Studies on Digital Transformation and its Implications for Business Models and Corporate Communication

Dissertation

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Abbreviations

AI .... Artificial Intelligence
BM(s) .... Business Model(s)
BMC .... Business Model Canvas
(D)BMI .... (Digital) Business Model Innovation
CC(s) .... Conference Call(s)
CDO .... Chief Digital Officer
CEO .... Chief Executive Officer
CFO .... Chief Financial Officer
CIO .... Chief Information Officer
DBS .... Digital Business Strategy
DL .... Deep Learning
DT .... Digital Transformation
DTBMI .... Digital Transformation-Driven Business Model Innovation
DTS .... Digital Transformation Strategy
H(1-2) .... Hypothesis (1-2)
HR .... Human Ressources
IoT .... Internet of Things
IS(R) .... Information Systems (Research)
IT .... Information Technology
ICT .... Information and Communication Technologies
M&A .... Mergers and Acquisitions
ML .... Machine Learning
MTB .... Market-To-Book Ratio
NLP .... Natural Language Processing
OLS .... Ordinary Least Squares
Q&A .... Question and Answer Section of Conference Call
R&D .... Research and Development
RoA .... Return on Assets
RQ .... Research Question
SD .... Standard Deviation
SEC .... United States Securities and Exchange Commission
SMACIT .... Social, Mobile, Analytics, Cloud, Internet of Things

SME(s) .... Small and Medium-Sized Enterprise(s)
S&P .... Standard & Poors
VHB .... Verband der Hochschullehrer*innen für Betriebswirtschaft e.V.

A. Foundations

The first part (A) of this cumulative dissertation deals with the foundations relevant to the individual research contributions. This part is subdivided into three sections. First, the motivation of the overall research topic, relevant research gaps, and resulting research questions are formulated and presented. Second, the structure of this dissertation is presented. Finally, in the third section of this part, an overview of the relevant literature, theories, concepts, and methods, as well as data used in the individual research contributions of this dissertation are presented and discussed.

1 Introduction

1.1 Motivation

Early discovery and intelligent use of novel technologies have the potential to create an immense competitive advantage. On the other hand, a lack of technological upgrades can lead to the loss of customers and a slump in market share. Due to an increasingly intense and complex competition between companies, it is vital for firms to stay up to date with technological advancements. Incumbent pre-digital firms even face the challenge of transforming their whole business to maintain or increase their market share and keep pace with existing industry peers and new emerging competitors (Westerman and Bonnet 2015; Hess et al. 2016; Sebastian et al. 2017).

This new type of competitive pressure is triggered by an ongoing emergence of new digital technologies which differ significantly from earlier technologies and can be described by three main characteristics: (1) re-programmability, (2) data homogenization, and (3) a self-referential nature (Yoo et al. 2010). The use of digital technologies to drive organizational changes in terms of modifying and improving existing product portfolios, internal processes, customer relationships, organizational structures, and business models can be defined as digital transformation (e.g., Matt et al. 2015; Hess et al. 2016; Sebastian et al. 2017; Vial 2019; Hanelt et al. 2021a). Since digital transformation is an indispensable but challenging endeavor for firms across industries, it has become a highly relevant topic for firm executives and researchers alike (e.g., Matt et al. 2015; Hess et al. 2016; Sebastian et al. 2017; Heavin and Power 2018; Chanias et al. 2019; Vial 2019).

Current research on digital transformation primarily focuses on developing and analyzing specific strategies to manage digital transformations (e.g., Bharadwaj et al. 2013; Matt et al. 2015; Hess et al. 2016; Gurbaxani and Dunkle 2019). A digital transformation strategy, thus, can be defined as a guiding plan for achieving the digital transformation of a firm's value propositions and identity and deals with how to plan, govern, and implement digital transformations (Stockghinger 2021). In many organizations, the chief digital officer plays a key role in formulating and executing digital transformation strategies. Hereby, the chief digital officer has the responsibility of driving and coordinating the digital transformation of an organization, including the formulation of a digital transformation strategy, and strengthening the strategic priority of digital transformation (Westerman et al. 2014a; Haffke et al. 2016; Singh and Hess 2017; Singh et al. 2020). This field of activity further includes coordinating and implementing digitalization initiatives, driving a cultural change toward a digital mindset, accelerating the digital transformation processes, and communicating digitalization initiatives with external stakeholders (Singh and Hess 2017; Tumbas et al. 2017; Tumbas et al. 2018; Singh et al. 2020). Since digital transformation is associated with high risk and uncertainty (e.g., Hess et al. 2016; Sebastian et al. 2017; Chanias et al. 2019; Moker et al. 2020), corporate communication on digital transformation-related activities is essential for external stakeholders to evaluate the future prospects of a firm.

Other research on digital transformation is concerned with the implications of digital transformation for existing business models or its consequences for developing new business models. The existing literature reveals that digital transformation impacts existing business models in manifold ways (e.g., Hanelt et al. 2015; Hess et al. 2016; Osmundsen et al. 2018; Caliskan et al. 2021; Levkovskyi et al. 2020; Li 2020; Metzler and Muntermann 2020). In addition, various digital transformation definitions refer to the reconfiguration of existing business models as the expected outcome of digital transformation (e.g., Hess et al. 2016; Vial 2019). Thereby, a successful digital transformation can alter existing business models or create entirely new (often digital) business models (Levkovskyi et al. 2020; Hanelt et al. 2021a).

Overall, research on digital transformation is continuously growing but still at an early stage (Lucas Jr. et al. 2013; Vial 2019; Hanelt et al. 2021a; Verhoef et al. 2021). Further, existing studies indicate that approximately 70% of all digital transformations fail (Bucy et al. 2016). Consequently, researchers are called to advance this critical field of research further (Vial 2019; Hanelt et al. 2021a; Verhoef et al. 2021). A special focus should be on the questions of how to manage digital transformations and how to deal with challenges arising in this process.

This cumulative dissertation aims at contributing to the ongoing research on digital transformation and therefore seeks to fill various existing research gaps. This is done by conducting five studies in two interrelated research areas. The first research area deals with the process of digital transformation with a focus on business models. The second research area deals with the implications of digital transformation for corporate communication strategies. In summary, this dissertation aims to address relevant research gaps at the intersection of digital transformation, business models, and corporate communication (see Figure 1).

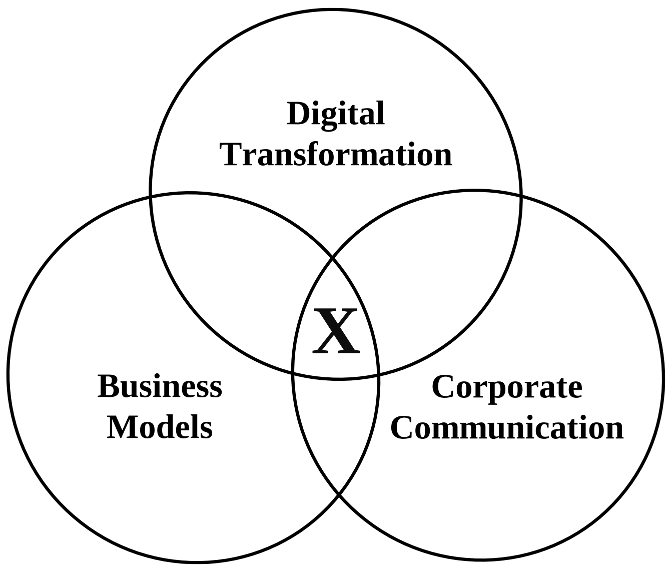

Figure 1. Thematically interconnected research fields in this dissertation

1.2 Research Gaps and Resulting Research Questions

This section presents the main research gaps and the resulting research questions of this cumulative dissertation. These are separated into two principal areas of research: (I) Digital Transformation and Business Model Innovation and (II) Digital Transformation and Corporate Communication.

Research Area I: Digital Transformation and Business Model Innovation

The first research area investigates the role of firms' business models in the context of digital transformation. The emergence of new digital technologies and new competitors that often have digital business models challenge the existing business models of firms. To stay competitive, firms formulate specific strategies aimed at undergoing a digital transformation (Matt et al. 2015; Hess et al. 2016). This change process affects firms' existing business models in manifold ways (e.g., Hanelt et al. 2015; Hess et al. 2016; Caliskan et al. 2021; Levkovskyi et al. 2020; Li 2020; Metzler and Muntermann 2020). According to Vial (2019), one major expected outcome of digital transformation is a reconfiguration of existing business models. In that regard, digital transformation can result in entirely new business models or altered existing ones (Levkovskyi et al. 2020; Hanelt et al. 2021a).

Since research on digital transformation in the context of business models is still in its early development stage, and no overview of the current state of research in this field previously existed, as a first step, a review of the existing literature in this field was of great importance. This is why Metzler and Muntermann (2021, **paper I.1**) conducted a systematic literature review to evaluate the current state of research in this field and derive future research opportunities. The underlying research questions are:

> **Research Question I.1**: How can existing research on digital transformation-driven business model innovation be systemized and what are the major insights?

> **Research Question I.2**: What are worthwhile future research directions concerning digital transformation-driven business model innovation?

The findings in Metzler and Muntermann (2021, **paper I.1**) indicate that digital transformation impacts firms' business models in several ways. Digital transformation-driven business model innovation is a complex endeavor with many facets and perspectives. Digital transformation as a whole, as well as the use of specific digital technologies as part of digital transformation, seem to lead to changes in specific business model functions up to the reconfiguration of entire business models. To analyze this phenomenon in a more detailed way, the following three studies investigate digital transformation-driven business model innovation from three different perspectives: (1) a holistic perspective (Metzler and Muntermann 2020, **paper I.2**), (2) a technology perspective (Metzler et al. 2021a, **paper I.3**), and (3) a business model function perspective (Metzler et al. 2022, **paper I.4**).

Since the scope of the existing literature in the field of digital transformation-driven business model innovation is limited to specific business model elements or specific industries (e.g., Hansen and Sia 2015; Piccinini et al. 2015; Li 2020; Rof et al. 2020), there lacks a more comprehensive and integrative view of the impact of digital transformation on firms' business models. Therefore, Metzler and Muntermann (2020, **paper I.2**) investigated the phenomenon with a holistic view by examining the impact of digital transformation on the overall business model of incumbent firms. A multiple case study in various firms active in several different traditional industries was conducted to answer the following research question:

> **Research Question I.3**: How does digital transformation impact the overall business model of incumbent firms in traditional industries?

One major aspect of digital transformation is the successful implementation and use of new digital technologies. Whereas Metzler and Muntermann (2020, **paper I.2**) investigated the impact of digital transformation as a whole (including the use and implementation of the whole range of digital technologies), the third study in this research area is characterized by a technology focus aiming at assessing the role of artificial intelligence as one specific digital technology in digital transformation-driven business model innovation. This is especially meaningful since the scope of existing research is primarily limited to the use of artificial intelligence in (individual aspects of) single business model functions (e.g., Stormi et al. 2018; Baryannis et al. 2019; Kshetri 2020; Lokuge et al. 2020) or the integration of artificial intelligence in the business models of specific industries (e.g., Lee et al. 2019). To approach this research gap, Metzler et al. (2021a, **paper I.3**) examined another multiple case study. The underlying research questions are the following:

> **Research Question I.4**: How does the use of AI impact the specific elements of incumbent firms' business models?

> **Research Question I.5**: How does AI drive Business Model Innovation in incumbent firms?

Finally, since the first studies aimed to analyze the impact of digital transformation or implementation of a specific digital technology as part of digital transformation on the whole business model of firms, the last study in this research area takes a business model function perspective. Metzler et al. (2022, **paper I.4**) focused on one specific business model function: the finance function. Thereby, two main research gaps were approached. First, existing literature only focuses on digital transformation strategy formulation and execution at an organizational level (e.g., Matt et al. 2015; Hess et al. 2016; Chanias et al. 2019; Gurbaxani and Dunkle 2019). Metzler et al. (2022, **paper I.4**) took another perspective by focusing on digital transformation strategy formulation and execution at the business unit level. Second, until now, no studies on the overall digital transformation process in finance units exist. Metzler et al. (2022, **paper I.4**) approached this research gap by analyzing the whole digital transformation process in a global finance function and examining the drivers, barriers, and outcomes of this process. By conducting a single case study in the finance function of a large pharmaceutical manufacturing firm, the paper aimed to answer the following research question:

> **Research Question I.6**: How does an incumbent pre-digital firm digitally transform its finance function and what are the drivers, barriers, and outcomes of this process?

By taking various perspectives on digital transformation-driven business model innovation, answering these questions has the potential to extensively expand the existing knowledge in the research field of digital transformation.

Research Area II: Digital Transformation and Corporate Communication

Existing research indicates that digital transformations are not only of interest to firms themselves, but also to external interest groups of firms, who are also interested in how firms plan and implement their digital transformation and how they perform within this complex process (Moker et al. 2020). A special interest group of firms is represented in current and potential investors. For this interest group, it is of great importance to evaluate firms' future prospects. In this context, information on a firm's performance in the process of digital transformation can play an important role for investors concerning their interest in that firm's shares (Moker et al. 2020).

Although existing literature indicates that a major responsibility of the chief digital officer is communicating and promoting digital transformation-related content (Singh and Hess 2017; Tumbas et al. 2017; Tumbas et al. 2018; Singh et al. 2020), the role of the chief digital officer as a mediator between firms and their external stakeholders, such as investors, and its potential in reducing digital transformation-related information asymmetries, remains unclear. Further, it remains unclear whether firm's information loads concerning their digital transformation endeavors differ across different external communication tools. To fill this research gaps, Metzler et al. (2021b, **paper II.1**) investigated the following research questions:

> **Research Question II.1**: How does CDO presence impact the volume of digital transformation-related signals in external communication tools?

> **Research Question II.2**: How does the volume of digital transformation-related signals differ across communication tools with different degrees of regulation?

Overall, the two research areas in this cumulative dissertation explore the effects of digital transformation on firms from two different viewpoints: a business model innovation view (research area I) and a corporate communication view (research area II). Further, the phenomenon in research area I was investigated from various perspectives. In the next section, the structure of this dissertation is presented. The section further gives an overview of how the two different research areas are (inter-)related.

2 Structure of the Dissertation

This section provides an overview of the structure of this cumulative dissertation. Overall, the dissertation is structured into three sections which build on each other. As shown in Figure 2, part A deals with the foundations of this dissertation, which includes the introduction, a presentation of the underlying structure, and an overview of the research background relevant to this dissertation. Afterward, in part B, the individual research contributions are presented. Finally, the bottom of Figure 2 illustrates the main contributions of the dissertation, including a summary of the most important findings, theoretical and practical implications, limitations, and relevant future research directions.

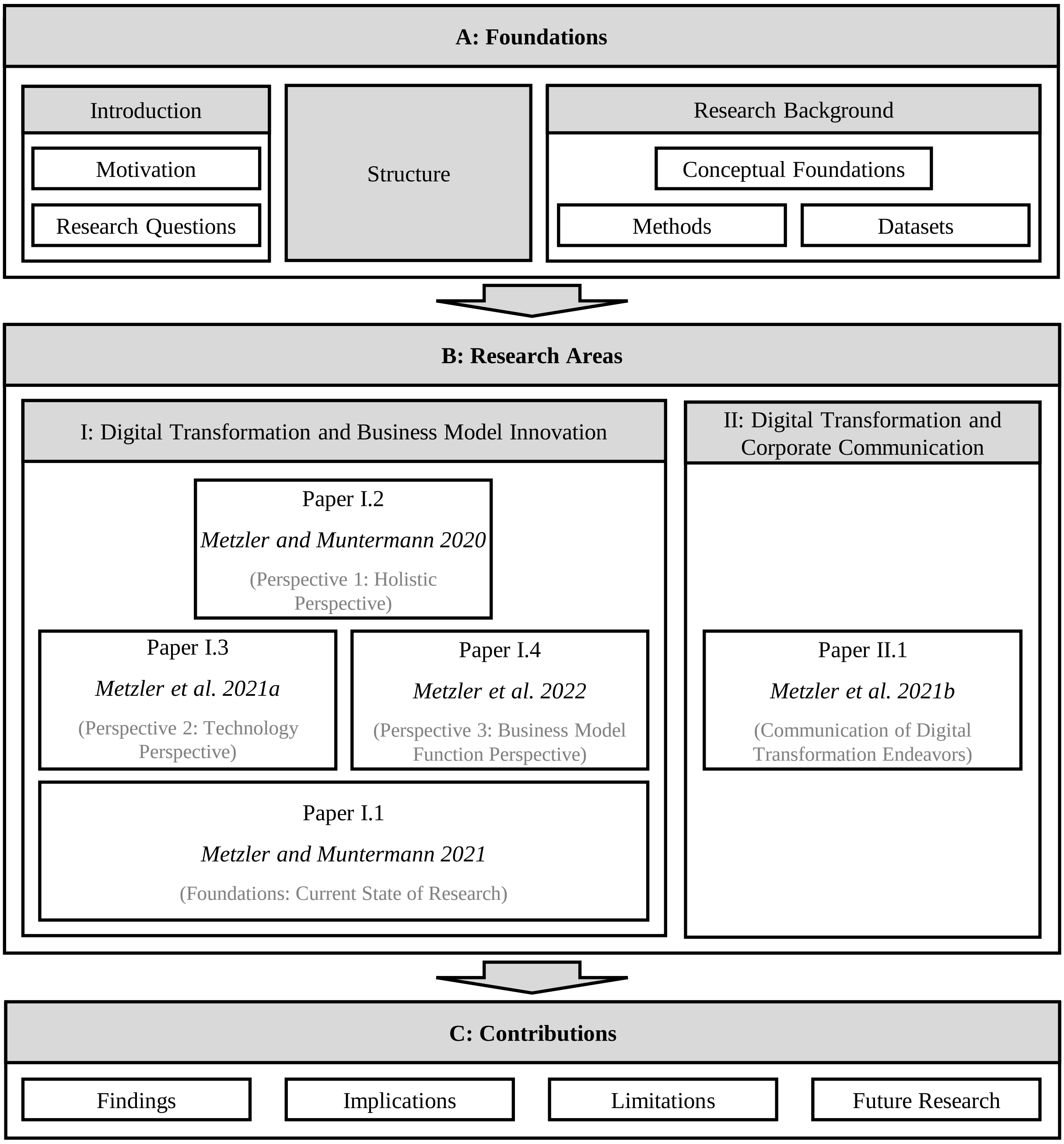

Figure 2. Structure of the dissertation

2.1 Part A: Foundations

The first part (A) deals with the foundations relevant to the individual research contributions. Since the first section of the foundational part of this cumulative dissertation aimed at introducing and motivating the topics of interest and the current section two presents the structure of the dissertation, the following section aims at providing insights into the relevant research background. Starting with the conceptual foundations, the main concepts of interest are presented. This comprises an overview of relevant research on digital transformation, business models, and strategic signaling through corporate communication. This is followed by a presentation of the most relevant research methods used in this dissertation. This includes an introduction to the methodological foundations of literature reviews, case studies, and natural language processing. Finally, the most important datasets, such as interview data, news documents, reporting tools, and board data, including their specific characteristics, are presented.

2.2 Part B: Research Areas

The individual research contributions of this dissertation are presented in part B. Table 1 provides a first overview of these studies, the specific publishing outlets, the current publication status, and the main contribution of each study.

No.	Title	Outlet (Methodology)	Main Contribution
I.1	Digital Transformation-Driven Business Model Innovation – Current State and Future Research Directions	PACIS 2021 (Literature Review)	Development of a research framework on digital transformation-driven business model innovation and presentation of the current state of research and future research avenues.
I.2	The Impact of Digital Transformation on Incumbent Firms: An Analysis of Changes, Challenges, and Responses at the Business Model Level	ICIS 2020 (Case Study)	Development of a framework explaining the impact of digital transformation on the overall business model of incumbent firms, including a presentation of changes, challenges, and responses for each business model element.
I.3	Artificial Intelligence and Business Model Innovation in Incumbent Firms: A Cross-Industry Case Study	Swiss Journal of Business Research and Practice (Case Study)	Provision of insights on the impact of artificial intelligence on existing business models and development of a framework explaining the role of artificial intelligence in innovating existing business models of incumbent firms.
I.4	Managing Digital Transformations at the Business Unit Level: An Exploratory Case Study of a Global Finance Function	Redacted (Case Study)	Conceptualization of the process of digital transformation strategy formulation and execution at the business unit level and presentation of insights on drivers, barriers, and outcomes of digital transformation in a global finance function.
II.1	The Role of CDOs in Signaling Digital Transformation Endeavors: An Analysis of Firms' External Communication Tools	ICIS 2021 (Natural Language Processing)	Provision of insights on the role of the chief digital officer in communicating digital transformation endeavors and reducing digital transformation-related information asymmetries.

Table 1. Papers included in this dissertation

The research contributions in this dissertation are divided into two different research areas with their specific viewpoint on digital transformation. Together, these research areas expand the research field of digital transformation to a great extent.

Research Area I – Digital Transformation and Business Model Innovation: The first area of research investigates the impact of digital transformation on existing business models and the role of digital transformation in business model innovation in manifold ways. Metzler and Muntermann (2021, **paper I.1**) lay the foundations of this research area by reviewing the existing literature in the field of digital transformation-driven business model innovation and deriving promising future research avenues. The three following papers provide insights on digital transformation-driven business model innovation from three different perspectives: (1) a holistic perspective, (2) a technology perspective, and (3) a business model function perspective.

