution* (Vol. 4, pp. 207–220). Springer-Verlag GmbH, DE.

Gaim, M., Wåhlin, N., e Cunha, M. P., & Clegg, S. (2018). Analyzing competing demands in organizations: a systematic comparison. *Journal of Organization Design*, *7*(1).

Howard-Grenville, J. A. (2005). The Persistence of Flexible Organizational Routines: The Role of Agency and Organizational Context. *Organization Science*, *16*(6), 618–636.

Limaj, E., & Bernroider, E. W. (2022). A taxonomy of scaling agility. *The Journal of Strategic Information Systems*, *31*(3), 101721. https://www.sciencedirect.com/science/article/pii/s0963868722000178

Nickerson, R. C., Varshney, U., & Muntermann, J. (2013). A method for taxonomy development and its application in information systems. *European Journal of Information Systems*, *22*(3), 336–359.

Kundisch, D., Muntermann, J., Oberländer, A. M., Rau, D., Röglinger, M., Schoormann, T., & Szopinski, D. (2021). An Update for Taxonomy Designers: Methodological Guidance from Information Systems Research. *Business & Information Systems Engineering*.

Rosemann, M. (2015). The Service Portfolio of a BPM Center of Excellence. In J. vom Brocke & M. Rosemann (Eds.), *International Handbooks on Information Systems. Handbook on Business*

Process Management 2: Strategic Alignment, Governance, People and Culture (2nd ed., pp. 381–398). Springer Berlin Heidelberg.

Santana, A. F. L., Alves, C. F., Santos, H. R. M., & de Lima Cavalcanti Felix, A. (2011). BPM Governance: An Exploratory Study in Public Organizations. In T. Halpin, S. Nurcan, J. Krogstie, P. Soffer, E. Proper, R. Schmidt, & I. Bider (Eds.), *Lecture Notes in Business Information Processing: Vol. 81. Enterprise, Business-Process and Information Systems Modeling: BPMDS EMMSAD 2011 2011* (Vol. 81, pp. 46–60). Springer Berlin Heidelberg.

Siggelkow, N., & Levinthal, D. A. (2003). Temporarily Divide to Conquer: Centralized, Decentralized, and Reintegrated Organizational Approaches to Exploration and Adaptation. *OrgSci*, *14*(6), 650–669.

Spanyi, A. (2015). The Governance of Business Process Management. In J. vom Brocke & M. Rosemann (Eds.), *International Handbooks on Information Systems. Handbook on Business Process Management 2: Strategic Alignment, Governance, People and Culture* (2nd ed., pp. 333–349). Springer Berlin Heidelberg.

Smith, W. K., & Tushman, M. L. (2005). Managing Strategic Contradictions: A Top Management Model for Managing Innovation Streams. *Organization Science*, *16*(5), 522–536.

vom Brocke, J., Zelt, S., & Schmiedel, T. (2016). On the role of context in business process management. *International Journal of Information Management*, *36*(3), 486–495.

vom Brocke, J., Baier, M.-S., Schmiedel, T., Stelzl, K., Röglinger, M., & Wehking, C. (2021). Context-Aware Business Process Management: Method Assessment and Selection. *BISE*, *63*(5), 533–550.