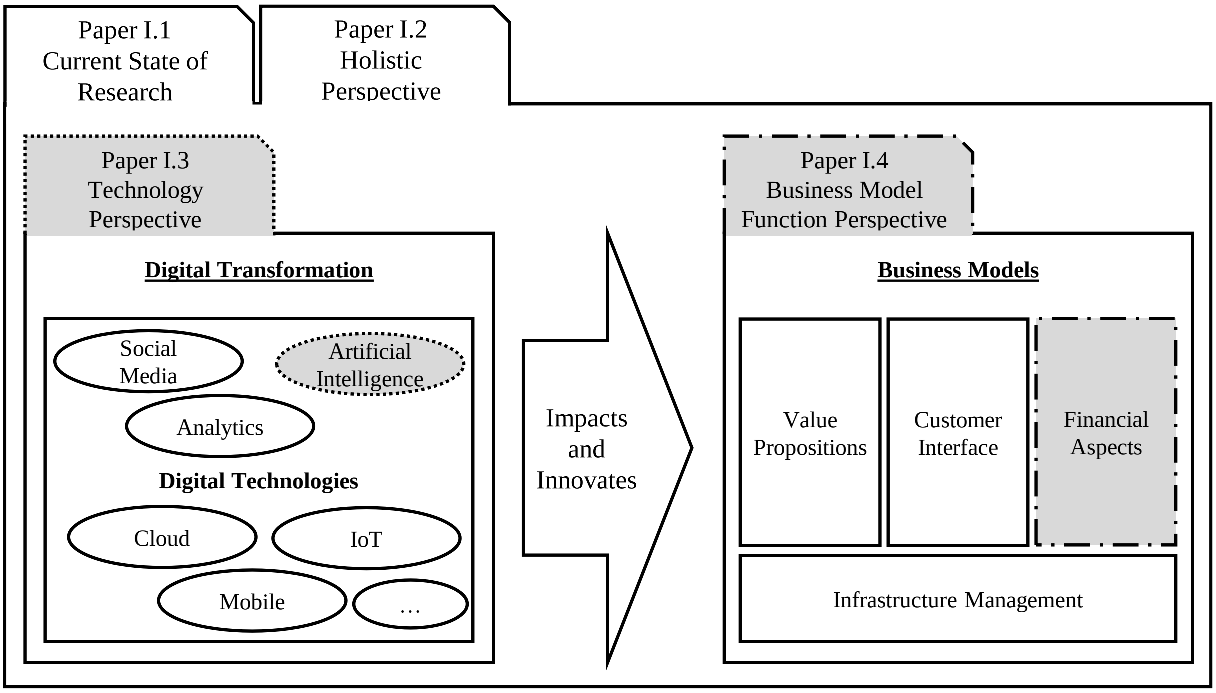

Figure 3. Different perspectives of studies in research area I

By conducting a multiple case study, Metzler and Muntermann (2020, **paper I.2**) provide a holistic view of the impact of digital transformation on the overall business model of incumbent firms in a variety of industries. Second, by conducting another multiple case study, Metzler et al. (2021a, **paper I.3**) assessed the role of the specific digital technology artificial intelligence in digital transformation-driven business model innovation. Finally, by conducting a single case study, Metzler et al. (2022, **paper I.4**) focused on the finance function within an incumbent firm's business model and analyzed the process of digital transformation strategy formulation and execution within this vital business model function, including an analysis of drivers, barriers, and outcomes of digital transformation in this business model function.

Research Area II – Digital Transformation and Corporate Communication: The second research area focuses on digital transformation from another perspective. Digital transformation does not only impact business models but also influences corporate communication. Since digital transformation is a complex endeavor for firms and can determine their future competitive position, external stakeholders such as investors search for digital transformation-related information to access the performance of firms in their digital transformation (Moker et al. 2020).

As illustrated in Figure 4, investors search for digital transformation-related information to evaluate the future prospects of a firm and subsequently decide whether to invest in a firm or not. Firms publish information using corporate communication tools (e.g., 10-K reports).

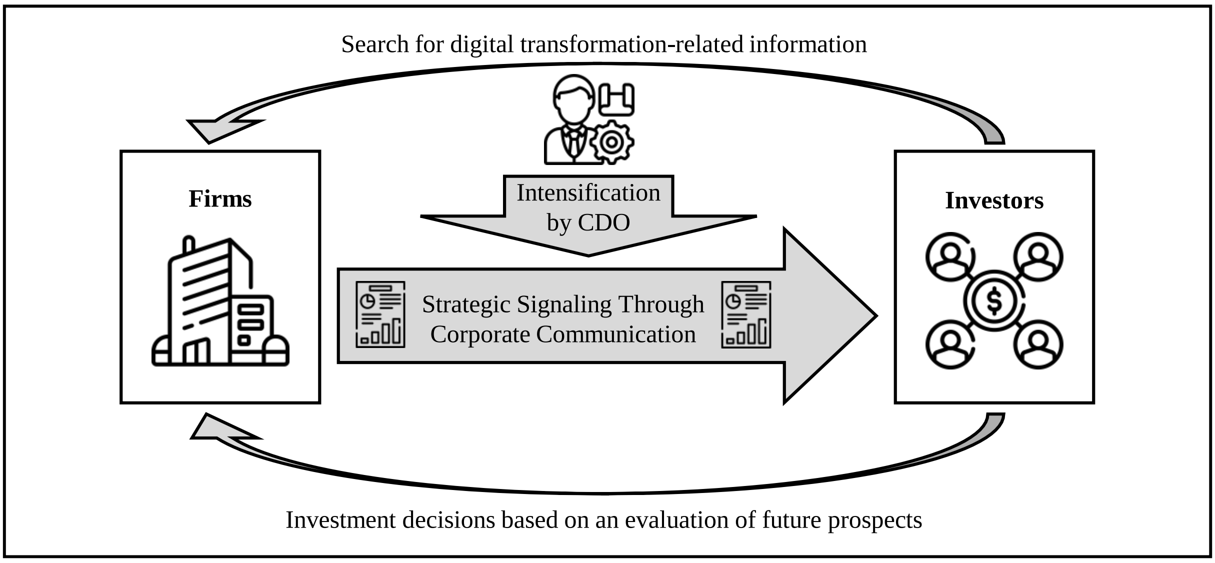

Figure 4. Explanation of research area II

Since the chief digital officer is responsible for communicating and promoting digital transformation endeavors (Singh and Hess 2017; Tumbas et al. 2017; Tumbas et al. 2018; Singh et al. 2020), Metzler et al. (2021b, **paper II.1**) investigated the specific role of the chief digital officer in digital transformation-related information sharing and in reducing potential information asymmetries between firms and external stakeholders, especially investors.

(Inter-)relations between research area I and research area II: Figure 5 illustrates the (inter-)relations within each research area and between both research areas. The upper part of Figure 5 illustrates the fact that incumbent firms need to undergo a digital transformation and therefore need to formulate and execute appropriate digital transformation strategies (e.g., Fitzgerald et al. 2013; Hanelt et al. 2015; Matt et al. 2015; Hess et al. 2016; Sebastian et al. 2017). Digital transformation, thus, leads to substantial changes within existing business models and should, finally, lead to business model innovation (e.g., Kurti and Haftor 2015; Priyono et al. 2020; Levkovskyi et al. 2020).

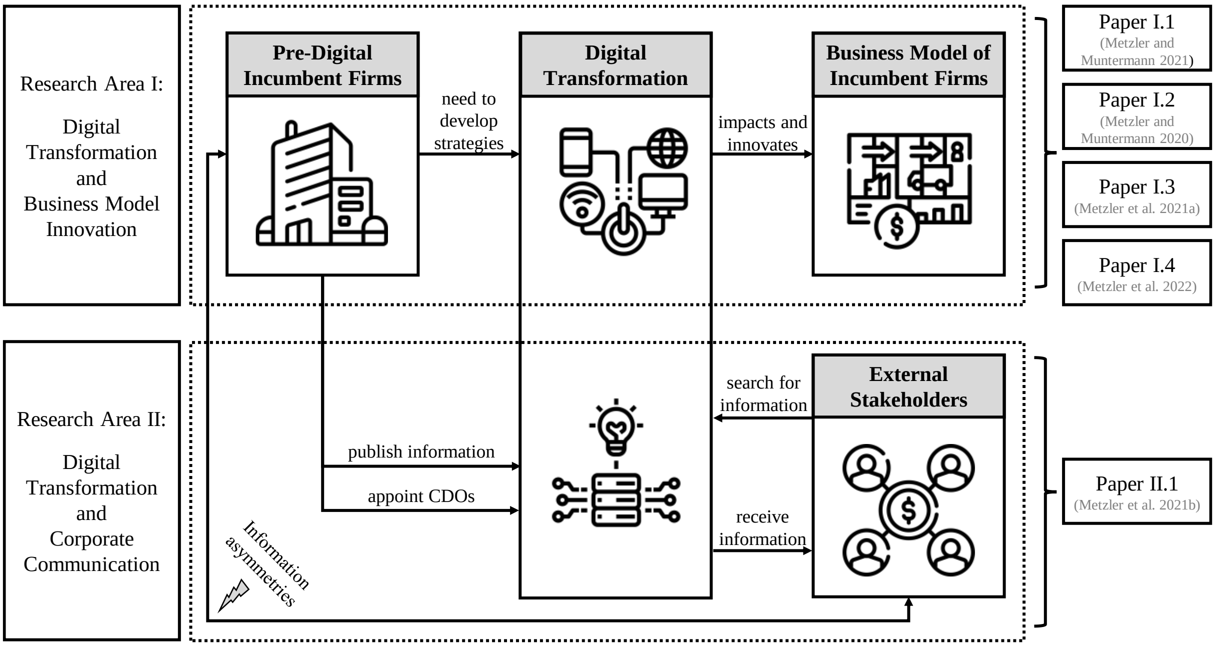

Figure 5. (Inter-)relations between research areas in this dissertation

The process of digital transformation and digital transformation-driven business model innovation is associated with high risk and uncertainty (e.g., Hess et al. 2016; Sebastian et al. 2017; Chanias et al. 2019; Moker et al. 2020). Many firms, therefore, appoint chief digital officers to manage the digital transformation successfully. On the other hand, since digital transformation is associated with high risk and uncertainty, information on digital transformation activities is important for external stakeholders, such as investors, to evaluate the degree of success in digital transformation and the associated future prospects of firms (Hess et al. 2016; Sebastian et al. 2017; Chanias et al. 2019; Moker et al. 2020). However, the level of information between a firm and its stakeholders, such as investors, can be different. The potential occurrence of information asymmetries is illustrated in the bottom part of Figure 5. Firms use external communication tools (e.g., 10-K reports) to inform about ongoing and completed projects. Since the chief digital officer is responsible for driving and communicating digital transformation endeavors, this role has the potential to increase the digital transformation-related information flow between firms and external stakeholders. This, ultimately, may have the potential to reduce information asymmetries.

2.3 Part C: Contributions

The final part, C, is intended to summarize the main contributions of each research article and research area. This part of the dissertation starts with a summary of the most important findings of this cumulative dissertation. Here, the main findings concerning each specific research question are discussed. Afterward, the main implications for research and practice for each research area are presented. This is followed by a discussion of the most relevant limitations concerning each research area. Finally, this section concludes with a presentation of important future research directions for each research area.

3 Research Background

This section first introduces the most important concepts, theories, and related literature relevant to the research objectives of this dissertation. Afterward, the research methods and the datasets used in the contributions of this dissertation are presented and discussed.

3.1 Conceptual Foundations

This subsection introduces the most essential concepts, theories, and literature relevant to this dissertation. First, the concept of digital transformation is defined and its high importance for firms and industries is highlighted. Afterward, the role of the business model and related concepts in information systems research, especially in digital transformation research, is discussed. Finally, the role of corporate communication and increasing strategic signaling in reducing information asymmetries is discussed.

3.1.1 Digital Transformation of Business

Digital transformation is a vital concept for all research contributions of this cumulative dissertation. Vial (2019, p. 118) defines digital transformation as "*a process that aims to improve an entity by triggering significant changes to its properties through combinations of information, computing, communication, and connectivity technologies.*" The combination of these so-called ICT technologies is often referred to as digital technologies, which have the power to change the way organizations communicate with different stakeholders, compete within markets, and operate their business (e.g., Bharadwaj et al. 2013; Hess et al. 2016). Sebastian et al. (2017) refer to such digital technologies as SMACIT, which is an acronym for social, mobile, analytics, cloud, and internet of things. However, SMACIT also comprises other novel technologies, such as blockchain, artificial intelligence, robotics, and virtual reality (Sebastian et al. 2017). Digital technologies differ significantly from earlier technologies and can be described by three main characteristics: (1) re-programmability, (2) data homogenization, and (3) a self-referential nature (Yoo et al. 2010).

Although existing literature often uses the terms "digitization," "digitalization," and "digital transformation" synonymously, it is important to distinguish these three terms from each other. Verhoef et al. (2021) argue that the three terms can be described as different consecutive phases of digital transformation. Figure 6 illustrates these phases in the form of a process model.

First, digitization deals with converting analog information into digital information (Tilson et al. 2010; Brennen and Kreiss 2016; Gobble 2018; Verhoef et al. 2021). On the other hand, digitalization deals with using (digital) technologies to alter existing (business) processes (Li et al. 2016; Verhoef et al. 2021). Finally, digital transformation is the most far-reaching term, describing a transformative change affecting whole organizations with the power to create entirely new business models (Iansiti and Lakhani 2014; Kane et al. 2015; Vial 2019; Verhoef et al. 2021).

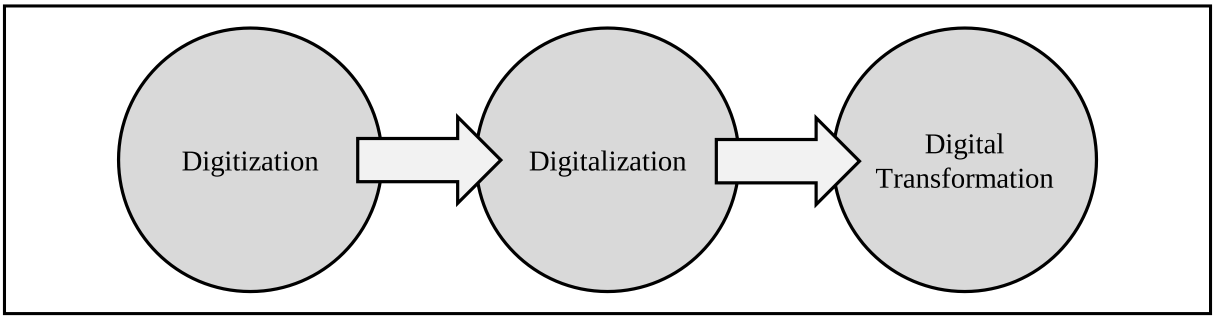

Figure 6. The context of digital transformation (Verhoef et al. 2021)

Another similar concept dealing with the transformation of organizations due to the use of information technology (IT) is that of IT-enabled organizational transformation. However, since the meanings and implications of digital transformation go far beyond the meanings of IT-enabled organizational transformation, it can be seen as an evolution of this concept (Vial 2019; Wessel et al. 2021).

Property	IT-enabled Organizational Transformation	Digital Transformation
Impetus	Initiated by the organization itself.	Based on industrial and societal developments; Initiated by the organization itself.
Target Entity	Unilateral: on the organization itself (only sometimes together with its immediate value network (e.g., supplier)).	Versatile: organization, platform, ecosystem, industry, or society.
Scope	Generally limited to process optimization within an organization and its immediate value network; only sometimes profound.	Mostly profound with implications going beyond an organization and its immediate value network.
Means	Focuses on individual IT artifacts.	Focuses on digital technology combinations (e.g., SMACIT).
Expected Outcome	Less far-reaching: optimized processes along with realized efficiency gains; only sometimes altered business models. Existing institutions (e.g., ethics, regulatory frameworks) remain stable.	More far-reaching: transformation (sometimes only optimization) of business processes and modification of business models. Existing institutions may be challenged and modified due to the transformation's ramifications at higher levels.
Locus of Uncertainty	Only internal: located within the organization itself.	External and internal: located outside the organization, as well as within the organization itself.

Table 2. Comparing IT-enabled organizational transformation with digital transformation (Vial 2019)

Whereas IT-enabled organizational transformation mainly focuses on digitizing resources and automating processes to support existing value propositions and reinforce an organization's existing identity, digital transformation is about completely (re-)defining value propositions and changing entire organizational identities (Vial 2019; Wessel et al. 2021).

As illustrated in Table 2, digital transformation impacts firms, industries, and today's society. Especially incumbent pre-digital firms need to digitally transform their business to secure or expand their competitive market position (Westerman and Bonnet 2015; Hess et al. 2016; Sebastian et al. 2017). Therefore, most existing literature focuses on the digital transformation of firms in traditional industries, such as the automotive industry (e.g., Hanelt et al. 2015) or the healthcare industry (e.g., Lucas Jr. et al. 2013; Agarwal et al. 2010). Incumbent pre-digital firms, which can be defined as firms that were established before the digital revolution and positioned in a traditional industry with business models that were not originally based on the use of digital technologies, need to adapt strategic directions, organizational structures, workforce, cultures and mindsets, and their existing business models (e.g., Matt et al. 2015; Sebastian et al. 2017; Eden et al. 2019; Metzler and Muntermann 2020). Due to its far-reaching implications for firms and the resulting chance to improve the business, digital transformation is one of the most essential topics for executives across geographical regions and industries (e.g., Matt et al. 2015; Hess et al. 2016; Sebastian et al. 2017; Chanias et al. 2019; Vial 2019).

To successfully digitally transform an organization, the formulation and execution of appropriate strategies are indispensable. Therefore, research on combining the fields of digital transformation and organizational strategizing has increased significantly over the last decade (Stockhinger 2021). Existing research in that field deals with different strategic concepts, including digital transformation strategy. Based on a literature review, Stockhinger and Teubner (2018) compared the most common terms regarding strategies in the context of digital transformation: “digital business strategy,” “digital IT/IS strategy,” and “digital transformation strategy”.

Concept	Description	Responsibility
Digital Business Strategy	Using digital technologies to build a competitive advantage	CEO (and other members of the top management team)
Digital IT/IS Strategy	Leveraging the potential of digital technologies through getting and allocating appropriate capabilities	CIO (in cooperation with top management team)
Digital Transformation Strategy	Planning, governing, and implementing digital transformation	CDO (sometimes CIO)

Table 3. Overview of digital strategy concepts (Stockhinger and Teubner 2018)

Recent research concludes that while digital business strategy focuses on strategic business and competition changes in the new digital age, leading to a business view on digital transformation (Bharadwaj et al. 2013; Stockhinger and Teubner 2018), digital IT/IS strategy focuses on IT/IS competencies leading to a technical strategic view to digital transformation (e.g., Peppard and Ward 2016; Stockhinger and Teubner 2018). Digital transformation strategy, however, aims at integrating both strategic views, focusing on concrete digital transformation initiatives and dealing with the question of how to plan, govern, and implement digital transformations (e.g., Stockhinger and Teubner 2018). A digital transformation strategy acknowledges the pervasive changes throughout an organization, not only incorporating the provision of IT services and infrastructure but also enabling the exploitation of business opportunities that arise from the use of digital technologies (Hess et al. 2016; Stockhinger and Teubner 2018). Therefore, a digital transformation strategy can be defined as a guiding plan concerning the digital transformation of a firm's value propositions and identity (Stockhinger 2021; Wessel et al. 2021). A digital transformation strategy comprises four key dimensions: (1) the use of technologies, (2) changes in value creation, (3) structural changes, and (4) financial aspects (Matt et al. 2015; Hess et al. 2016).

As illustrated in Table 3, in most organizations, the chief digital officer plays a key role in formulating and executing digital transformation strategies. In general, the chief digital officer carries the responsibility of driving and coordinating the digital transformation of an organization, including the formulation of a digital transformation strategy and strengthening the strategic priority of digital transformation (Westerman et al. 2014a; Haffke et al. 2016; Singh and Hess 2017; Singh et al. 2020). This field of activity further includes coordinating and implementing digitalization initiatives, driving a cultural change toward a digital mindset, accelerating processes, and communicating digitalization initiatives with external stakeholders (Singh and Hess 2017; Tumbas et al. 2017; Tumbas et al. 2018; Singh et al. 2020;).

Research on digital transformation gained increasing importance over the last years. However, many aspects have not been investigated so far (Vial 2019; Hanelt et al. 2021a; Verhoef et al. 2021). To structure the existing literature, Hanelt et al. (2021a) developed a multi-dimensional research framework on digital transformation.

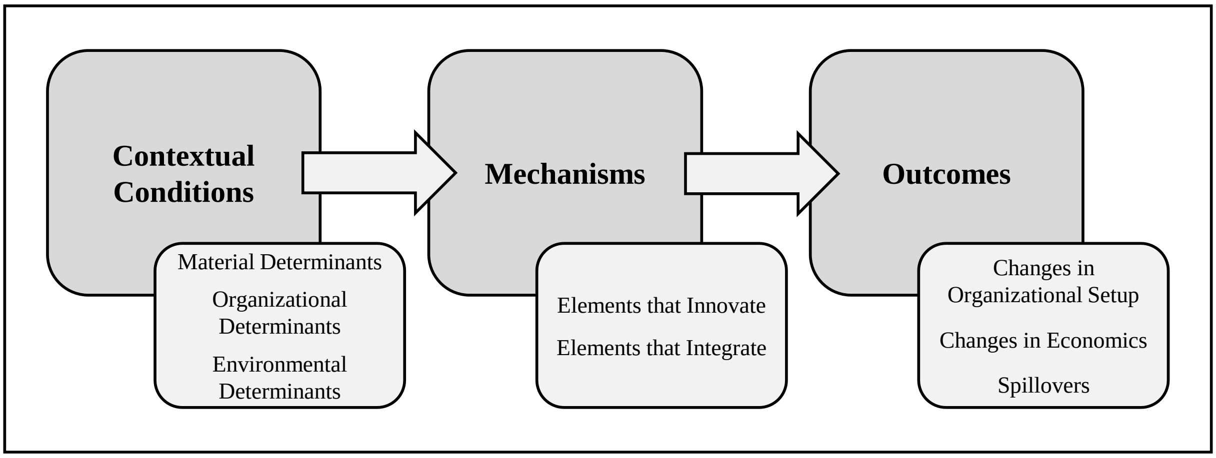

Figure 7. A framework of research on digital transformation (Hanelt et al. 2021a)

As illustrated in Figure 7, the framework of Hanelt et al. (2021a) shows that research on digital transformation is primarily about (1) contextual conditions, (2) mechanisms, and (3) outcomes of digital transformation. Research on the contextual conditions of digital transformation mainly deals with antecedents (material, environmental, and organizational) triggering and shaping the digital transformation. Research on mechanisms deals with instruments aiming at conceiving and bringing about digital transformation. Finally, research on outcomes deals with the impact of digital transformation on economics, spillovers, and organizational setups (Hanelt et al. 2021a).

The specific research articles in this cumulative dissertation contribute to all of these three areas of digital transformation research. Most papers contribute to more than one of these areas simultaneously. Metzler and Muntermann (2020, **paper I.2**) and Metzler et al. (2021a, **paper I.3**) mainly contribute to the research area's mechanisms and outcomes. The papers Metzler and Muntermann (2021, **paper I.1**) and Metzler et al. (2022, **paper I.4**) significantly contribute to all three research areas simultaneously. Finally, the paper Metzler et al. (2021b, **paper II.1**) mainly contributes to the mechanisms of digital transformation.

3.1.2 The Business Model Concept

The business model concept has been identified as one of 12 different schools of thought in digital transformation research (Risanow et al. 2019). In addition, it is an essential tool of analysis for a variety of research disciplines, including entrepreneurship research, innovation research, technology research, and information systems research (e.g., Johnson et al. 2008; Zott et al. 2011; Veit et al. 2014). In general, a business model serves as an intermediate part between a subordinate business strategy and the underlying operational business processes (Al-Debei and Avison 2010).

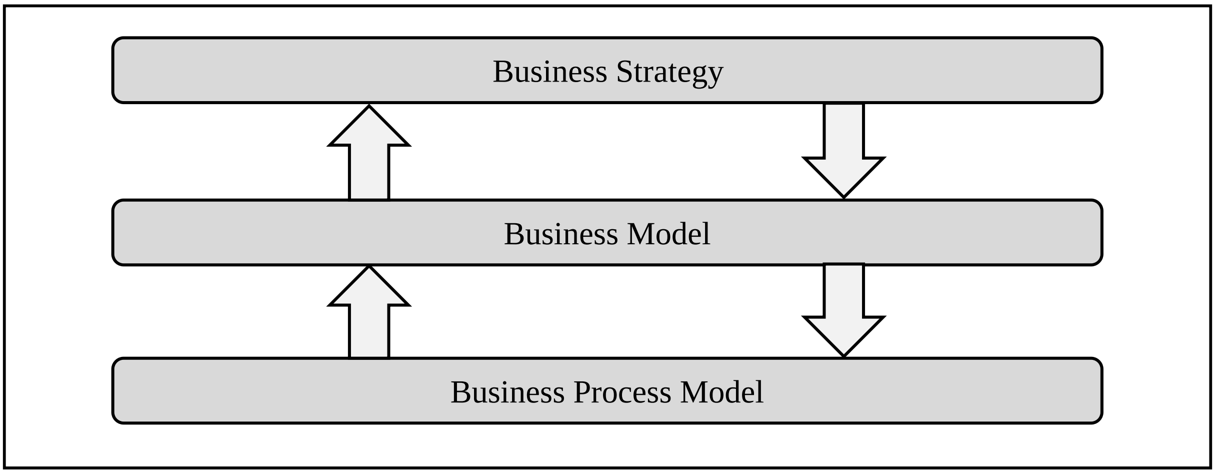

Figure 8. The mediating role of business models (Al-Debei and Avison 2010)

As illustrated in Figure 8, for firms to achieve the objectives of a business strategy, they need to convert it into smaller and more specific business architectural elements. These elements make the business model. Once the business model is derived from the business strategy, it acts as a foundation to derive specific processes for the operational business (Al-Debei and Avison 2010).

Despite the great popularity and importance of the business model concept, there still does not exist a consensus regarding its definition (Veit et al. 2014; Röder et al. 2018). As one exemplary definition, Magretta (2002, p. 87) argues that business models are "*stories that explain how enterprises work*." In greater detail, Zott et al. (2011, p. 1038) describe the business model as "*a new unit of analysis, offering a systemic perspective on how to 'do business,' encompassing boundary-spanning activities (performed by a focal firm or other), and focusing on value creation as well as on value capture*." A relatively similar definition stems from Osterwalder and

Pigneur (2010, p. 15), who describe a business model as a "*blueprint for a strategy to be implemented through organizational structures, processes, and systems*."

In addition, also concerning the different components of a business model, there exists no consensus. Osterwalder and Pigneur (2010) argue that this stems from the lack of consensus concerning its definition. As one example, Hamel (2000) argues that a business model can be divided into the four components of core strategy, strategic resources, customer interface, and value network. Another approach was undertaken by Al-Debei and Avison (2010). By developing a taxonomy concerning the business model concept, the authors identified four components as the main business model elements: (1) value proposition, (2) value architecture, (3) value network, and (4) value finance. Osterwalder and Pigneur (2010), argue that a business model comprises four pillars, including nine different elements: (1) value propositions (specified by the value propositions of products and services), (2) customer interface (specified by customer relationships, customer segments, and communication and sales channels), (3) infrastructure management (specified by key activities, key resources, and key partners), and (4) financial aspects (specified by cost structure and revenue streams).

Over the last years, the business model concept gained increasing importance, especially in information systems research. According to Veit et al. (2014), literature referring to the business model concept in information systems research can be categorized into three different research perspectives, which are illustrated in Figure 9.

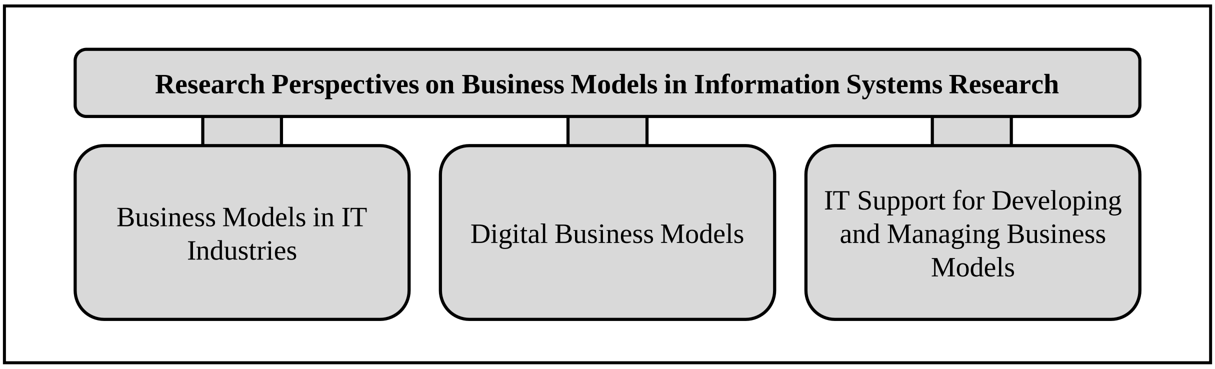

Figure 9. Research perspectives on business models (Veit et al. 2014)

The first perspective is about literature dealing with classifying business models, identifying business model elements, or analyzing the performance of business models in IT industries. The second perspective deals with the emergence and analysis of so-called digital business models (e.g., El Sawy and Pereira 2013; Weill and Woerner 2013; Remane et al. 2016; Bock and Wiener 2017; Remane et al. 2017). Research on data-driven business models (e.g., Engelbrecht et al. 2016; Hartmann et al. 2016; Sorescu 2017; Zolnowski et al. 2017) and (digital) platform business models (e.g., Staykova and Damsgaard 2015; Täuscher and Laudien 2018) can also be assigned to this perspective. All these business model concepts have in common that they use the power of digital technologies and digitization to achieve a competitive advantage (Guggenberger et al. 2020). Research in this perspective primarily focuses on analyzing the transformative nature of such business models, their impact on industrialization, and the emergence of new product and service models. Finally, the third perspective deals with exploring conceptual models, formulating graphical and morphological representations, and supporting the development of business models through designing software tools (Veit et al. 2014).

Anchored in the third research perspective is research dealing with the innovation of existing business models (especially in the context of digital technologies and digital transformation). Existing literature agrees that implementing specific digital technologies and digital strategies impacts existing business models in various ways (e.g., Burmeister et al. 2016; Hess et al. 2016; Vial 2019; Neuhüttler et al. 2020). The term business model innovation can be defined as the "*designed, novel, nontrivial changes to the key elements of a firm's business model and/or the architecture linking these elements*" (Foss and Saebi 2017, p. 201). Whereas business model innovation in its basic form can be driven by various internal and external circumstances, the concept of digital business model innovation refers to business model innovation triggered by digital technologies (Böttcher and Weking 2020). Finally, digital transformation-driven business model innovation can be defined as a "*strategic renewal (i.e., through significant changes) of an existing business model, or at least critical elements of an existing business model, as part of a firm's digital transformation*" (Metzler and Muntermann 2021, p. 3). Digital transformation-driven business model innovation aims at adapting existing business models for the digital age and can result in digitally enhanced existing business models or in entirely new (often digital) business models (Levkovskyi et al. 2020; Hanelt et al. 2021a; Metzler and Muntermann 2021).

In this cumulative dissertation, the concept of digital transformation-driven business model innovation especially plays an important role. Specifically, in the first research area, the papers analyze the role and power of specific digital technologies and digital transformation as a whole in changing, innovating, and renewing existing business models and business model elements.

3.1.3 Corporate Communication and Strategic Signaling

Digital transformation and related activities are bound to risk and uncertainty (e.g., Hess et al. 2016; Sebastian et al. 2017; Chanias et al. 2019; Moker et al. 2020). Therefore, a proper information flow between a firm's management and its stakeholders, especially investors, is of great importance to avoid potential information asymmetries between these parties. A continuous information flow concerning firm-specific information (e.g., concerning its digital transformation endeavors) is highly important for investors to form an opinion on the future prospects of a firm.

The theory of information asymmetries descends from the principal-agent theory, which describes the presence of contractual relations between different individuals or groups that have mismatched goals (Pavlou et al. 2007).

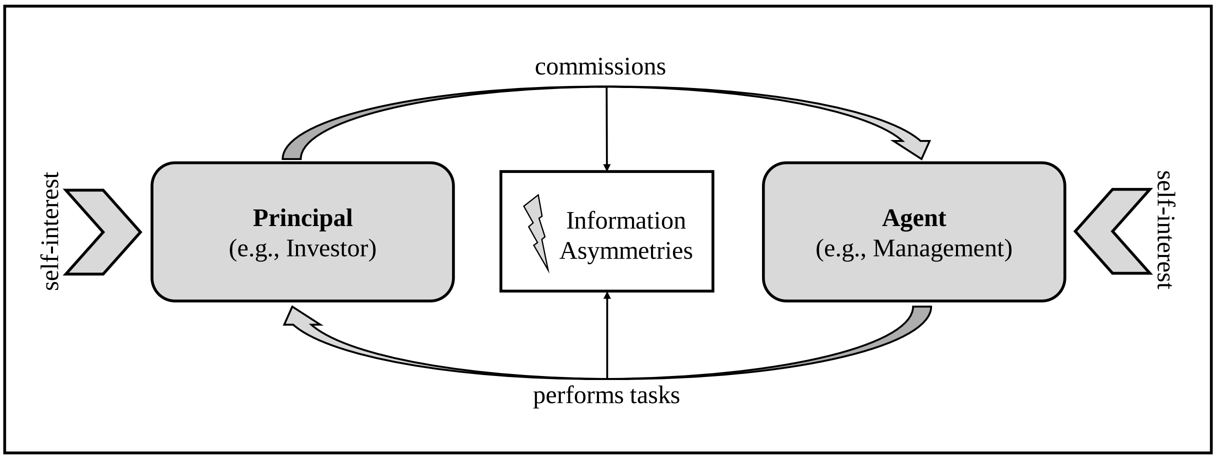

Figure 10. Principal-agent-theory

As illustrated in Figure 10, the principal-agent theory describes the situation in which a principal (e.g., investor) delegates tasks to an agent (e.g., management). The agent should perform these tasks for the benefit of the principal (Eisenhardt 1989a). However, in general, the agent has more detailed information than the principal. For example, the management of a firm has a better overview and understanding of strategic events and decisions. This makes it difficult for the principal to assess the agent's decisions. In the worst case, the agent does not perform the tasks per the principal's expectations but rather acts to maximize his or her own benefit. According to Pavlou et al. (2007), the mismatched goals between an agent and a principal lead to two often discussed problems: (1) adverse selection (pre-contractual problem) and (2) moral hazard (post-contractual problem).

Adverse selection describes a situation in which information about the true quality of an agent is private (hidden). In this case, the principal is in a bad position because he or she cannot distinguish the good agents from the bad (Akerlof 1970; Wilson 1980; Pavlou et al. 2007). To tackle issues concerning adverse selection, principals can implement self-selection instruments for agents and screen agents and can examine signals from agents (Pavlou et al. 2007). On the other hand, moral hazard describes a situation in which the principal hires an agent who does not perform his or her tasks to the satisfaction of the principal. This is because the principal cannot completely monitor the performance or behavior of the agent. Sometimes the agent is even engaged in so-called hidden actions to profit from his or her own utility, which negatively impacts the principal's utility (Jensen and Meckling 1976; Rothschild and Stiglitz 1976; Pavlou et al. 2007). To tackle moral hazard issues, principals can rely on implementing incentives, bonding, performance or behavior monitoring, and signaling (Pavlou et al. 2007).

Information asymmetries have multiple negative effects on investors in the relationship between investors (principals) and the management of a firm (agents). For example, Grossman and Hart (1983) show that the existence of information asymmetries can reduce investors' welfare. To avoid such negative effects, firms communicate information with their stakeholders, which can be described as signaling. The theory behind this procedure is called signaling theory, which describes the circumstances of two different individuals or groups with asymmetric information regarding the same topic (Spence 2002; Connelly et al. 2011). Signaling theory describes the processes of how an individual or group with more information (the sender) uses signals to communicate to lower information asymmetries and how the individual or group with less information (the receiver) interprets these signals (Connelly et al. 2011). As one of the first authors dealing with signaling theory, Spence (1973) found out how job applicants can improve their selection process regarding potential employers by reducing information asymmetries (Connelly et al. 2011).

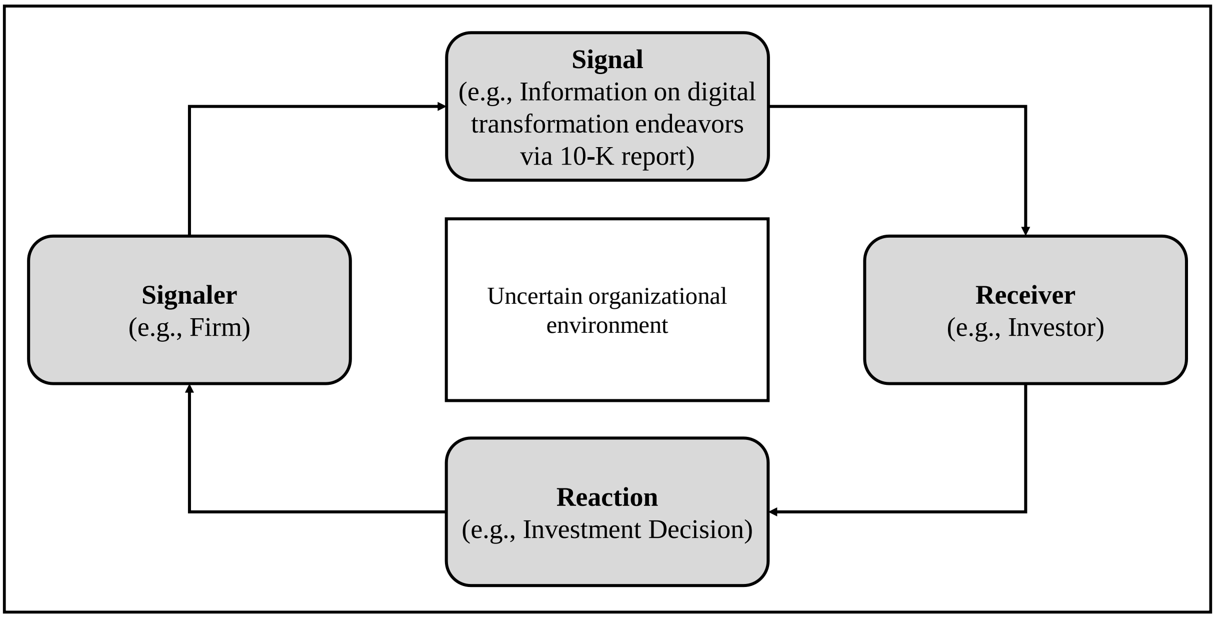

Figure 11. Signaling theory

Signaling of firms can take a variety of forms. For example, a firm's reputation can be seen as a signal for stakeholders (e.g., Deephouse 2000). Furthermore, other firm-specific aspects, such as the number of patents (e.g., McGrath and Nerkar 2004) or alliance announcements (e.g., Park and Mezias 2005), can be seen as signals for different interest groups of a firm. Additionally, signaling can be seen in the composition of a board, in the appointment of special board members (Kralina 2018), or in the reputation of the board or specific board members (e.g., Zhang and Wiersema 2009).

Firms primarily use external communication tools, such as highly regulated 10-K reports and rather less regulated conference calls to communicate with external stakeholders and reduce potential information asymmetries concerning various topics (Moker et al. 2020). On the other hand, stakeholders search such corporate communication tools for important visible signals (Moker et al. 2020). Existing research in this field, for example, shows that firms can reduce information asymmetries by increasing financial reporting frequency (Fu et al. 2012) and that conducting conference calls leads to a lower degree of information asymmetry in the long-term (Brown et al. 2004). However, not all signals are inevitably useful or effective for the receiver. In that regard, signal reliability determines the degree of trustworthiness (as a combination of signal fit and honesty) of a specific signal (Connelly et al. 2011).

Recent research has already started discussing signaling theory in relation to special CxO positions. For example, Kralina (2018) shows that firms with a chief data officer in their top management team tend to send more data-related signals in their annual reports. Further, Drechsler et al. (2019) show that chief digital officer appointments and related public announcements are used as strategic signals to investors. Metzler et al. (2021b, **Paper II.1**) join this field of research by analyzing whether chief digital officer presence is associated with a higher volume of digital transformation-related signals in external communication tools and whether a potential increase in digital transformation-related signaling through chief digital officer appointments has the potential to reduce information asymmetries.

3.2 Methods

In this dissertation, a great mixture of qualitative and quantitative research methods was applied. This section is intended to give a brief overview of these methods, including an introduction to the application areas of each method and a presentation of the strengths and weaknesses of each method.

3.2.1 Literature Review

Literature reviews are essential for information systems research projects to advance scientific knowledge. As stated by Webster and Watson (2002), a rigorous review of the existing literature in a specific research field fosters the identification of relevant research gaps and facilitates theory development. An ideal literature review in the field of information systems research should, therefore, be creative and explanatory and follow seven specific rules: (1) motivating the topic of interest and explaining the desired research contribution, (2) describing the theoretical underpinnings, (3) underlining relevant research boundaries, (4) reviewing the entire quantity of topic-relevant articles in information systems research and other related research fields, (5) deriving a conceptual model from existing literature, (6) presenting the main theoretical, empirical, and practical findings to justify the derived model, and (7) suggesting theoretical and practical implications (Webster and Watson 2002).

A literature review can be conducted for different reasons using different approaches. In that regard, Paré et al. (2015) developed a typology of nine different literature review types. The narrative, descriptive, and scoping reviews aim to summarize prior knowledge. The meta-analysis, qualitative systematic review, and umbrella review aim to aggregate and integrate data. The theoretical and realist reviews aim at explanation building. Finally, the critical review aims at assessing the extant literature in a critical way (Paré et al. 2015). An overview of all nine types can be obtained from Table 4.

Type of Review	Aim of Review
Narrative Review	In its simplest form, it is about identifying what has been written on a specific topic. Mostly without explanations of the review procedure.
Descriptive Review	Reviews existing literature to analyze whether it reveals or supports trends or patterns concerning existing research results.
Scoping Review	Provides a first exploratory impression on the question of whether it makes sense to conduct a full systematic review.
Meta-Analysis	Uses statistical methods and data extraction techniques to aggregate quantitative data.
Qualitative Systematic Review	Uses quantitative studies to identify, search, appraise, abstract, and select data. Aims at analyzing and discussing the data and results of these studies.
Umbrella Review	Development of a summary of multiple existing reviews.
Theoretical Review	Aims to develop theoretical models or frameworks based on existing empirical and conceptual studies.
Realist Review	Aims to use heterogeneous evidence to enhance existing conventional systematic reviews.
Critical Review	Analyzes existing literature on a specific topic concerning weaknesses, inconsistencies, controversies, or contradictions.

Table 4. Types of literature reviews in information systems research (Paré et al. 2015)

In the context of this dissertation, Metzler and Muntermann (2021, **paper I.1**) used a descriptive literature review to access the current state of research on digital transformation-driven business model innovation. The paper follows the guidelines provided by Webster and Watson (2002). Whereas Metzler and Muntermann (2021, **paper I.1**) explicitly used a literature review as the main methodology, of course also all other presented research papers developed their research gap and research contributions based on an implicit use of the literature review methodology.

3.2.2 Case Study Research

The case study is one of several ways of doing qualitative research. In information systems research, it is a common method to conduct interpretive investigations (Walsham 1995). According to Yin (2014, p. 16), a case study is an "*empirical inquiry that investigates a contemporary phenomenon (the "case") in depth and within its real-world context, especially when the boundaries between phenomenon and context may not be clearly evident.*" This research strategy comprises research design elements, techniques for data collection, and techniques for data analysis. Therefore, it can be seen as an all-encompassing research method (Yin 2014).

Apart from case studies, there exist various other qualitative research approaches, such as experiments, surveys, histories, and the analysis of archival information. According to Yin (2014), each strategy has particular advantages and disadvantages, depending on three conditions: (1) the form of the research question, (2) the control an investigator has over behavioral events, and (3) the degree of focus on contemporary events.

As shown in Table 5, case studies are the most appropriate strategy when the underlying research questions are "how" or "why" questions, when the investigator has only little control over contemporary events, and when the research topic focuses on a contemporary event (Yin

2014). In Metzler and Muntermann (2020, **paper I.2**), Metzler et al. (2021a, **paper I.3**), and Metzler et al. (2022, **paper I.4**), “how” questions are the focus of the investigation, control of behavioral events is not required, and all analyses focus on contemporary events. Therefore, case study research is an appropriate research strategy in these studies.

Strategy	Type of Research Question	Requires Control of Behavioral Events?	Focuses on Contemporary Events?
Experiment	How, why?	Yes	Yes
Survey	Who, what, where, how many, how much?	No	Yes
Archival Analysis	Who, what, where, how many, how much?	No	Yes/No
History	How, why?	No	No
Case Study	How, why?	No	Yes

Table 5. Relevant situations for different research strategies (Yin 2014)

Depending on the research area, there exist different ways to classify case studies (e.g., Levy 2008; Yin 2014). According to Yin (2014), case studies can be carried out as a single case study or as a multiple case study. Whereas a single case design makes sense when a specific case can be seen as a critical, unique, representative, or revelatory case, a multiple case study makes sense when researchers follow a replication or exploration logic (Yin 2014). In that regard, Metzler and Muntermann (2020, **paper I.2**) and Metzler et al. (2021a, **paper I.3**) use multiple case studies which (1) provide an opportunity to strengthen findings in light of replication logic (Eisenhardt 1989b; Yin 2014) and (2) can lead to more robust results by being more compelling (Herriott and Firestone 1983). On the other hand, Metzler et al. (2022, **paper I.4**) use a single case study design with a representative case to gain in-depth initial holistic insights on one specific topic which is ubiquitous in all incumbent firms (Yin 2014).

The overall goal of case study research is developing new theory or refining existing theory (Eisenhardt 1989b; Yin 2014). In the research articles of this dissertation, case study research is used to refine existing theory or theoretical constructs, especially with regard to digital transformation and business model innovation.

There exist many different ways of collecting qualitative data for case studies. This, among others, includes observations, documents, interviews, physical artifacts, and audio-visual materials (Creswell 2014; Yin 2014). All of these data collection methods have their specific strengths and weaknesses, and for every research project, one has to decide which data collection method could be the best.

In Metzler and Muntermann (2020, **paper I.2**), Metzler et al. (2021a, **paper I.3**), and Metzler et al. (2022, **paper I.4**), interviews were used as the primary source of evidence. Interviews are an especially insightful source of evidence by providing explanations and personal views and directly focusing on the topic under investigation (Yin 2014). Since interviews pose the potential weakness of inaccuracies due to poor recall and response biases, in all case studies, additional documents, provided mainly by the interview partners, were used to confirm or extend insights. In Metzler et al. (2021a, **paper I.3**), firm-specific news articles and annual reports were also used. However, this is only a useful source of evidence if they are retrievable with manageable effort (Yin 2014).

The collected data within each case study was analyzed using different qualitative coding techniques with the help of the qualitative research software, MAXQDA. In all case studies, the data analysis approach aims to analyze the material step by step, following concrete coding rules, and divide the data into analytical units.

In the case studies in Metzler and Muntermann (2020, **paper I.2**) and Metzler et al. (2021a, **paper. I.3**), the data analysis followed the rules of deductive category development as part of qualitative content analysis (Mayring 2000). When using a deductive category development approach, the researcher has to pre-define categories and sub-categories on a theoretical basis. On the other hand, when using an inductive category development approach, the researcher must determine the selection criteria for potential categories. These criteria should be deduced from the research question(s). Afterward, the researcher has to formulate categories from the material. In both ways of category development, the category system should be revised during the research process. Also, a formative and summative check of reliability should be carried out in both ways (Mayring 2000; Kaiser 2014).

In the case study by Metzler et al. (2022, **paper I.4**), coding techniques from the grounded theory methodology were applied: (1) open coding, (2) axial coding, and (3) selective coding (Corbin and Strauss 1990). These coding rules were applied since they are more precise in explaining how to analyze qualitative data inductively. In open coding, first, open codes are assigned to topic-relevant text sections. Afterward, in axial coding, the open codes are sorted and related to each other. Finally, in selective coding, emerged categories are related to each other, and one core category should emerge. As in the qualitative content analysis approach, the whole category system should be revised during the research process (Corbin and Strauss 1990).

Instead of achieving statistical generalization (i.e., extrapolating probabilities), the goal of case study research is achieving analytic generalization (i.e., expanding and generalizing theories) (Yin 2014). In that regard, a case study does not represent a “sample” and analytic generalization describes the approach to try to generalize case study findings to circumstances different to the original case study to further expand theories (Yin 2014).

More details on how the interview data and additional documents were collected and what the raw data looks like can be obtained from the method sections 3.3.1 and 3.3.2.

3.2.3 Natural Language Processing

Whereas the textual data in Metzler and Muntermann (2020, **paper I.2**), Metzler et al. (2021a, **paper I.3**), and Metzler et al. (2022, **paper I.4**) was analyzed qualitatively, in Metzler et al. (2021b, **paper II.1**), textual data was analyzed quantitatively with natural language processing techniques. This section gives a brief introduction to the procedure of using such techniques.

Natural language processing is "*the attempt to extract a fuller meaning representation from free text*" (Kao and Poteet 2007, p. 1). According to Liddy (2001), there exist six different objectives for applying natural language processing techniques, which can be obtained from Table 6.

Objective	Description
Information Retrieval	A response to a user request by providing a list of potentially relevant documents from a database.
Information Extraction	Recognition and extraction of key information, such as persons, companies, or places from text and converting it into a structured format.
Question Answering	Response to a user inquiry by providing a specific text(-passage).
Summarization	Reduction of a larger text to a constituted shortened narrative text.
Machine Translation	Translation into another language.
Dialogue Systems	Communication between humans and computers, e.g., via chatbot or a voice assistant.

Table 6. Objectives for using natural language processing techniques (Liddy 2001)

In Metzler et al. (2021b, **paper II.1**), natural language processing techniques were used to analyze the content of firm's external communication tools (i.e., 10-K reports and conference calls) to identify the amount of digital transformation-related content in these communication tools. Therefore, natural language processing was applied with the objective of information extraction. Following a so-called dictionary approach, the relative number of digital transformation-related sentences within 10-K reports and conference calls was calculated. Whereas most dictionaries are developed to conduct sentiment analyses (e.g., Loughran and McDonald 2015), other dictionaries are developed to determine the frequency of certain words or word groups in texts (e.g., Chen and Srinivasan 2019).

Before applying the dictionary to the textual data, a pre-processing of the data is needed. In Metzler et al. (2021b, **paper II.1**), the pre-processing comprises two major steps: (1) sentence tokenization and (2) lower case transformation. First, after reading the textual data from one or more specific databases, the text of each document needs to get tokenized, which means splitting the text into separate pieces, which in the case of Metzler et al. (2021b, **paper II.1**) are sentences (e.g., Manning and Schütze 1999; Sharda et al. 2021). In this step, non-word content, such as points, commas, and semicolons, gets removed. Since the sentences are searched for digital terms to classify each sentence as digital or non-digital, this step is of great importance. The remaining sentences are the tokens. Afterward, a lower case transformation is carried out where upper case letters are turned into lower case letters. This is important since all words in the dictionary only comprise lower case letters.

Another often used pre-processing step is the stop word removal where so-called stop words are going to be removed from the remaining text. Stop words are words that do not comprise any content-relevant information (e.g., “I” or “in”). Also, stemming is often used as a pre-processing step. In this step, all remaining words are reduced to their stems. Stemming is important to have the possibility of grouping words with the same word stem and classifying them as the same (e.g., Sharda et al. 2021).

More details on the textual data used and how the textual data was collected can be obtained from section 3.3.3.

3.3 Datasets

In this section, the datasets used in this dissertation are presented. This section aims at explaining the relevant terminology regarding the used datasets and gives more detailed information about the data sources of each study. Further, this section explains the appropriateness of the used datasets within each study. The most frequently used datasets are interview data, firm-specific news documents, external reporting tools, and board data. All datasets are presented and discussed below.

3.3.1 Interview Data

Semi-structured expert interviews were used as the main database in the case studies of Metzler and Muntermann (2020, **paper I.2**), Metzler et al. (2021a, **paper I.3**), and Metzler et al. (2022, **paper I.4**). The reason for using interviews was to investigate insufficiently researched topics and derive findings to refine existing theory or even generate new theories from the interviewees’ knowledge with information that may not be obtainable elsewhere (Bogner and Menz 2002; Kaiser 2014; Flick 2019). Overall, interviews can be classified as an extraordinarily insightful data source since they contain a vast amount of detailed case-specific explanations as well as specific personal views (Yin 2014). In information systems research, interviews are one of the most often used data gathering tools for qualitative studies (Myers and Newman 2007).

According to Flick (2019), qualitative interviews can be categorized as verbal data. Other verbal data comprises narratives and group discussions or focus groups. Qualitative interviews can be further divided into focused interviews, semi-structured interviews, problem-centric interviews, ethnographic interviews, and expert interviews (Flick 2019). In the studies of this dissertation, the advantages of semi-structured interviews and expert interviews were combined. Thus, semi-structured expert interviews were conducted in the studies of Metzler and Muntermann (2020, **paper I.2**), Metzler et al. (2021a, **paper I.3**), and Metzler et al. (2022, **paper I.4**). The expert, in this case, is defined by a specific position and status and/or specific functional knowledge which is relevant to the scientific analysis (Kaiser 2014). Experts additionally may carry the responsibility for developing, implementing, or monitoring specific problem solutions or have privileged access to potentially important information (Meuser and Nagel 1991). The experts interviewed in the studies in this dissertation are characterized by a unique knowledge concerning important case-specific processes stemming from their specific positions or roles within the case firms.

When conducting interviews, researchers primarily need to think about three major aspects: (1) interview preparation, (2) construction of the research question, (3) implementation of the interviews, and (4) interpretation of the interview data (Turner 2010; Creswell 2014; Kaiser 2014). The data collection process of all interviews followed the guidelines of Kaiser (2014) which comprises five major steps that can be obtained from Figure 12. To optimize the overall time of the data collection procedure, some of these steps can be conducted in parallel (Kaiser 2014).

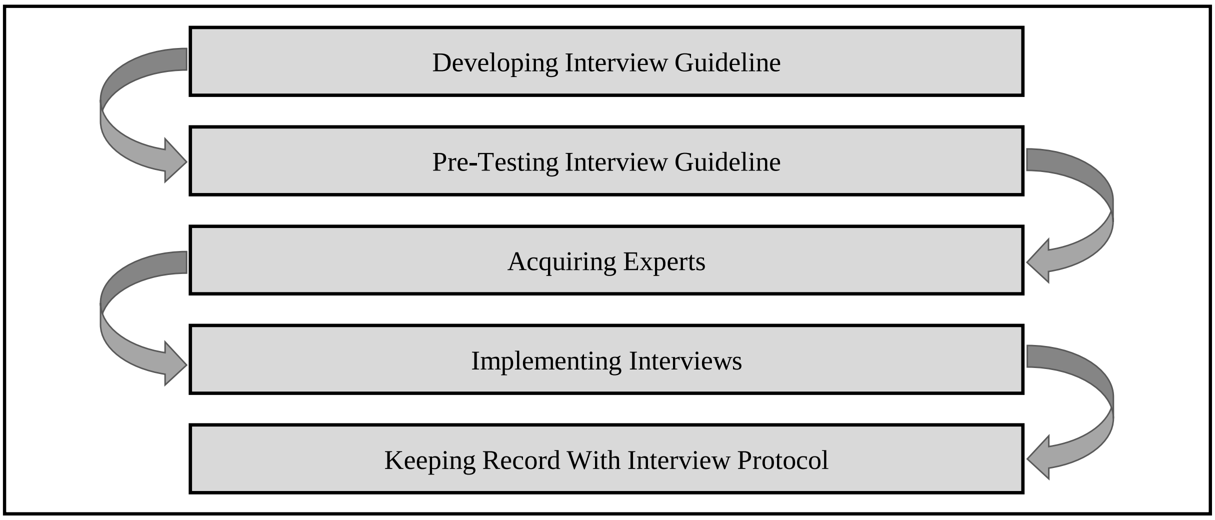

Figure 12. Data collection through interviews (Kaiser 2014)

The overall procedure starts with developing an interview guideline. This guideline consists of several questions carefully derived from the pre-determined research questions. For the interviews in this dissertation, a semi-structured interview approach is used. The semi-structured interview approach allows the questionnaire to be modified iteratively based on experiences from previous interviews and enables follow-up questions, but also requires improvisation in the explicit situation (Myers and Newman 2007; Kaiser 2014). In addition, by conducting a semi-structured interview, the interview partners may more easily discuss sensitive issues (Yin 2014). The developed interview guideline should be pre-tested with selected persons to avoid misleading questions (Kaiser 2014).

Once the interview questionnaire is finalized and has passed the pre-test, a group of experts needs to be acquired as interview partners. For each research project of this dissertation, several experts are interviewed to increase the reliability and validity of the information obtained. At the same time, it must be ensured that the competencies of the interviewees are high enough to obtain appropriately qualified results (Kumar et al. 1993; Kaiser 2014). Therefore, selecting experts is critical in obtaining valuable results (Kaiser 2014; Flick 2019). Another advantage of interviewing several interviewees is that a variety of people in different positions of responsibility can generate diverse assessments of a topic from different points of view (Kumar et al. 1993; Kaiser 2014). The interviewees in the research articles in this dissertation were consulted either via the personal network of the authors or via cold calls (e.g., via LinkedIn).

After finishing the acquisition process, the interviews can be conducted. The interviews in Metzler and Muntermann (2020, **paper I.2**) and Metzler et al. (2021a, **paper I.3**) were held face to face. Due to the pandemic situation, the interviews in Metzler et al. (2022, **paper I.4**) were held by videoconference. All interviews should be accompanied by keeping records in the form of an interview protocol (Kaiser 2014).

3.3.2 Firm-Specific News Documents

In Metzler et al. (2021a, **paper I.3**), firm-specific news documents were used as an additional source of evidence. The aim of using firm-specific news documents was to extend the insights gained from expert interviews and tackle potential inaccuracies due to poor recall and potential response biases from the interview partners (Yin 2014). In Metzler et al. (2021a, **paper I.3**), this approach was feasible since the focus was on one specific technology. In Metzler and Muntermann (2020, **paper I.2**) and Metzler et al. (2022, **paper I.4**), this approach was not realizable since the focus was on digital transformation as a whole (including all associated technologies and methods). Therefore, creating a search string to search for relevant news articles was not practicable in these studies. In Metzler et al. (2021a, **paper I.3**), a theme-specific search string was developed, tested, and subsequently applied on the official websites of the firms under investigation. This procedure ensures that the specific firms themselves generated the news articles. Therefore, the possibility of a potential false statement from external sources can be excluded. However, indeed, statements made by the specific firms themselves can also be incorrect or incomplete.

3.3.3 External Reporting Tools

Firms use various external reporting tools with different degrees of regulation. In Metzler et al. (2021b, **paper II.1**), such tools were analyzed to explore the amount of digital transformation-related content in firms' external communication tools. This dataset includes 10-K reports and transcriptions of conference calls. Both external reporting tools contain financial and strategic information about firms and aim to reduce potential information asymmetries (e.g., Bowman 1984; Brown et al. 2004; Kloptchenko et al. 2004; Lee and Hong 2014). However, a significant difference between these two communication tools concerns their different degree of standardization and regulation. More detailed explanations concerning the two reporting tools are presented below.

10-K Reports

In Metzler et al. (2021b, **paper II.1**), 10-K reports are used as one main data source. The 10-K reports were extracted from the Edgar database of the U.S. Securities and Exchange Commission (SEC). 10-K reports are externally audited filings that have to be published once a year, in which the management team has to report all material information, including qualitative statements (Cannon et al. 2020; SEC 2021a; SEC 2021b). Therefore, 10-K reports represent a highly relevant external communication tool that provides insight into a firm's financial situation and into ongoing, planned, and completed strategic issues. Their publication is mandatory for most U.S. public companies. The 10-K report has to be submitted to the SEC. In contrast to other annual reports (e.g., in the European area), 10-K reports are generally more detailed (especially, concerning financial key figures) but lack graphical elements (since they are not used as marketing instruments).

The structure of 10-K reports is highly standardized. The SEC requires that 10-K reports follow a set order of topics, including financial statements, internal controls, disclosures, and management discussions and analyses (SEC 2021a; SEC 2021b). A 10-K report is divided into four parts with different items (SEC 2021b). Table 7 gives an overview of each part and item.

Part	Item(s)	
1	Item 1	Business
	Item 1A	Risk factors
	Item 1B	Unresolved staff comments
	Item 2	Properties
	Item 3	Legal proceedings
	Item 4	Mine safety disclosures
2	Item 5	Market for registrant's common equity, related stockholder matters, and issuer purchases of equity securities
	Item 6	Selected financial data
	Item 7	Management's discussion and analysis of financial condition and results of operations
	Item 7A	Quantitative and qualitative disclosures about market risk
	Item 8	Financial statements and supplementary data
	Item 9	Changes in and disagreements with accountants on accounting and financial disclosure
	Item 9A	Controls and procedures
	Item 9B	Other information
3	Item 10	Directors, executive officers, and corporate governance
	Item 11	Executive compensation
	Item 12	Security ownership of certain beneficial owners and management and related stockholder matters
	Item 13	Certain relationships and related transactions, and director independence
	Item14	Principal accountant fees and services
4	Item 15	Exhibits, financial statement schedules

Table 7. Structure and content of 10-K reports (SEC 2021b)

At first glance, many parts and items of a 10-K report do not contain any digital transformation-relevant content. However, these supposedly irrelevant parts and items can also contain relevant information on digital transformation endeavors. For example, as part of the risk factors item (Item 1A), firms may talk about their initiatives to oppose the digitalization pressure. Therefore, in Metzler et al. (2021b, **paper II.2**), the whole 10-K report, including all parts and items, is analyzed.

Due to their high degree of standardization and the fact that they are audited, the trustworthiness of 10-K reports is highly secured.

Conference Calls

Conference calls were utilized as a second data source in Metzler et al. (2021b, **paper II.1**). In contrast to 10-K reports that are highly standardized, conference calls are rather less standardized and non-audited in-person or digital meetings between corporate representatives and analysts. These conference calls are held around the announcement of quarterly and annual earnings and represent a highly relevant form of disclosure (Huang et al. 2018). The transcripts of the conference calls used in this dissertation were gathered from the Thomson One database.

The primary goal of conference calls is to inform analysts and investors about the business developments within a firm. Whereas 10-K reports are one-sided communication tools, in conference calls, the corporate representatives also have to answer questions by analysts or other participants spontaneously. Overall, there are five regular conference calls for a firm in a year. In exceptional circumstances, additional conference calls may be scheduled (Eickhoff and Muntermann 2016a; Eickhoff and Muntermann 2016b). Due to their low degree of standardization and the fact that they are not audited, the trustworthiness of the content in conference calls is not necessarily secured.

3.3.4 Board Data

Board data was used in Metzler et al. (2021b, **paper II.1**) to analyze the impact of chief digital officer presence on the amount of digital transformation-related content in firms' external communication tools. To generate a great universe of board data, the data of the following three databases was combined: (1) Boardex, (2) Amadeus, and (3) Crunchbase. The databases provide information concerning former and current board members of various firms. This information includes personal information, such as name, age, sex, educational background, and former positions, information on their current and former board positions, such as start and end date, role name, and role description, and information on their current employers, such as head office country and sector. Missing information was, if possible, complemented, and contradictory information was clarified and unified through additional investigations (e.g., on professional social networks such as LinkedIn and firm websites).

For the paper by Metzler et al. (2021b, **paper II.1**), especially chief digital officer positions (as the main variable) and related CxO positions (as the control variable) are of relevance. According to Kunisch et al. (2020), to identify chief digital officers, all senior executives having the term "digital" in their role title are classified as potential chief digital officers. The role titles of these potential chief digital officers are further checked manually to eliminate persons who are not chief digital officers. This procedure ensures that chief digital officers with different role titles are also considered. Therefore, the final list of chief digital officers solely contains senior executives responsible for digital transformation activities. To identify "*Related CxO*" positions, board positions with areas of responsibility that have at least some connecting points to the digital transformation of firms were considered. This includes chief information officers, chief innovation officers, chief data officers, chief strategy officers, and other similar CxO positions. To identify senior executives with such roles, the role titles of all executives in the BoardEX and Amadeus database have been searched for role-specific keywords. As a result of the data preparation, data for various different chief digital officers and related CxOs was obtained.

B. Research Areas: Individual Research Contributions

The second part of this cumulative dissertation comprises a detailed presentation of the five individual research contributions. The presentation of the individual research contributions is divided into the two research areas presented in part A. The following Figure 13 illustrates the two research areas and groups the five individual research contributions to the specific research areas.

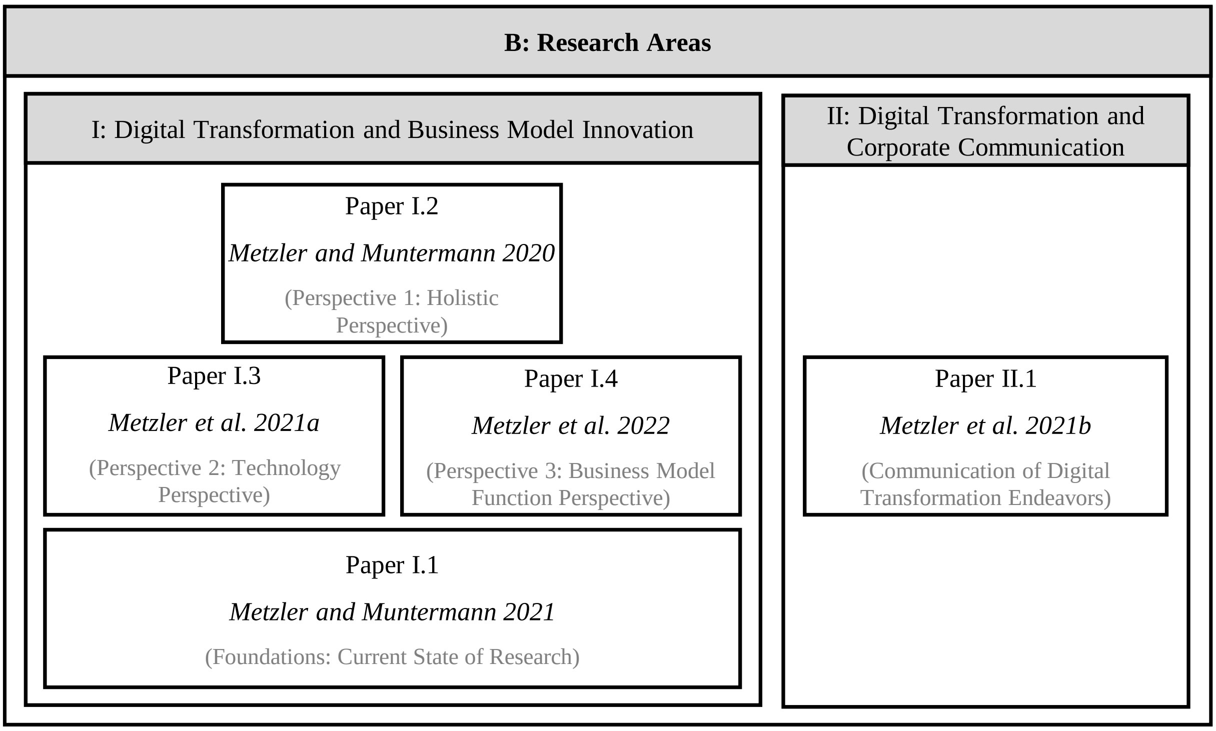

Figure 13. Grouping of research papers in research areas

I. Research Area:
Digital Transformation and Business Model Innovation

The first research area comprises various articles that focus on digital transformation's complexity in relation to business models. The articles investigate the phenomenon of digital transformation-driven business model innovation from different perspectives.

Metzler and Muntermann (2021, **paper I.1**) provide a holistic overview of the current state of research concerning the phenomenon of digital transformation-driven business model innovation. This paper suggests that research in this field is still in its infancy and, therefore, derives potential future research directions. Metzler and Muntermann (2020, **paper I.2**) also take a holistic perspective and access the impact of digital transformation on the overall business model of incumbent firms across a variety of industries. It becomes clear that digital transformation has a huge impact on every single business model element. Hence, executives need to rethink the design of each element to stay competitive in an increasingly digitalized world. Whereas Metzler and Muntermann (2020, **paper I.2**) do not have a technology-specific focus, Metzler et al. (2021a, **paper I.3**) takes a technology-specific perspective and focus on the role of artificial intelligence as a driver of business model innovation in the context of digital transformation. Finally, Metzler et al. (2022, **paper I.4**) take a business model function perspective and take a closer look at one specific business model function – the finance function. By conducting a single case study, the study provides insights into digital transformation strategy formulation and execution at the business unit level. Further, the study presents the drivers, barriers, and outcomes of this process. This research area addresses the following simplified research questions:

> **Research Question I.1:** What is the current state of research on digital transformation-driven business model innovation and what are worthwhile future research directions?
>
> **Research Question I.2:** How does digital transformation impact the overall business model of incumbent firms in traditional industries?
>
> **Research Question I.3:** How does artificial intelligence impact the specific elements of incumbent firms' business models and how does artificial intelligence drive business model innovation in these firms?
>
> **Research Question I.4:** How does an incumbent pre-digital firm digitally transform its finance function and what are the drivers, barriers, and outcomes of this process?

I.1. Literature Review on DT-driven BMI (Study 1)

Paper Title:

Digital Transformation-Driven Business Model Innovation – Current State and Future Research Directions

Abstract: Existing research on digital transformation agrees that digital transformation impacts the transforming firms' existing business models in manifold ways. However, research examining the underlying mechanisms and the specific impact is still rare. This study introduces the concept of digital transformation-driven business model innovation, subsequently conceptualizes and summarizes the existing literature in this field, and finally presents recommendations on future research directions. Based on a systematic literature review, we show that digital transformation-driven business model innovation gained increasing importance in the information systems and management literature in recent years. Existing research primarily focuses on conceptual foundations, antecedents, processes, outcomes, and the evaluation of digital transformation-driven business model innovation. Nevertheless, research in this field is still in its infancy, which is reflected by research gaps that we have identified in all of these research directions.

Outlet: Pacific Asia Conference on Information Systems (PACIS) 2021

Citation: Metzler, D. R. and Muntermann, J. 2021. "Digital Transformation-Driven Business Model Innovation – Current State and Future Research Directions," in *Proceedings of the 25th Pacific Asia Conference on Information Systems*, Dubai, VAE.

Keywords: Digital Transformation, Business Models, Business Model Innovation, Literature Review, Qualitative Research

1 Introduction

The emergence of new disruptive digital technologies impacts firms across industries. Changing customer needs and the emergence of new competitors with novel, often digital, business models (BMs) put pressure on firms' existing BMs. To stay competitive in an increasingly digitized environment, firms need to undergo a digital transformation (DT). A DT can be defined as the transformational process of using digital technologies and appropriate human and technical capabilities to adapt the existing BM for the requirements of the digital age (Bharadwaj et al. 2013; Fitzgerald et al. 2013; Vial 2019). The process of DT has various effects on firms' existing BMs (e.g., Hanelt et al. 2015; Vial 2019; Böttcher and Weking 2020; Levkovskyi et al. 2020; Metzler and Muntermann 2020). In that regard, various definitions of DT refer to the reconfiguration of existing BMs as the expected outcome of DT (Vial 2019). Thereby, a DT can end up in altered existing BMs or entirely new (often digital) BMs (Levkovskyi et al. 2020). However, whereas research on DT agrees that DT has a huge impact on existing BMs, research focusing on analyzing how DT impacts and innovates existing BMs of firms is still rare. In order to access the current state of research in that field, it is of great importance to structure the existing literature and to derive future research opportunities. Based on this, future research can expand the existing field of research with new insights.

As two of the first researchers, Buck and Eder (2018) aimed at structuring the field of DT concerning BMs. However, their article's focus was rather on the digitization of BMs (i.e., a purely technical process) instead of the impact of DT on BMs (i.e., an organizational process with a transformational impact) (Tilson et al. 2010). Other researchers conducted literature analyses that only partially bring together the concepts DT and BM (e.g., Böttcher and Weking 2020), only focus on specific industries (e.g., Caliskan et al. 2021), or differ in their research focus or applied methodology (e.g., Parida et al. 2019; Caputo et al. 2021). What is still missing is an all-encompassing analysis of the current state of research regarding the impact of DT on existing BMs and DT as a driver of business model innovation (BMI). With this study, we want to close this research gap by analyzing the current state of research and giving recommendations for future research to encourage researchers to extend the existing knowledge. Thereby, our study helps to draw a holistic picture of DT-driven BMI and to better understand the relationship between DT and BMI. Against this background, this paper investigates the following research questions (*RQ*):

RQ1: *How can existing research on digital transformation-driven business model innovation be systemized and what are major insights?*

RQ2: *What are worthwhile future research directions concerning digital transformation-driven business model innovation?*

To answer these research questions, we conducted a systematic literature review across various relevant databases following the guidelines of Webster and Watson (2002). Our results show that DT-driven BMI gained increasing importance in the information systems (IS) and management literature during the last years. Nevertheless, research in this field is still in an early stage.

In order to provide sound theoretical foundations and to gain valuable insights, this paper is structured as follows: Starting with the theoretical foundations, we introduce DT and BMs as the main underlying concepts. Second, we describe the methodological foundation of the study. Third, we present the findings. Fourth, the discussion highlights the implications, limitations, and future research directions. Finally, the conclusion summarizes the most important findings.

2 Theoretical Foundations

2.1 Digital Transformation of Firms and Industries

The ongoing emergence of new digital technologies is shaping businesses across different geographical regions and industrial sectors. Digital technologies can be defined as a combination of information, computing, communication, and connectivity technologies (Bharadwaj et al. 2013). Some of the most common digital technologies include social media, mobile, analytics, and cloud computing (Sebastian et al. 2017). The use of digital technologies with the aim to "*improve an entity by triggering significant changes to its properties*" can be described as DT (Vial 2019, p. 118). In a business context, DT has implications that reach far beyond an organization's processes and its immediate value network (Vial 2019). Instead, DT has the power to automate organizational processes, replace or enhance products and services by digital offerings, transform supply chains into networks, and innovate and disrupt the sales and communication channels of firms (Matt et al. 2015; Böttcher and Weking 2020; Metzler and Muntermann 2020). Overall, DT comprises of various transformational processes with the power to lead to an innovation (e.g., through an alteration or (re)definition) of existing BMs (e.g., Vial 2019).

Although the term DT differs significantly from the terms "digitization" and "digitalization," some researchers use these terms synonymously. Therefore, it is important to distinguish the terms from each other. Whereas the term digitization describes a purely technical process of transforming analog signals into a digital format, digitalization refers to a socio-technical phenomenon at a societal and institutional level (Tilson et al. 2010). Finally, the term DT, which is a relatively new concept in IS research, goes far beyond these terms by referring to a transformational process of using digital technologies and appropriate human and technical capabilities to adapt the existing BM for the requirements of the digital age (Bharadwaj et al. 2013; Fitzgerald et al. 2013; Vial 2019). Thereby, DT differs from other concepts of strategic change in that regard that changes driven by digital technologies are particularly fast, resulting in a more volatile, uncertain, and complex environment (Matt et al. 2015; Warner and Wäger 2019). With its power of altering or (re)defining a firms' BM and changing its whole identity, DT also exceeds earlier forms of IT-enabled organizational change (Vial 2019; Wessel et al. 2021).

DT is especially relevant for incumbent firms. Since these firms typically have to deal with long-grown corporate structures and legacy IT infrastructures, it is even more important to adapt the corporate culture and reinvent the BM for the digital age (Metzler and Muntermann 2020). Without undergoing a DT, these firms risk losing market share to emerging firms with novel BMs based on using digital technologies (Veit et al. 2014). In that regard DT has the potential to force changes to a part of an existing BM or even to change the whole BM in a way that a completely new one is created (Levkovskyi et al. 2020).

Risanow et al. (2019) found that DT literature can be divided into 12 different schools of thought. BMs are one of these. However, although existing literature on DT agrees that DT has a major impact on the BM of firms, this school of thought is rather underrepresented in DT research.

2.2 Digital Transformation-Driven Business Model Innovation

In DT research, the BM has emerged as a promising analytical framework highlighting its increasing importance for research and practice (Al-Debei and Avison 2010; Veit et al. 2014). While existing literature builds upon different definitions of the BM, most of them agree that a BM aims at structuring a business into value creation functions, delivery functions, and capturing functions (e.g., Chesbrough and Rosenbloom 2002; Osterwalder and Pigneur 2010; Teece 2010; Zott et al. 2011). Thereby, a BM can be seen as a blueprint representing the architecture of a firm's overall business and describing how a firm creates value and how the firm delivers this value to relevant stakeholders (Osterwalder and Pigneur 2010; Foss and Saebi 2017). The existing literature agrees that a firm's BM consists of different elements. For example, Osterwalder and Pigneur (2010) structure a BM into the following nine elements: (1) key resources, (2) key activities, (3) key partners, (4) value proposition, (5) customer relationships, (6) channels, (7) customer segments, (8) cost structure, and (9) revenue streams. This so-called business model canvas (BMC) is especially characterized by its granularity and industry-independence. Ojala (2016), in turn, defines the BM in a more compact way comprising four elements: (1) product/service, (2) value network, (3) value delivery, and (4) revenue model. As the BM of a firm is of great importance for value creation and market success, it is also important for innovation processes within firms (Chesbrough and Rosenbloom 2002; Teece 2010). Research in that field is mostly undertaken under the term BMI, which can be defined as "*designed, novel, nontrivial changes to the key elements of a firm's business model and/or the architecture linking these elements*" (Foss and Saebi 2017, p. 201). More recently, the concept "digital business model innovation" (DBMI) emerged in the literature, referring to BMI triggered by digital technologies (Böttcher and Weking 2020). The existing literature agrees that (D)BMI is a constitutive element of DT (Risanow et al. 2019). However, both concepts do not necessarily have to occur in the context of DT. Further, DT does not inevitably comprise a BM transformation (e.g., Fitzgerald et al. 2013; Vial 2019). Finally, some research is done under the rather less frequently used term "digital business model transformation" (e.g., Kurti and Haftor 2015; Baber et al. 2019; Priyono et al. 2020), which refers to transforming a BM through digitalization.

Although there exist various concepts concerning BMI, current literature lacks a common concept that brings together existing concepts in order to describe (D)BMI in the explicit context of DT (i.e., how DT impacts and innovates existing BMs). As a first attempt to close this gap and to structure the field, we conceptualize this phenomenon under the term "digital transformation-driven business model innovation" (DTBMI), which we define as a strategic renewal (i.e., through significant changes) of an existing BM, or at least critical elements of an existing BM, as part of a firm's DT. Thereby, DTBMI can be described as the process of (D)BMI as part of the DT of a firm, which can either result in a digitally enhanced traditional BM or a newly created (digital) BM. The strategic aim of DTBMI is to adapt the existing BM for the digital age.

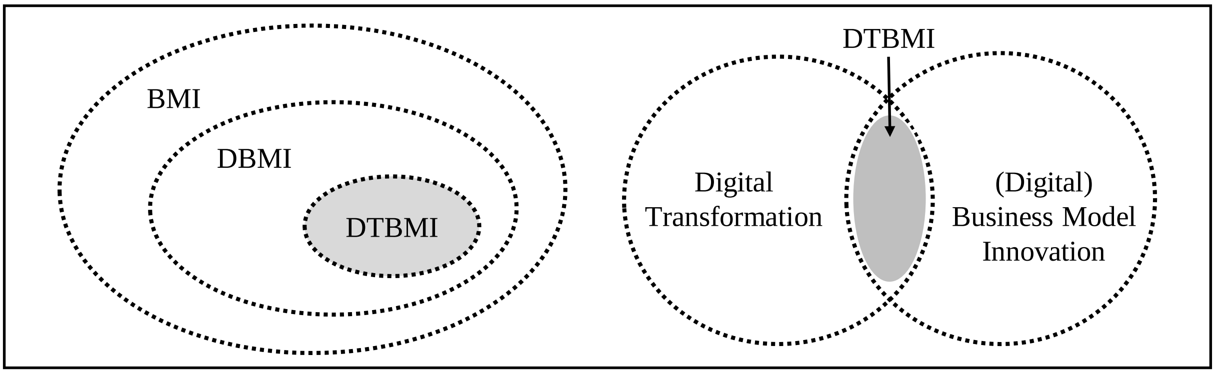

Figure 14. The context of DTBMI

As illustrated in Figure 14, DTBMI can be seen as a subset of DBMI with a substantial difference in the way that DTBMI not only focuses on simply implementing digital technologies into the existing BM. Instead, it considers the whole process of transforming the existing BM as part of DT. This, among other things, includes challenges and tensions that arise from BM changes colliding with existing organizational structures, as well as appropriate strategic responses (Metzler and Muntermann 2020; Rof et al. 2020). Furthermore, DTBMI is different to other forms of BMI as digital technology-driven changes are particularly fast. Firms, therefore, need to adapt and reconfigure their BMs accordingly fast and more frequently (Matt et al. 2015; Warner and Wäger 2019).

Within the last years, research on DT gained increasing attention across disciplines. Recently, especially the BM of firms has become a central unit of analysis (e.g., Metzler and Muntermann 2020; Soto Setzke et al. 2020). Thereby, researchers analyzed a variety of different aspects of this field of research. Additionally, few literature analyses exist regarding DT and BMs. However, these studies either only partially bring together the concepts DT and BM (e.g., Böttcher and Weking 2020), only focus on specific industries (e.g., Caliskan et al. 2021), or differ in their research focus or applied methodology (e.g., Buck and Eder 2018; Parida et al. 2019; Caputo et al. 2021). Overall, this article, to the best of our knowledge, is the first that rigorously systematizes, and structures existing literature analyzing how DT impacts and innovates existing BMs of firms (i.e., DTBMI). In addition, based on the main findings, this article identifies relevant research gaps and derives potential research directions for the future.

3 Methodology

To answer the formulated research questions, we conducted a systematic literature review based on the guidelines of Webster and Watson (2002). Since this article aims to analyze the current state of research regarding DTBMI, a systematic literature review was selected as an appropriate method to identify relevant scientific work. At first, based on our research questions, an appropriate search string for the subjects DT and BM was derived. Based on this selection, we identified the first fundamental literature to derive further relevant key terms for the search string. For example, we found that some researchers use the terms digitization, digitalization, and DT synonymously – therefore, we included all these terms in our final search string. Since we only consider articles that clearly refer to the BM concept, we refrained from adding additional keywords for every single BM element. We subsequently tested the final search string in the used databases to ensure its functionality. The final search string was applied to the title, abstract, and keywords in seven different databases. This provides a broad selection of relevant articles. The final composition of the search string can be obtained from Figure 15.

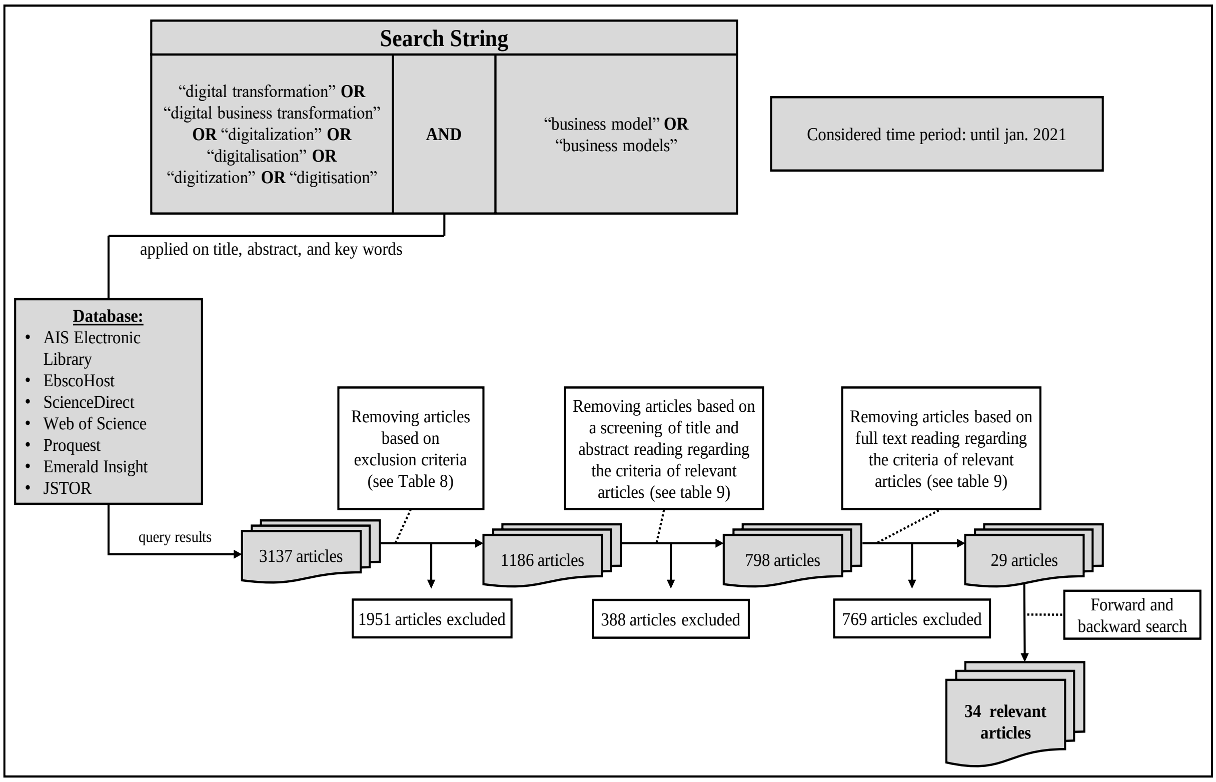

Figure 15. Process of the systematic literature review

Figure 15 illustrates the different process steps to identify relevant articles. We conducted several queries for each database over time. This increases the probability that even the latest publications can be considered. Furthermore, we have refrained from limiting the time period for our literature search. Hence, our literature review considers all scientific articles until January 2021. Since the research field under investigation is still young, conference and journal papers are included. After applying the search string on the different databases, duplicates and irrelevant articles were eliminated based on our exclusion criteria. The overall criteria for exclusion can be obtained from Table 8.

Criteria	Description
1	Removing publications not published in a peer-reviewed journal or conference.
2	Removing articles that are not written in the English language.
3	Removing white papers, commentaries, editorials, and similar articles as they were often rather vague and did not undergo a comprehensive review process.

Table 8. Exclusion criteria

Afterward, we eliminated articles that do not deal with the subject under investigation. We removed some publications after reading the title and some publications after reading the abstract. To finally decide whether an article is relevant or not, two researchers independently read through the pre-selected articles. For each article, both researchers decided whether it is relevant or not. After that, the results were compared, and mismatches were discussed to reach a consensus on their relevance. As part of our decision process, we pre-defined some relevance criteria, which can be obtained from Table 9. To get an all-encompassing overview and not avoid important insights, also previous topic-relevant literature reviews (as discussed in the introduction and theoretical foundations) with relevant information were considered.

Criteria	Description
1	Relevant articles must examine DTBMI (i.e., focusing on (D)BMI as part of DT).
2	Relevant articles must be anchored clearly in the DT literature stream and therefore explicitly refer to the concept of DT.
3	Articles are classified as irrelevant if they only briefly pick up the concept DT and/or the concept BM.
4	Irrelevant are articles that examine the implementation of specific technologies and their impact on BMs (i.e., focusing on digitization instead of DT).
5	Irrelevant are articles that examine the development or emergence of new (digital) BMs without referring to the transformational process of DT regarding existing BMs.

Table 9. Criteria of relevant articles

Lastly, we conducted a forward and backward search based on the remaining relevant articles. During this last step, we found five additional publications not included in the previous database search. This led to a total of 34 relevant publications suitable for answering our research questions.

After selecting the relevant articles, we applied coding techniques borrowed from the grounded theory methodology to identify the relevant concepts of interest (Wolfswinkel et al. 2013). Thereby, we followed the core principles of open coding, axial coding, and selective coding (Corbin and Strauss 1990). As a first coding step, we read the identified articles and coded all relevant excerpts that refer to the general idea of DTBMI as described in the theoretical foundations. Afterwards, we started the process of axial coding. While axial coding, we related the identified codes to each other. As a result of axial coding, first categories and subcategories emerged. Finally, while selective coding, we connected all categories and subcategories and came up with one core category: DTBMI. All related categories can be seen as relevant aspects of research concerning DTBMI. The subcategories represent different expressions of the categories. The coding process ended after a theoretical saturation was achieved. To ensure reliability, the coding process has been done by two researchers.

According to the guidelines of Webster and Watson (2002), the categories and subcategories were transferred to a concept matrix. The final concept matrix, a derived organizing framework, as well as the main insights of the identified articles are discussed in the following section.

4 Results

The main results of our literature review are presented in the form of a concept matrix connecting the identified research articles with the specified concepts of interest (Webster and Watson 2002). The final concept matrix can be obtained from Table 10.

Authors & Year	Research Method	Industry Focus	Concept. Found.	Transformation Aspects			
				Antecedents	Processes	Outcome	Evaluation
Ahmad et al. 2020	Lit. Analysis	not specified				X	
Baber et al. 2019	Case Study	software publ.				X	
Berman 2012	Framework	cross-industry		X	X		
Bican/Brem 2020	Case Study	cross-industry	X				
Bleicher/Stanley 2016	Case Study	cross-industry			X		
Bock/Wiener 2017	Framework	not specified				X	
Böttcher/Weking 2020	Lit. Analysis	not specified		X			
Bouwman et al. 2019	Survey	cross-industry				X	
Caliskan et al.2021	Lit. Analysis	marketing serv.				X	
Delmond et al. 2017	Case Study	cross-industry				X	
Demlehner/Laumer 2020	Lit. Analysis	manufacturing				X	
Doukidis et al. 2020	Framework	cross-industry	X		X	X	
Hanelt et al. 2015	Cont. Analysis	automotive				X	
Hildebrandt et al. 2015	Math. Model	automotive			X		
Klos et al. 2017	Case Study	cross-industry			X	X	
Kotarba 2018	Framework	not specified				X	
Kurti/Haftor 2015	Case Study	book publ.			X		
Levkovskyi et al. 2020	Lit. Analysis	not specified	X	X		X	X
Li 2020	Lit. Analysis	media ind.				X	
Loebbecke/Picot 2015	Lit. Analysis	not specified	X			X	
Mancha/Gordon 2020	Case Study	cross-industry		X	X		
Metzler/Muntermann 2020	Case Study	cross-industry				X	
Nastjuk et al. 2016	Framework	automotive				X	
Priyono et al. 2020	Case Study	manufacturing			X	X	
Remane et al. 2017	Framework	not specified				X	
Rof et al. 2020	Case Study	high. education			X	X	
Sathananthan et al. 2017	Framework	cross-industry			X		
Schallmo et al. 2017	Lit. Analysis	cross-industry		X	X		
Soto Setzke et al. 2020	Case Study	cross-industry			X		
Toutaoui/Benlian 2020	Case Study	cross-industry			X		
Van Tonder et al. 2020	Lit. Analysis	not specified	X				
Venkatesh et al. 2019	Lit. Analysis	service prov.	X				
Warner/Wäger 2019	Case Study	cross-industry	X	X		X	
Weill/Woerner 2013	Framework	cross-industry	X			X	

Table 10. Results of the systematic literature review

4.1 Descriptive Analysis

As illustrated in the following Figure 16, research regarding DTBMI gained increasing attention in recent years. More than half of the analyzed articles were published within the last two years. The number of articles per year (starting year 2012) can be obtained from Figure 16.

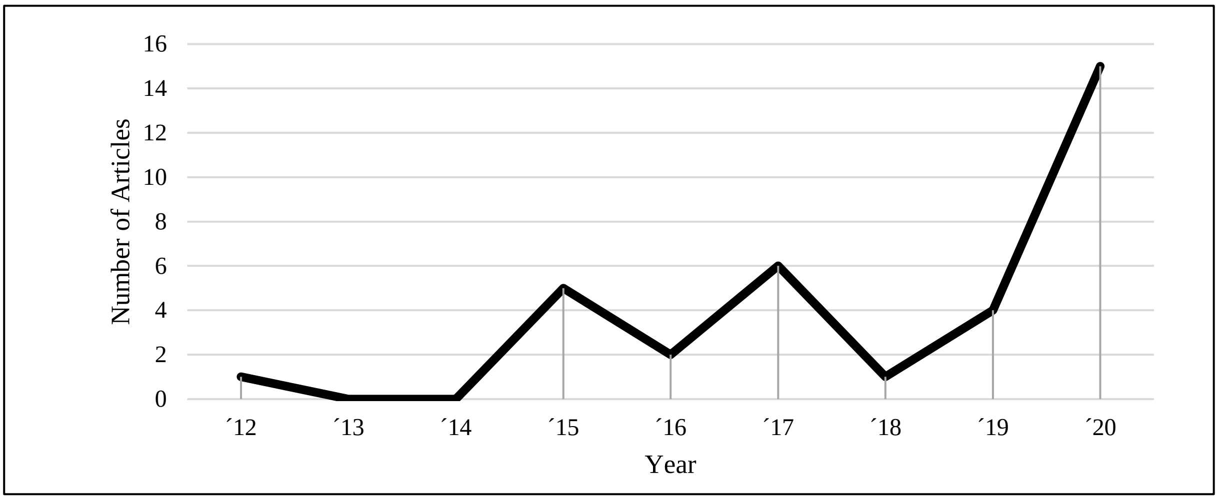

Figure 16. Number of articles per year

Most papers were published in IS journals or IS conference proceedings. Others were published in management or technology and innovation (incl. computer science) literature. Thereby, we distinguished between the different subject areas according to the classification of the VHB Jourqual 3 (*https://vhbonline.org/en/vhb4you/vhb-jourqual/vhb-jourqual-3/complete-list*). The number of articles per subject area is shown in Figure 17.

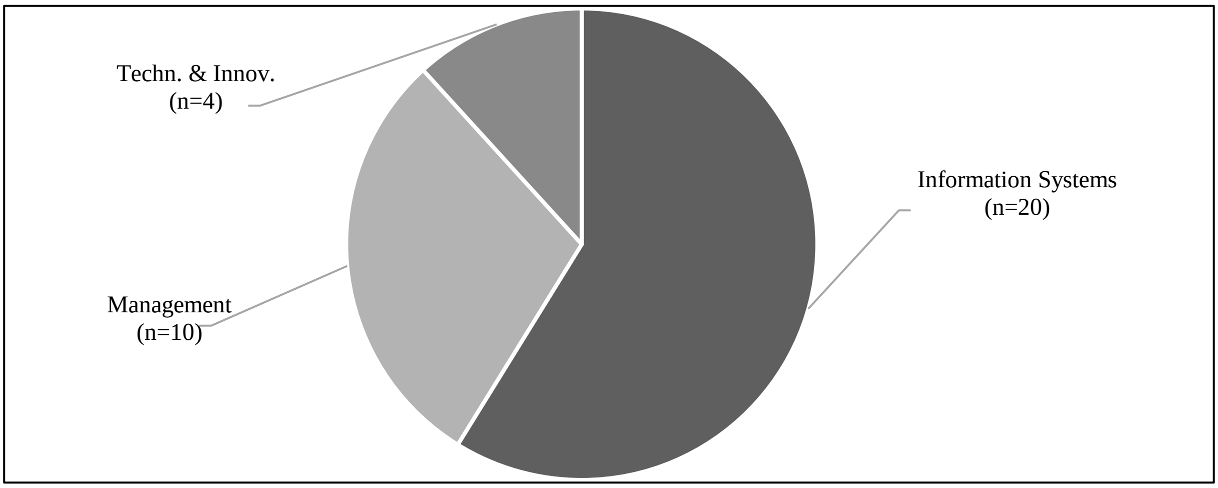

Figure 17. Number of articles per discipline

The distribution of the applied research methods can be obtained from Figure 18. We distinguish between different research methods as proposed by Palvia et al. (2004). Our results show that existing research on DTBMI is primarily qualitative, especially including case studies, literature analyses (not only reviews), and the conceptual development of frameworks and models. Thereby, each article covers only partial areas of DTBMI.

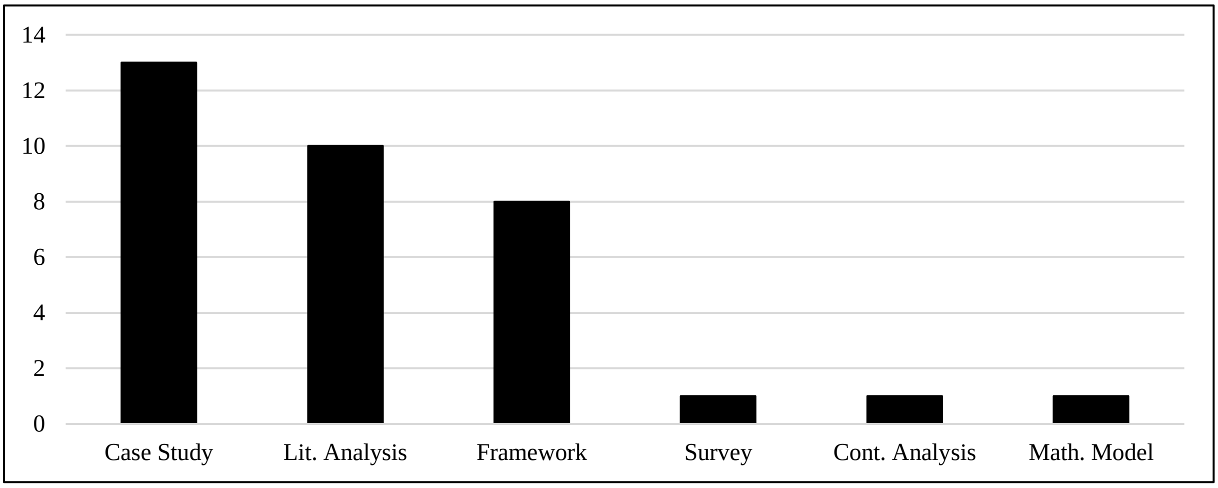

Figure 18. Number of articles per research methodology

In addition, existing literature covers a wide range of industries. Whereas some articles focus on specific industries, others focus on cross-industry phenomena or are written independently of specific industries. The automotive, manufacturing, and specific media industries are strongly represented, whereas other industries, such as the financial services industry and the public sector, are rather underrepresented. The entire distribution of articles by industry is shown in Figure 19.

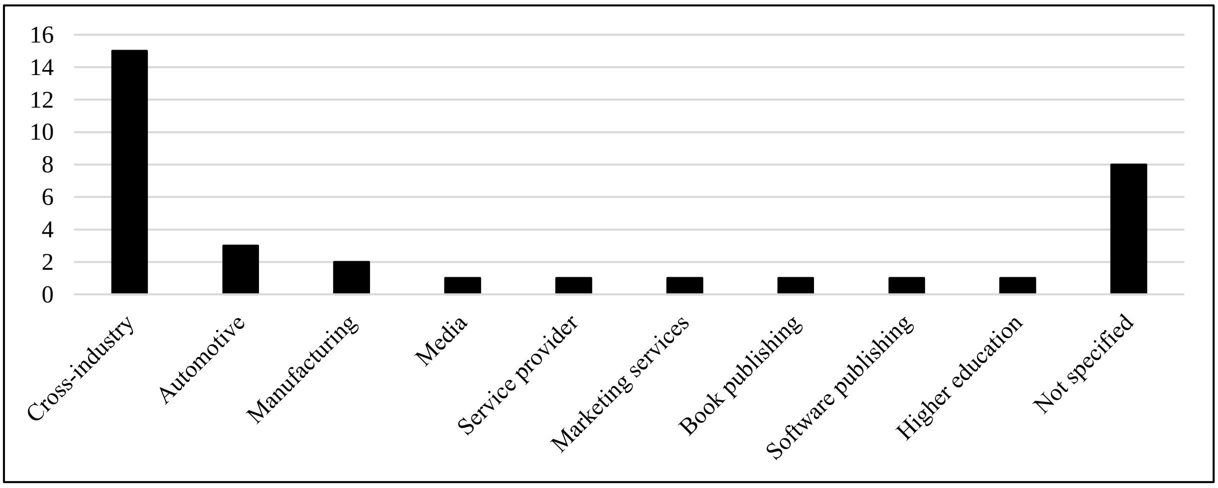

Figure 19. Number of articles per industry

4.2 Organizing Framework of Research on DTBMI

As a result of our analysis, we came up with five main categories (i.e., concepts) representing different perspectives on DTBMI. Across the main categories, we further identified specific subcategories. The final organizing framework serving as a systematization of DTBMI research is represented in Figure 20.

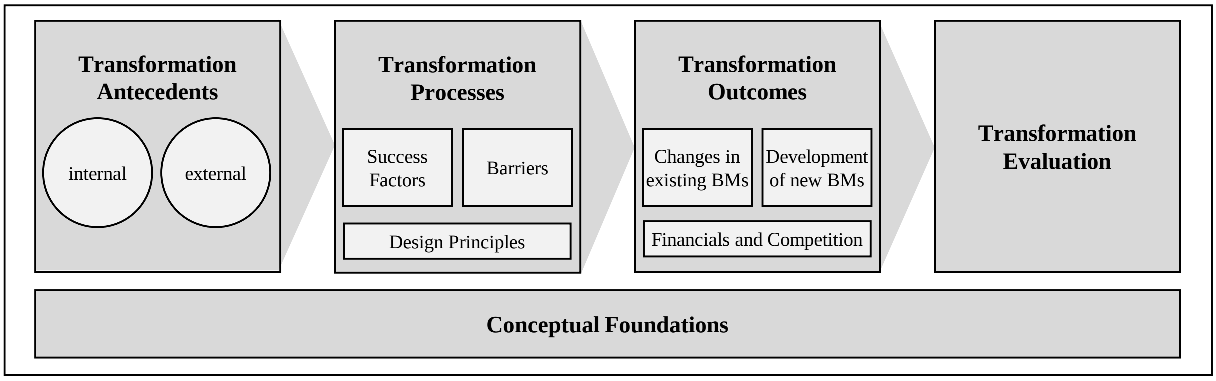

Figure 20. Organizing framework of research on DTBMI

Whereas some articles are related to the conceptual foundations of DTBMI, most articles focus on specific transformation-related aspects. Research focusing on transformation antecedents addresses internal and external antecedents that trigger DTBMI (Böttcher and Weking 2020). Those articles focusing on the processes of DTBMI primarily examine related design principles, success factors, and barriers to DTBMI. Research focusing on outcomes on DTBMI implies that there are two different possible BM-related transformation outcomes: (1) changes in an existing BM or (2) the development of a new (digital) BM. In addition, existing research found financial and competitive outcomes of DTBMI. Finally, literature on transformation evaluation deals with different success measures concerning DTBMI. In the following, we discuss the main insights of each category.

4.2.1 Conceptual Foundations

Some of the identified articles deal, at least partially, with the conceptual foundations regarding the connection of the concepts DT and BM. Authors agree that the BM represents a core element concerning the DT of firms (e.g., Warner and Wäger 2019; Bican and Brem 2020; Soto Setzke et al. 2020). DTBMI, thereby, should be anchored in a firm's digitalization strategy (Rof et al. 2020). Especially the digitalization of firms' ecosystems makes innovating the BM indispensable (Bican and Brem 2020). In that regard, existing research indicates that BM transformation is one central element of DT leading to digital organizational modifications, the establishment of new BMs, and an international digital expansion (Doukidis et al. 2020; Levkovskyi et al. 2020; Soto Setzke et al. 2020). Warner and Wäger (2019) highlight that a strategic renewal of the existing BM is an intermediary step of DT to achieve a cultural change within an organization.

4.2.2 Transformation Antecedents

External Antecedents

Existing research agrees that changing customer needs and market conditions are among the most important triggers demanding a strategic renewal of the existing BM (Warner and Wäger 2019; Böttcher and Weking 2020). For example, due to advances in mobile technology, more customers are always connected, leading to the possibility to interact with them anytime (Schallmo et al. 2017). Furthermore, an ongoing need for a servitization logic triggers the replacement of traditional product logics with a BM combining digital products and personal services (Warner and Wäger 2019). In addition, ongoing technological developments are enablers for DTBMI (Berman 2012; Schallmo et al. 2017). In this context, Schallmo et al. (2017) categorized digital enablers and applications into four categories: digital data (e.g., big data and IoT), automation (e.g., robotics and drones), networking (e.g., cloud computing, platforms, and smart factory), and digital customer access (social networks, e-commerce, mobile internet). In addition, Mancha and Gordon (2020) as well as Warner and Wäger (2019) found that digital platforms drive DTBMI in many incumbent firms. Finally, competitive pressure is another antecedent for DTBMI (Böttcher and Weking 2020).

Internal Antecedents

Internal antecedents that trigger DTBMI include financial need (e.g., shrinking profits), technology exploitation (e.g., existing technological skills that could be exploited by BMI), or BM limitations (e.g., when an existing BM is not suitable for further growth) (Böttcher and Weking 2020).

4.2.3 Transformation Processes

Design Principles

Some researchers developed roadmaps describing a BM design process as part of DTBMI. For example, Schallmo et al. (2017) introduced a five-step roadmap for a successful DT of BMs: (1) digital reality, (2) digital ambition, (3) digital potential, (4) digital fit, and (5) digital implementation. Other researchers introduced BM design processes (e.g., Bleicher and Stanley 2016; Remane et al. 2017; Sathananthan et al. 2017). All these models have in common that they highlight the importance of describing the current BM, identifying existing and potential value drivers, and exploiting digitization to discover new BMs.

Success Factors

The importance of different capabilities to succeed in DTBMI is highlighted in many articles (e.g., Berman 2012; Soto Setzke et al. 2020). For example, Soto Setzke et al. (2020) investigated pathways for successful BMI in the context of DT and found that particularly IT capabilities and dynamic capabilities are major success factors. Concerning IT capabilities, Mancha and Gordon (2020) and Warner and Wäger (2019) emphasize that especially digital platforms and mobile technologies play a major role in innovating the BM as part of a DT and, therefore, represent major success factors. For example, digital platforms and mobile technology can be used to create supplementary multisided value propositions or to develop a servitization logic (Warner and Wäger 2019). On the other hand, dynamic capabilities are especially important in terms of learning from failure to develop the capabilities that are needed to implement and realize future changes (Soto Setzke et al. 2020). Due to the need for a large-scale organizational and cultural transformation, a digital enrichment of an existing BM requires more capabilities than establishing a completely new BM. Firms that establish completely new BMs mostly build subsidiaries or new departments, implying that existing parts of the organization can remain unaffected by transformation. Transforming a traditional BM, however, requires evolving the whole existing organization (Soto Setzke et al. 2020). Other important capabilities include the ability to navigate innovation ecosystems to collaborate with external partners, strategic agility, and the development of a prosumer logic (Warner and Wäger 2019).

As many firms lack essential capabilities, Hildebrandt et al. (2015) argue that executing mergers and acquisitions (M&As) is an appropriate way to obtain missing capabilities. Specifically, their research results indicate that incumbent firms can use M&As to acquire complementary capabilities relevant for developing BMs that combine physical and digital components (Hildebrandt et al. 2015).

Barriers

The process of DTBMI holds various barriers and organizational challenges. Especially the transformation from traditional/analog to digital causes major difficulties in manifold ways (e.g., Kurti and Haftor 2015; Rof et al. 2020). Recently, Rof et al. (2020) identified a list of tensions and corresponding solutions arising within the process of DTBMI. The tensions and solutions are structured across the value creation, value proposition, and value capturing function of a BM. In addition, Warner and Wäger (2019) found that balancing potential new (digital) BMs with existing BMs is another major challenge requiring transformational leadership and decentralization for a good alignment. In that regard, a good alignment can lead to multiple synergy effects as a benefit for both the digital and the traditional BM (Toutaoui and Benlian 2020). These synergies mainly concern existing key resources, the established cost structure, shared channels, and customer relationship issues where the new BM can profit from and an enhanced value proposition and complementary key resources where the traditional BM can benefit from (Toutaoui and Benlian 2020). Overall, firms that successfully align the physical and digital components of both variants are particularly successful in DTBMI (Berman 2012; Toutaoui and Benlian 2020).

4.2.4 Transformation Outcomes

Our analysis indicates that DT can enable two different kinds of BMI – transformational changes within the existing BM or the invention of a new (digital) BM (e.g., Warner and Wäger 2019; Doukidis et al. 2020; Levkovskyi et al. 2020). In that regard, Li (2020) argues that DT-driven changes in BMs can be classified into automation (digital technologies are used to enhance or automate existing processes and tasks), extension (using digital technologies to supplement existing activities and processes through new ways of conducting business), and transformation (using digital technologies to replace the traditional business). Irrespective of this, existing research suggests that DT concerning BMs involves more than implementing minor adjustments to a selected BM element (e.g., introducing new distribution channels). Rather, it impacts the entire BM of a firm or at least major parts of it (e.g., Hanelt et al. 2015; Piccinini et al. 2015; Metzler and Muntermann 2020). However, its impact differs across industries. Whereas firms of some selected industries (e.g., music industry, banking industry) are undergoing revolutionary changes within their BMs, firms of other industries (e.g., manufacturing industry) lag behind (Demlehner and Laumer 2020). These findings reflect the specific dynamics of DT varying across different industries.

Finally, according to Weill and Woerner (2013), firms should choose between four promising BMs for the digital era: omnichannel business, ecosystem driver, supplier, or modular producer. A related choice depends on the end customer's knowledge and the business design (value chain or ecosystem).

Changes in Existing Business Models

There is already a rich amount of research on the changes that DT causes within BMs (e.g., Hanelt et al. 2015; Li 2020; Metzler and Muntermann 2020; Rof et al. 2020; Caliskan et al. 2021). Mostly, BM frameworks (e.g., the BMC) are used to highlight such changes within each BM element of firms (e.g., Kotarba 2018; Baber et al. 2019; Li 2020; Metzler and Muntermann 2020). Researchers indicate that usually the whole BM of a firm (i.e., all its elements) is affected by DT endeavors (Li 2020; Metzler and Muntermann 2020). Thereby, Metzler and Muntermann (2020), as well as Rof et al. (2020), indicate that DT-driven changes within a BM evoke major challenges that need to be addressed by the management through appropriate organizational responses. Research analyzing changes in existing BMs indicates that the impact of DT on BMs differs across different BM elements. Whereas some elements are rather strongly affected by DT ventures, others experience rather small changes (Metzler and Muntermann 2020; Rof et al. 2020). Major changes especially comprise a co-production of the value proposition, an increasing importance of complementary key resources and partnerships, and a closer customer relationship (e.g., Delmond et al. 2017; Metzler and Muntermann 2020). Whereas most research articles examine incumbent firms across traditional industries (e.g., Hanelt et al. 2015; Metzler and Muntermann 2020), Baber et al. (2019) indicate that digital entrepreneurial firms are also affected by DTBMI. In the BM of these firms, effectuation logic and causation logic play an important role, especially when moving from physical distribution channels to digital distribution platforms.

Finally, a few articles found negative impacts of DT on specific BM elements. Loebbecke and Picot (2015) indicate a negative impact on the key resource human labor (e.g., human labor gets replaced by robots). Nastjuk et al. (2016) found a negative impact of digitalized BMs on customer relationships through an increased stress perception of customers (e.g., through automated pricing systems).

Development of New Business Models

DT has the power to fuel the development of entirely new BMs driven by the use of digital technologies (e.g., Remane et al. 2017; Ahmad et al. 2020). Existing literature primarily refers to such BMs as digital BMs, which can be defined as "*the mixed utilization of smart products and digital smart services, the digitization of internal processes, the operation within an ecosystem, the accessibility of a platform, as well as the utilization of data analytics*" (Ahmad et al. 2020, p. 4553). As part of taxonomy development, Bock and Wiener (2017) found that these digital BMs can be conceptualized across five dimensions: (1) digital offering, (2) digital experience, (3) digital platform, (4) data analytics, and (5) digital pricing, differentiating digital BMs from traditional BMs.

Even though the transformation of an existing BM can be seen as an elementary component of DT, Warner and Wäger (2019) argue that transforming the BM is just an intermediate step to trigger more profound changes in a firm's corporate culture.

Financial and Competitive Outcomes

Very few articles deal with the financial and competitive outcomes of DTBMI. Bouwman et al. (2019) found that firms allocating more resources to BMI as part of their DT have an increased level of BM experimentation, finally leading to increased firm performance. In addition, Böttcher and Weking (2020) found seven possible financial and competitive outcomes: funding, stock value, market share, cannibalization, expansion, financial improvement, and intangibles.

4.2.5 Transformation Evaluation

Concerning evaluation measures, Levkovskyi et al. (2020) introduced some financial measures to evaluate the success of DTBMI. The authors indicate that appropriate success measures are: (1) Net revenue, (2) return on investment, and (3) market share.

5 Discussion

5.1 Future Research Directions

Our study shows that DTBMI is a growing field of research but still at an early stage. To synthesize worthwhile future research directions, we especially analyzed the discussion part (i.e., limitations and future research opportunities) of our final sample of literature. For each concept of our literature review, we derived open research questions, which can be found in Table 11.

Concept	Selected Open Research Questions
Conceptual Foundations	• How do the different concepts of BMI relate to DT? • To what extent does the success of DT depend on DTBMI?
DTBMI Antecedents	• How do DTBMI antecedents differ across industries and geographical regions? • How do DTBMI antecedents differ across incumbent and non-incumbent firms?
DTBMI Processes	• How do specific IT and dynamic capabilities create a competitive advantage concerning DTBMI? • How can firms be divided concerning individual needs of specific capabilities concerning DTBMI? • How does the process of DTBMI differ across incumbent and non-incumbent firms? • How should the process of DTBMI be implemented in a firm's DT strategy?
DTBMI Outcomes	• How can the specific DTBMI outcomes be further unraveled and categorized? • How does DTBMI impact the customer perception of the transforming firms?
DTBMI Evaluation	• What are appropriate financial and non-financial success measures of DTBMI? • How should an appropriate (re-)evaluation process of DTBMI look like?

Table 11. Selected open research questions

Research referring to the *conceptual foundations* of DTBMI agrees that the BM is an important concept in the DT of firms and BMI is an essential tool to drive such DT. However, it remains unclear how the existing BMI concepts relate to DT and which concrete role DTBMI plays in the success of DT. Furthermore, whereas existing research found that internal and external DTBMI antecedents exist, future research on *transformation antecedents* could explore and discuss industrial and geographical differences as well as differences between incumbents and non-incumbents. We found relatively much research regarding *transformation processes*. However, it is, for example, not yet clear how specific IT and dynamic capabilities create a competitive advantage concerning DTBMI and how firms can be divided concerning individual needs of specific capabilities concerning DTBMI. Regarding *transformation outcomes*, most articles focus on changes within existing BMs or the emergence of new BMs. However, it would be interesting to see how DTBMI outcomes can be further unraveled and categorized, e.g., by taxonomy development. Furthermore, little is known about the impact of DTBMI on the customer perception of the transforming firms. Future research could elaborate on this. Finally, future research on *transformation evaluation* should investigate how to measure and (re-)evaluate the success of DTBMI. In addition, elaborating an evaluation process of DTBMI would be beneficial.

5.2 Implications and Limitations

In this study, we conceptualized DTBMI, which can be seen as an essential and growing DT research stream and provide an organizing framework serving as a systematization of DTBMI research. Based on our literature review, we can confirm existing statements in the sense that DT has a massive impact on existing BMs (e.g., Bharadwaj et al. 2013; Fitzgerald et al. 2013; Hess et al. 2016). This impact is primarily reflected in changes within the existing BM or the development of an entirely new (digital) BM. However, innovating the BM as part of DT is a complex endeavor. Literature examining this process primarily focuses on design principles, success factors, and barriers. Other identified articles examine relevant antecedents or evaluation opportunities regarding DTBMI. The results of our literature review show that research on DTBMI is still at an early stage. In each of the identified research avenues, we found relevant research gaps that can be addressed by future research.

Despite the careful design of our research approach, this study is subject to some limitations. First, the methodological approach could be enhanced by additionally applying the search string on the full text of potential articles. The search string could also be adjusted by adding specific keywords for different BM elements. In addition, since this study primarily focuses on examining the content-related state of research, other aspects such as the identified articles' underlying research methods and theoretical lenses could be analyzed in more detail in future research. Finally, since we first introduced the concept of DTBMI in this paper, we analyzed articles that refer to this concept in different ways (e.g., BMI and DBMI as part of DT). Overall, all of these potential extensions provide the opportunity for gaining more information. However, some of these potential extensions also entail the risk of losing the research focus.

6 Conclusion

Many definitions of DT indicate that it has a major impact on firms' BMs. However, existing research regarding the impact of DT on BMs is still in its infancy. Against this background, we aimed to structure the existing literature in this field and derive future research directions. By conducting a systematic literature review, we found that the insights of the existing literature can be classified into five categories: (1) conceptual foundations, (2) transformation antecedents, (3) transformation processes, (4) transformation outcomes, and (5) transformation evaluation. Research concerning DTBMI is still rare and future research is encouraged to close research gaps to make the picture of DTBMI clearer.

I.2. DT of Incumbent Firm's BM (Study 2)

Paper Title:

The Impact of Digital Transformation on Incumbent Firms: An Analysis of Changes, Challenges, and Responses at the Business Model Level

Abstract: The digital transformation has become a key concern for incumbent firms in traditional industries. However, the impact of digital transformation on the business model of such firms has been insufficiently investigated so far. Particularly, existing research lacks a cross-industry overview of the impact of digital transformation on the overall business model of incumbent firms in traditional industries, including detailed elaborated dimensions and characteristics of this impact. This paper aims to address this specific research gap by analyzing the impact of digital transformation, which we conceptualize as changes, challenges, and responses, on each business model element of incumbent firms in traditional industries. By conducting in-depth multiple case study research in incumbent firms across four major traditional industries, we contribute to the literature of digital transformation by providing new insights on changes within the business model, resulting challenges, as well as potential organizational responses on how to react to these challenges.

Outlet: International Conference on Information Systems (ICIS) 2020

Citation: Metzler, D. R. and Muntermann, J. 2020. "The Impact of Digital Transformation on Incumbent Firms: An Analysis of Changes, Challenges, and Responses at the Business Model Level," in *Proceedings of the 41st International Conference on Information Systems*, Hyderabad, India.

Keywords: Digital Transformation, Incumbent Firms, Business Model Change, Case Study Research, Qualitative Research

1 Introduction

The phenomenon of digital transformation remains one of the most relevant topics for both researchers and practitioners alike. Digital transformation can be described as "*the changes digital technologies can bring about in a company's business model, which result in changed products or organizational structures or in the automation of processes*" (Hess et al. 2016, p. 124). The central message of this and other definitions is that digital transformation is triggered by digital technologies and comprises of major changes within the business model of firms (e.g., Fitzgerald et al. 2013; Matt et al. 2015; Hess et al. 2016). Especially for incumbent firms, which we define as firms, that (1) are positioned in a traditional industry, (2) were established before the digital revolution, and (3) whose business models were not originally based on the use of digital technologies, these changes are needed to compete in an increasingly digitalized world. Traditional industries thereby can be defined as industries, whose focus is mainly on producing and selling physical goods. Without undergoing changes through digital transformation, these firms would lose market share to new firms with business models based on the use of digital technologies entering traditional industries. It is not uncommon that such firms can better adapt to fast-moving market conditions and changing customer needs (Sebastian et al. 2017). However, even though significant changes are needed to improve the business and subsequently to compete in a digitalized world, these changes encompass major challenges for incumbent firms, including the need to exploit existing capabilities while also explore new (digital) capabilities and the adaption of these new capabilities to the firm's existing infrastructure (Gregory et al. 2014; Svahn et al. 2017). Furthermore, incumbent firms in traditional industries are particularly strong affected by digitalization challenges as their core products usually cannot be completely digitized (Hanelt et al. 2015). Consequently, executives of incumbent firms need to drive changes within their existing business models, while also being prepared to find ways to react on resulting challenges.

Prior research has started discussing digital transformation in relation to business models; however, its scope is limited to specific business model elements or to specific industries (e.g., Hansen and Sia 2015; Piccinini et al. 2015). Most existing literature primarily focus on customer- and product-centric elements of the business model. For example, Barrett et al. (2015) have found that digital technologies enable the creation of new value propositions that rely increasingly on the provision of services. Additionally, firms use digital technologies to augment the sales of physical products with the sales of services or even replace physical products by services (e.g., Porter and Heppelmann 2014). Other researchers, like Hansen and Sia (2015), focus on marketing and sales channels and show that firms use digital technologies to digitize their distribution and sales channels. However, because the different elements of a business model are interrelated and therefore cannot be examined in isolation, the impact of digital transformation should be additionally investigated on the overall business model.

Additionally, there is a lack of clarity regarding the impact of digital transformation on incumbent firm’s business models. In existing literature, this impact is mainly associated with changes through the use of digital technologies (e.g., Piccinini et al. 2015; Hess et al. 2016; Vial 2019). However, it is not clear whether the impact of digital transformation is not even more far-reaching. In this context, by analyzing extant definitions of digital transformation, Vial (2019) show that the bulk of literature conflates the concept of digital transformation and its impact. Furthermore, he found that digital transformation primarily has an impact on a firm’s organizational level. This is reflected in operational efficiency (i.e., automation and improvement of process performance as well as costs savings) and organizational performance (e.g., innovativeness, financial performance, and competitive advantage). However, while the author gives insights on the impact of digital transformation on an overall firm-level, it remains unclear how this impact can be conceptualized at the business model level and how it differs regarding the specific business model elements of incumbent firms.

Overall, there is a lack of a comprehensive and cross-industry overview of the impact of digital transformation on the overall business model of incumbent firms, including detailed elaborated dimensions and characteristics of this impact. This paper aims to address this specific research gap by analyzing the impact of digital transformation, which we conceptualize as changes, challenges, and responses, on each business model element of incumbent firms in traditional industries. Therefore, the underlying research question is as follows:

How does digital transformation impact the overall business model of incumbent firms in traditional industries?

In order to answer this research question, we conducted an exploratory case study based on the guidelines of Yin (2014). In our data collection, we conducted in-depth semi-structured expert interviews with senior management executives of incumbent firms of four different traditional industries: (1) automotive, (2) pharmaceutics, (3) industrial products, and (4) consumer & retail. In addition, to get a more comprehensive overview, we conducted further interviews with consultants and partners of a major international consulting firm who have longstanding experiences within the relevant industries. Since existing research already indicates that digital transformation primarily comprises changes within a firm’s business model (e.g., Hess et al. 2016), the business model concept provides a solid basis for exploring the impact of digital transformation on incumbent firms and therefore serves as the main theoretical lens for the subsequent data analysis. In this context, the business model canvas, introduced by Osterwalder and Pigneur (2010), is considered to be a well-accepted and detailed description of a firm’s business model. The results of our study provide new insights on changes, challenges, and responses regarding the digital transformation of incumbent firms at the business model level.

In order to provide sound theoretical foundations and to gain valuable insights regarding our research question, this paper is structured as follows. Starting with the theoretical foundations, we introduce digital transformation and business models as the main concepts of our paper.

Secondly, we introduce the methodological foundation of the conducted case study. Thirdly, we present findings of the case study. Fourthly, in the context of a discussion, limitations of our study and implications for research and practice are presented. Finally, the conclusion summarizes the most important findings.

2 Theoretical Foundations

2.1 Digital Transformation of Incumbent Firms in Traditional Industries

The rapid pace of development in information technology (IT) has significantly shaped the turbulent economic environment and societal disruptions we face today. In the last decade, we saw the advent of so-called digital technologies, which had a severe impact on the way we live, and the way business is done across various industries (Hess et al. 2016; Nambisan et al. 2017). Digital technologies can be conceptualized as technologies that combine information, computing, communication and connectivity technologies (Bharadwaj et al. 2013). More specifically, digital technologies can be characterized by using the acronym SMACIT, which refers to social, mobile, analytics, cloud computing, and internet of things (IoT) (Sebastian et al. 2017). Other technologies, such as artificial intelligence, blockchain, robotics, and virtual reality are also implied when referring to SMACIT (Sebastian et al. 2017). Previous research has shown that digital technologies have the potential to enable the development of new products, services, or even business models (Yoo et al. 2012; Fichman et al. 2014; Lyytinen et al. 2016).

The use of digital technologies to enable major business improvements (such as enhancing customer experience, streamlining operations, or creating new business models) can be described as digital transformation (Fitzgerald et al. 2013). Digital transformation is a relatively new concept in IS research and its implications for firms reach far beyond process automation and resource digitization. Rather, it has the potential to (re)define a firms' value propositions(s) and to change its whole identity (Wessel et al. 2021). Therefore, digital transformation can be seen as an evolution of the concept of IT-enabled transformation, which deals with the use of digital technologies to support already existing value propositions and to reinforce a firms' existing identity (Vial 2019; Wessel et al. 2021). Existing research on digital transformation has dealt with novel strategic concepts, especially digital business strategy (DBS) and digital transformation strategy (DTS). Whereas a DBS can be defined as an organizational strategy that aims to create differential value by leveraging digital resources (Bharadwaj et al. 2013), a DTS represents the central concept to coordinate, prioritize, and implement the process of digital transformation within a firm, leading to a desired future state of being digitally transformed (Matt et al. 2015). Other research on digital transformation, which did not primarily focus on such strategic concepts, has been done under a variety of homonymous labels including digitization, digitalization, and DT (Muehlburger et al. 2019).

Especially in incumbent firms across traditional industries, the digital transformation has become a high-level strategic goal on the agendas of executives (Fitzgerald et al. 2013; Hess et al. 2016; Sebastian et al. 2017; Svahn et al. 2017). For a general understanding, in this paper we define incumbent firms as firms, that (1) are positioned in a traditional industry, (2) were established before the digital revolution, and (3) whose business models were not originally based on the use of digital technologies. Traditional industries thereby can be defined as industries, whose focus is mainly on producing and selling physical goods. For incumbent firms in such industries, the advent of digital technologies is not only an opportunity to bring about positive changes to improve the business, but they also pose major challenges. A major challenge of such firms is the fact that their business models are typically based on physical goods that usually cannot be completely digitized (Hanelt et al. 2015). Another challenging endeavor is the emergence of new firms with business models based on the use of digital technologies that enter traditional industries and claim part of the market share (Veit et al. 2014). It is not uncommon that these firms can better adapt to fast-moving market conditions and changing customer needs (Sebastian et al. 2017). To be able to compete in an increasingly digitalized world, it is essential for incumbent firms to undergo a digital transformation. To successfully digital transform their firms, executives need to consider the potential of digital technologies and how they can bring about positive changes in the processes, organizational structures, and business model of a firm (Hess et al. 2016). However, although changes through digital transformation are essential to compete in a digitalized world, executives at the same time have to consider that related changes encompass major challenges, including the need to exploit existing capabilities while also exploring new (digital) capabilities and adapting these new capabilities to the firm's existing infrastructure (Svahn et al. 2017). In this regard, the development of ambidextrous capabilities to address contrasting demands and resolve paradoxical tensions is essential (Gregory et al. 2014). An additional complicating factor is the asset-heaviness of most incumbent firms' business models and the typically high number of established employees (Zhang et al. 2018; Sebastian et al. 2017). Overall, executives of incumbent firms must drive change, while at the same time they need to resolve potential challenges by finding appropriate organizational responses.

2.2 Business Models

Since the early 2000s, research on business models gained an increasing popularity across various disciplines, including information systems, entrepreneurship, innovation management, and technology management (e.g., Johnson et al. 2008; Zott et al. 2011; Veit et al. 2014). There exist many different approaches for defining the business model concept. In this paper, we refer to the definition of Osterwalder and Pigneur (2010), who define a business model as a blueprint that describes the basic principles of how an organization creates value and how this value is transferred to stakeholders (e.g., customers, the focal firms, partners). Therefore, the business model concept can be seen as a link between business strategy and business operations. Consequently, the business model concept is an important tool in supporting strategic choices of an organization (Myrthianos et al. 2014; Parry et al. 2014). The definition of Osterwalder and Pigneur (2010) is largely consistent with the definitions provided by other researchers, who also refer to the value-creation functions, delivery functions, and capturing functions of a business model (e.g., Chesbrough and Rosenbloom 2002; Shafer et al. 2005; Zott et al. 2011). Besides many different approaches to define a business model, there are also various approaches to define the individual elements of a business model. For example, Hamel (2000) defines the components of a business model as core strategy, strategic resources, customer interface, and value network. More recently, Osterwalder and Pigneur (2010) introduced the so-called business model canvas, which is independent of industry affiliation and describes the business model of a firm as a combination of four business model pillars, comprising nine elements: (1) value propositions (value propositions of products/services), (2) customer interface (customer relationships, customer segments, channels), (3) infrastructure management (key activities, key resources, key partners), and (4) financial aspects (cost structure, revenue streams). In recent years, the business model canvas has gained increasing attention from both researchers and practitioners alike.

By representing an essential "tool of alignment" to bring together the business strategy of a firm and the operationalization of this strategy, the business model concept is of great importance for research focusing on digital transformation (Al-Debei and Avison 2010). Consequently, researchers already anticipate "*the beginning of an academic era in which business models form the central unit of analysis*" (Veit et al. 2014, p. 46). According to various definitions, the digital transformation of a firm is associated with changes in the existing business model of firms or the creation of completely new business models (e.g., Fitzgerald et al. 2013; Piccinini et al. 2015; Hess et al. 2016). By covering the many different aspects that describe the basic functioning of a firm's business in a holistic manner, and typically being independent of industry affiliation, the business model concept provides a solid basis for exploring the impact of digital transformation on incumbent firms across traditional industries in a holistic manner.

Recent literature already shed light on specific changes digital technologies cause in selected elements of the business model of incumbent firms. For example, digital technologies cause changes within customer expectations and demands. In order to remain competitive, firms need to be responsive to supplement or reevaluate their traditional value propositions (e.g., Weill and Woerner 2013; Aversa et al. 2017). Digital technologies also cause a shift regarding the expectations of employees and other interest groups of a firm, which requires significant change within a firm's infrastructure (e.g., Parry and Strohmeier 2014; Singh and Dangmei 2016). In general, to gain business benefits from digital technologies and to compete in a digitalized world, firms should rethink every aspect of their traditional business model and must therefore drive change as needed (Westerman et al. 2014a; Loonam et al. 2018). Executives across all industries should be prepared to reinvent their business model(s) as needed. According to

Westerman et al. (2014), on a firm-level, three main reasons exist to reinvent the traditional business model. First, by reinventing their business model, firms have the opportunity to reorganize value chains and improve their competitive position. Second, firms can create a unique selling proposition. And third, due to ever-emerging new digital technologies, which lead to opportunities and threats, firms of all industries must rethink the way they do business continuously. However, despite these suggestions, Westerman et al. (2014) found that most firms remain with their traditional business model without launching new businesses. Mainly, because they consider it too risky. Thus, firms favor existing models with higher gross margins in order to not threaten the profitability of established business models. However, from a long-term perspective, it seems risky to ignore the potential of new, digitalized business models, because, by trying to protect the status quo, executives hinder experimentation with innovative business model archetypes (Warner and Wäger 2019). Overall, existing literature shows that a major barrier for incumbent firms is the challenge of balancing new learning with existing performance (Itami and Nishino 2010).

Whereas prior research has already started discussing the impact of digital transformation in relation to business models, the focus has mainly been on specific business model elements or specific industries (e.g., Hanelt et al. 2015; Hansen and Sia 2015; Piccinini et al. 2015). However, because the different elements of a business model interrelate and therefore cannot be examined in isolation from each other, it is more appropriate to investigate the impact of digital transformation on the overall business model of a firm. Additionally, a clear conceptualization of the impact of digital transformation on incumbent firm's business models is missing. With this study, we approach these research gaps by providing new insights on the impact of digital transformation on the overall business model of incumbent firms in traditional industries, including detailed elaborated dimensions and characteristics of this impact.

3 Methodology

To answer the underlying research question, we conducted an exploratory case study. The case study as a research method was chosen because this study deals with a contemporary phenomenon in a real-life context where control over behavioral events is not required (Yin 2014). Furthermore, since the addressed phenomenon is complex and relatively new, we formulated an exploratory "how" research question, which also justifies a case study as an appropriate research method (Yin 2014).

3.1 Case Study Setting

Given the investigative nature of this research, we chose a multiple case study design (Yin 2014). The use of a multiple case study was motivated by (i) the possibility to strengthen our findings in light of replication logic (Eisenhardt 1989b; Yin 2014), and (ii) the awareness that evidence from multiple cases can lead to more robust conclusions by being more compelling

(Herriott and Firestone 1983). As the aim of this research is to get a cross-industry overview of the impact of digital transformation on the individual business model elements of incumbent firms in traditional industries, we decided to conduct the case study within four different industries: (1) automotive, (2) pharmaceutics, (3) industrial products, and (4) consumer & retail. The reason for choosing these industries was that all of them meet our definition of traditional industries, whose focus is mainly on producing and selling physical goods and therefore are strongly affected by digitalization issues. Furthermore, discussions with industry experts and further investigations as part of our pre-study have shown that these industries are particularly well suited to observe the impact of digital transformation on the business model of incumbent firms. Finally, these industries play a major role in the European economy.

Once the industries were defined, we decided to choose at least two firms for each industry as the main units of analysis. This allowed us to validate insights and to perform cross-firm comparisons. We chose the specific firms based on our definition of incumbent firms, i.e., they are all firms that (1) are positioned in a traditional industry, (2) were established before the digital revolution, and (3) whose business models were not originally based on the use of digital technologies. Furthermore, potential firms had to be in the process of digital transformation. The decision to choose the specific firms and industries was additionally discussed with domain experts of a major international management consulting firm as part of our pre-study. The following Table 12 gives a comprehensive overview of the selected firms, which all matched our requirements.

Business	Industry Sector	Field of Activity	Age	Revenue (€)
B1	Automotive	Automotive Manufacturer	>80 yrs.	>200 bn.
B2		Automotive Supplier	>140 yrs.	>40 bn.
B3	Pharmaceutics	Pharmaceutical Manufacturer	>180 yrs.	>7 bn.
B4		Pharmaceutical Manufacturer	>130 yrs.	>16 bn.
B5		Pharmaceutical Manufacturer	>350 yrs.	>15 bn.
B6	Industrial Products	Manufacturer of Chemicals	>150 yrs.	>60 bn.
B7		Building Material Manufacturer	>70 yrs.	>0,5 bn.
B8	Consumer & Retail	Consumer Goods Manufacturer	>140 yrs.	>20 bn.
B9		Consumer Goods Wholesaler	>50 yrs.	>20 bn.
B10		Apparel Wholesaler	>50 yrs.	>5 bn.

Table 12. Overview of selected firms and industries

As illustrated in Table 12, we selected a total of ten firms, with an average age of more than 100 years and a minimum age of 50 years. The average revenue of the firms is more than 10 billion Euro per year, which justifies the economic relevance of these firms. All firms have their headquarters in Europe.

For each firm, we conducted an interview with a purposefully selected participant. All participants were selected based on their expertise and experience regarding digitalization activities within their respective firms. All of the selected participants were senior management executives with a comprehensive overview of digital transformation activities within the specific firms (e.g., Chief Information Officer (CIO) or Chief Digital Officer (CDO), or management executives in similar positions), since they are key people in the management of digital transformation in their firms.

Moreover, to deepen the industry-specific insights of the senior management executives of the selected firms and to gain further industry-specific information, we additionally conducted interviews with six senior consultants (or partners) of a major international management consulting firm who advise companies of at least one of the four examined industries. For each industry, we conducted interviews with at least one senior consultant (or partner). These senior consultants (or partners) are characterized by the fact that they advise several firms of the examined industries regarding their digital transformation activities. Following a replication logic, this multiple-case design with multiple units of analysis was chosen to generate comprehensive results regarding the underlying research question. The multiple case-design allows us comparisons and cross-case analyses and helps to broaden empirical evidence (Yin 2014). Furthermore, the evidence from a multiple case-design can be considered as more compelling, which makes the overall study more robust (Herriott and Firestone 1983).

3.2 Data Collection

The data collection method was in-depth semi-structured expert interviews conducted in 2019. We chose expert interviews as the main data source because an interview focuses directly on the specific case study topic. Furthermore, interviews are an insightful data source, as they provide detailed explanations as well as personal views (Yin 2014). The semi-structured approach was chosen to receive answers to selected predetermined questions and to clarify the reasons behind these answers. Furthermore, in a semi-structured interview, participants may more easily discuss sensitive issues like strategic mechanisms (Yin 2014). Data collection involved a total of 16 interviews with purposefully selected participants. The allocation of the specific interview partners to the four industries, as well as the position of the interview partners, can be obtained from Table 13. The second column indicates whether it is a firm-expert (B1-B10) or a consulting-expert (C1-C6).

Industry Sector	Business (B) / Consulting (C)	Position of Interviewed Person	Duration in Min.
Automotive	B1	Head of Digitalization	90
	B2	Head of Innovation & Digitalization	30
	C1	Manager	100
	C2	Senior Associate	120
Pharmaceutics	B3	Chief Information Officer	60
	B4	Chief Information Officer	80
	B5	Head of Digital Products	120
	C3	Partner	180
Industrial Products	B6	Head of Digitalization and Ecosystems	80
	B7	Manager, Strategy- and Product Management	95
	C4	Senior Partner	45
	C5	Senior Manager	90
Consumer & Retail *(Short Form: Retail)*	B8	Chief Digital Officer	110
	B9	Chief Information Officer	70
	B10	Head of Investor Relations	70
	C6	Partner	110

Table 13. Overview of conducted expert interviews

A semi-structured interview questionnaire was designed based on the research objective. During the interviews, the participants were asked to provide their background information and an overview of their specific definition of digital transformation. After this, the interviews focused on the impact of digital transformation on each element of the business model canvas within the specific firms and industries the participants relate to. All questions were selected based on a review of relevant literature and background discussions with knowledgeable parties. The interviews were held informally face-to-face and by videoconference and averaged a duration of 60-90 minutes, with a total time of 1450 minutes. All interviews were digitally recorded and transcribed. All participants received a transcript of the interview and were asked to review the specific transcript and to add appropriate comments. Afterwards, the transcripts were uploaded to the qualitative data analysis software MAXQDA to facilitate content analysis. In addition, to minimize potential inaccuracy biases due to poor recall, after each interview, we made further investigations regarding interesting statements of the participants. For this purpose, we analyzed additional documents provided by the interview partners. However, this procedure only served as an informational enrichment of statements already made within the interviews.

3.3 Data Analysis

Content analysis was used to analyze the sample of interview transcripts. Already introduced in the theoretical background, the business model canvas (Osterwalder and Pigneur 2010) served as the foundation for data analysis, as it provides a well-accepted, comprehensive, and industry-unspecific description of a firm's business model. Hence, a deductive approach of qualitative content analysis was chosen, where a category system (i.e., the elements of the business model canvas) has been deduced from a theoretical basis (Kaiser 2014). After that, a coding scheme was developed, which represents this category system. The category system has been continually adjusted during the research process. The data analysis was conducted in two major steps. First, the impact of digital transformation on each element of the business model was coded separately for each industry (i.e., case). For each interview within an industry, we coded every statement that refers to the impact of digital transformation and assigned it to one or more affected business model element(s). This has shown us how firms within each industry are affected by digital transformation. In this process, changes, challenges, and responses have emerged as sub-categories. In order to get a cross-industry overview and to strengthen our findings in light of replication logic, within the second step, the results of each industry were compared to those of the other industries. Due to great overlaps within the results, we saw the high potential of generalization across the cases. Therefore, our main findings represent cross-industry phenomena occurring in several industries. Using a dual coder approach, the first researcher coded all transcripts. Afterwards, another researcher verified the codes of the first researcher by checking transcripts and codes. This has ensured that the context and codes are related. To finalize the names of the specific codes, a discussion between the researchers took place.

To assess the rigor of case studies, commonly four criteria are used: construct validity, internal validity, external validity, and reliability (e.g., Eisenhardt 1989b; Yin 2014). To ensure construct validity, we used multiple interview partners of multiple firms for each industry within the data collection process. In addition, the data analysis was conducted by a team of researchers, as already mentioned before. During the phase of data analysis, we used pattern-matching and explanation-building to validate the causal relationships and inferences in the conclusions and thus ensuring internal validity (Yin 2014). Testing the results by replicating the findings in various firms for each industry, where the theory has specified that the same results should occur, strengthened external validity. Finally, to ensure reliability within our case study, we used case study protocol and developed a case study database.

4 Findings

The following Tables 14 - 17 illustrate the findings of our case study. We conceptualize the impact of digital transformation on the individual business model elements of incumbent firms as (1) changes, (2) challenges, and (3) responses. The following findings are divided into (a) value propositions, (b) customer interface, (c) infrastructure management, and (d) financial aspects, which represent the pillars of the business model canvas (Osterwalder and Pigneur 2010). The content of the tables summarizes our findings, which were generalized from insights gained from several interviews across several industries. The results therefore represent cross-industry phenomena. Additionally, the most relevant cross-industry results, as well as outstanding industry-specific findings, are described in more detail below the specific tables.

4.1 Value Proposition

The major changes, challenges, and responses regarding the value propositions of incumbent firms can be obtained from Table 14.

BM Element	Changes	Challenges	Responses
Value Propositions	Digital enrichment of products	Pricing of additional value	Higher price or customer data as contribution
		Lack of customer education	Incentivization of retailers
	Service transformation	Uncertain future value proposition	Clear definition of future value proposition
	Increasing individualization	Need for changes in production processes Problematic data situation	Use of appropriate technologies

Table 14. Changes, challenges, and responses regarding the value propositions

A major change regarding the value propositions of incumbent firms is ***the digital enrichment of existing physical products***. The enrichment of existing physical products with digital technologies, like mobile or cloud components, or additional digital services improves the customer benefit and can help to build a closer relationship with customers or even to obtain product-specific or customer-specific data (e.g., Automotive: B1). The integration of digital technologies enables new usage possibilities and features (e.g., Automotive: B1; Pharmaceutics: B3; Industrial Products: B6; Retail: B8). For example, cars are increasingly enriched by digital services, like connectivity- and entertainment applications (Automotive: B1). Additionally, in combination with data gathering, integrated digital technologies can ensure the long-term proper functioning of a product, e.g., through predictive maintenance applications (e.g., Automotive: B2; Industrial Products: B7). Furthermore, also data have the potential to form a new intellectual property (IP), which becomes part of the product (Pharmaceutics: C3). For most executives, it is especially challenging to price this additional value (e.g., Automotive: B1). Widespread are the approaches to offer the additional value for free (respectively to gather customer data as an exchange) (Industrial Products: B7; Retail: B9) or to charge the additional value which raises the price (e.g., Automotive B1; Automotive B2). However, across all firms and industries of the sample, no clear solution could be provided. Another challenge concerns the customer education. Especially in industries with a complex distribution system, like the automotive industry, the customers often did not even know anything about the additional value and functionalities. To address this issue, executives consider incentivization strategies for retailers (Automotive: B1).

Across some industries, changed customer needs and changed customer behaviour cause a ***service transformation***. Customers increasingly prefer to pay for services used instead of buying products (e.g., Automotive: B1; Retail: B8). For example, customers increasingly want to consume mobility services, instead of buying cars (Automotive: B1). Manufacturers face the challenge to decide whether their future value propositions should be based on a product or a service offering (Automotive: C1; Industrial Products: B7; Retail: B8). This issue becomes even more complex through the emergence of new low-asset competitors offering competitive services instead of products. A major risk for manufacturers is to fall behind in the value chain, i.e., becoming a supplier for new business models (Automotive: B1). Established manufacturers therefore need to carefully determine their future value propositions.

Driven by new opportunities provided by digital technologies and changed customer needs, firms increasingly focus on the ***individualization of products and services*** (e.g., Pharmaceutics: C3; Industrial Products: C5; Retail: C6). An interviewed consultant gave the example of an international brand that starts offering individualized sports shoes. In flagship stores, feet can be measured with digital sensors on an individual basis. The customers afterwards choose the preferred design and the ideal fitting shoes will be delivered within a few days (Retail: C6). Even within the pharmaceutical industry this change becomes visible. Another consultant mentioned thoughts within the pharmaceutical industry to adapt medicine to a specific person. Based on the diagnosis, medications can be adapted to a specific patient (Pharmaceutics: C3). A major challenge in individualizing products and services is the requirement of completely different material planning and production planning processes (e.g., Industrial Products: C5). However, the use of digital technologies can help optimizing the underlying processes and making the production of individualized products and services more efficient (Industrial Products: C5).

4.2 Customer Interface

Table 15 represents the findings regarding the changes, challenges, and responses within the business model elements customer relationships, customer segments, and communication and sales channels.

BM Element	Changes	Challenges	Responses
Customer Relationships	Personalization of Communication	Need for an adequate database Need for appropriate know-how	Aligned distribution system Data collection activities Formation of a new sales force
Customer Segments	Forward integration	Need for skipping the retail level Privacy issues and legal aspects	Establishment of own distribution channels Close relationship to intermediaries
Communication and Sales Channels	Digitization of channels	Resistance of customers Different product specifications	Maintaining offline channels in a supportive manner

Table 15. Changes, challenges, and responses regarding the customer interface

4.2.1 Customer Relationships

By analyzing the impact of digital transformation on customer relationships, a trend towards a ***personalization of communication*** can be observed across all examined industries. Executives and consultants of all industries stated that firms increasingly want to understand their customers as accurately as possible to derive preferences and to finally address every customer in an individual way (e.g., Automotive: B1; Automotive: B2; Pharmaceutics: B5; Industrial Products: B7; Retail: B10). The major aim of this personalization strategy is the development of a stronger customer relationship (e.g., Retail: B9). According to an interviewed consultant, firms usually combine self-gathered customer data with social media data purchased from third-party data vendors to apply data analytics techniques and thereby derive preferences to optimize their personalization strategy (Retail: C6). However, many industries already fail at gathering dedicated customer data, i.e., they currently have a poor data situation. The reasons are many and varied. For example, executives of the automotive industry stated that the three-stage distribution system causes that automotive manufacturers have only limited information about their customers (Automotive: B1; Automotive: C1). Because of that, firms within the automotive industry even try to change the entire distribution structure in order to obtain first-hand customer data (Automotive: B1). Another challenge is the need for appropriate know-how in terms of a customer and market understanding in the digital age and a domain-specific knowledge (e.g., Retail: B9). Many firms create special sales forces to address this challenge (e.g., Retail: B9; Retail: B10).

4.2.2 Customer Segments

A cross-industry phenomenon, we observed from the data, is an increasing ***forward integration***. Via disintermediation strategies, manufacturers increasingly try to build up direct contact with end customers instead of using traditional distribution structures (e.g., Automotive: B1; Pharmaceutics: C3; Industrial Products: C5). Also, the other way around, customers try to build up direct contact with manufacturers (Automotive: B2). By skipping the retail level, producers expect to increase their margin and gain first-hand customer data. Especially for industries with a poor data situation as a result of a complex retail structure (e.g., automotive industry, pharmaceutical industry), this is considered an appropriate way to build up a solid database of customer data for the first time (Automotive: B1). On the other hand, customers expect to get lower prices when purchasing goods directly from the manufacturer. While in some industries the retail level can be skipped easily by building up own (mostly digital) communication and sales channels, in some industries a forward integration to the end customer cannot be realized easily. Especially within the pharmaceutical industry, a range of policies prohibits the producers to directly approach the end customer (Pharmaceutics: C3; Pharmaceutics B4). As a compromise, in highly regulated industries, a close relationship with relevant intermediaries (e.g., doctors in the pharmaceutical industry) is recommended.

4.2.3 Communication and Sales Channels

The major change regarding the design and structure of communication and sales channels is the continuing ***digitization of communication and sales channels***. The digitization of communication channels can be associated with an increasing level of automation (e.g., Retail: C6). By digitizing communication channels, firms can reduce costs, e.g., through the replacement of call centers with chat bots (Retail: C6). A pioneer in the digitization of sales channels is the retail industry with many digital sales channels already implemented (e.g., Retail: C6; Retail: B10). Other industries, such as the automotive industry, still lag somewhat behind (Automotive: B2; Automotive: C1). Communication and sales channels are not only added for providing a better convenience to customers. Digital communication and sales channels also serve as an appropriate way to gather additional customer data (e.g., through mobile apps) (Retail: B10). However, firms should evaluate which types of products are (not) suitable for being offered via digital sales channels. For example, automotive manufactures consider selling selected basic models online, whereas the specifications for other special models are so complex, that no online platform manages this complexity sufficiently (Automotive: C1). Other complex goods like food can be offered easily via digital sales channels, but the shipping of these goods is highly uneconomical and the selling via digital channels is not worthwhile (Retail: B9; Retail: C6). For such products, offline sales channels are indispensable. Another major challenge is the negative predisposition of some customers who defend themselves against the use of digital channels (e.g., Automotive: C1; Retail: B10). Especially for these customers, it is important to maintain offline channels at least in a supportive manner.

4.3 Infrastructure Management

The changes, challenges, and responses within a firm's key activities, key resources, and key partners can be obtained from Table 16.

BM Element	Changes	Challenges	Responses
Key Activities	Use of innovative methods in R&D	Structure and work ethics in incumbent firms	Formation of special teams
	Use of new technologies in production lines	Established machine parks	Rebuilding of factories
		Legal aspects	Long planning period
	Shift to cloud computing	World-wide coverage	Cooperation with various partners
		Data security and privacy policies	
Key Resources	Digital technologies as new key resources	Need for appropriate know-how	Formation of special teams
	Emergence of data as a new key resource	Need for an adequate database	Implementation of data collection activities
		Privacy issues	Data governance resources
		Appropriate know-how	Formation of special teams
	Transformation of work force and culture	Need for support of established workforce	Employee Incentivization
		Hiring of new talents	Formation of Tech-Hubs
Key Partners	New partnerships with customers	Privacy issues	Customer Incentivization
			Good data governance
	New partnerships with technology firms	Unresolved profit-sharing situation	Strategic planning of profit-sharing models
	New partnerships with competitors	Difficult competitive situation	Awareness of individual competitive advantage

Table 16. Changes, challenges, and responses regarding the infrastructure management

4.3.1 Key Activities

Firms increasingly employ ***new innovative methods and technologies in their R&D activities*** to improve their innovative outcome (e.g., Automotive: B1; Pharma: C3; Industrial Products: B7; Retail: B9). This includes methods like design thinking, agile, and scrum, as well as technologies like artificial intelligence, data analytics, and 3D-printing. However, governance structures and work ethics of incumbent firms often hinder the process of implementing such methods and technologies (e.g., Automotive: C1). Some firms address this challenge by the formation of special teams (e.g., digital labs) outside their core business and detached from deadlocked corporate structures, where digital experts can think outside the box and test new methods and technologies. These teams work in close collaboration with the core team.

The production lines of the examined firms experience change through the ***use of new technologies within the production processes***. The topic industry 4.0, including the high potential of cyber-physical systems and interconnected machines, plays an increasingly important role across industries (e.g., Automotive: B2; Pharmaceutics: C3; Industrial Products: C5). The use of digital technologies, such as artificial intelligence, data analytics, or IoT can help to increase productivity of production lines and thereby increases profitability. Additionally, according to consultants of the industrial products industry, especially the advent of the 3D-print technology will revolutionize production lines (Industrial Products: C5). With 3D data, production processes can be simplified, and an individualization of products can be realized more easily. Furthermore, the complexity of spare part production and sales can be reduced substantially by selling the 3D data of those parts instead of the spare part itself (Industrial Products: B7). In this context, the use of new technologies within the production processes also serves as an essential prerequisite for the integration of digital technologies into new or existing products. However, this goes along with the requirement of changes in procurement processes, the supply chain management, and the existing workforce. For example, because of the increasing electrification of cars, firms within the automotive industry must completely rebuild existing factories. In general, because the production lines of incumbent firms are typically large and durable, the process of integrating new technologies and synchronizing them with existing machines and technologies becomes a complex issue. Some industries also must consider legal aspects when trying to integrate new digital technologies into the production line. For example, the whole production line of a pharmaceutical manufacturer must be validated by government authorities. Therefore, every change within the production line must be reported and the validation process starts over. Changes in such industries, consequently, proceed very slowly (Pharmaceutics: B3).

Within the infrastructure management of incumbent firms, a ***shift from data centres to cloud computing*** can be observed. One major reason is the desire of a closer collaboration with partners across the world (Pharmaceutics: B4). Other reasons include the acceleration of processes and the saving of resources. The shift to cloud computing comes along with a reduction of workforce and a decentralization and externalisation of data (Retail: C6). Some of the examined firms use solutions from external cloud providers (e.g., Amazon Cloud or Microsoft Azure), whereas others use their own established solutions (e.g., Automotive: B2; Pharmaceutic: B3). When establishing their own cloud solutions, firms additionally employ in-house security experts to ensure data security (Automotive: B2). A major challenge that comes with the use of external cloud solutions is that these solutions do not cover all required destinations. For specific regions, like China or Russia, additional solutions are needed (Retail: B9). Other challenges include concerns regarding data security and privacy policies. To address these challenges, some firms develop cloud solutions in cooperation with knowledgeable partners (Industrial Products: B7).

4.3.2 Key Resources

New digital technologies, like data analytics, cloud computing, or artificial intelligence are becoming new key resources offering novel opportunities for gaining competitive advantages. These new technologies are mainly used to enhance products or services or to improve internal processes (e.g., Automotive: C1; Pharmaceutics: B5; Industrial Products: B7; Retail: B8). However, in order to get the most out of new technologies, it is challenging for most firms to build up appropriate know-how, which would consist of a mixture of the technological know-how and domain-specific know-how (e.g., Automotive: B2). Many incumbent firms lack the appropriate know-how to use these technologies sensibly (e.g., Automotive: C1; Retail: B9). The most common reaction to this issue is the creation of special teams (e.g., digital teams) that work outside the core business and offer the appropriate know-how as a service to all departments of a firm (e.g., Pharmaceutics: B4).

Data increasingly becomes a key resource for firms across all industries (e.g., Automotive: B1; Industrial Products: B6; Pharmaceutics: C3; Retail: C6). This includes customer specific data, as well as product specific data. Data can help firms to improve the unique selling point (USP) of products and services or the personalization of products, services and marketing campaigns (Pharmaceutics: C3; Retail: C6). Furthermore, data can serve as a product itself, which can be sold to third parties (Automotive: C1; Pharmaceutics: C3). Data also help firms to improve business processes like the production process or the supply chain management (e.g., Industrial Products: B7; Retail: C6). To establish an adequate database, firms set up a variety of activities to gather and analyze data. For example, automotive manufactures revamp their whole distribution structures to establish direct contact with end customers to gather first-hand customer data (Automotive: C1). Furthermore, firms equip their products with technologies (e.g., sensors) to gather data (e.g., Automotive B1; Automotive B2; Industrial Products: B7). The main challenges regarding the handling of data are privacy issues, the availability of appropriate know-how, and the requirement of a high-quality and well-integrated database (Automotive: B2; Pharmaceutics: B3; Industrial Products: B7; Retail: B9). To address these data-specific issues, firms build up data governance resources, as well as data warehouses and data lakes within the firm (e.g., Pharmaceutics: B4; Industrial Products: B7). In order to build up the required competencies, firms establish data analytics teams offering their know-how as a service to all departments of a firm (e.g., Pharmaceutics: B4; Retail: B9).

Whereas new digital technologies and data become new key resources, the work force has always been one of the most important key resources of a firm and humans play a major role during transformation (Industrial Products: C5). However, the process of digital transformation requires a ***transformation of the established work force and culture***. This transformation includes a shift in know-how (e.g., new technological know-how), in methods (e.g., new methods like agile, design thinking, or scrum), in mindset (e.g., to be more open minded), and in culture.

This transformation is an ongoing process, and most firms face a lot of challenges while transforming work force and culture. These challenges concern the support of the established workforce, as well as the hiring process of new talents. Especially the tendency for inertia of the existing staff in incumbent firms demands for a change in mindset and culture (e.g., Pharmaceutics: B5). Also, the need for re-education within the established workforce causes problems (e.g., Pharmaceutics: C3). Although there exists no general blueprint to solve these issues, some firms use incentivization mechanisms. Another challenge concerns the hiring process of new talents. Because incumbent firms across all industries are not competitive in many fields with their established workforce, hiring of new staff is essential (e.g., Automotive: B1). To build up new competencies in areas with the greatest gaps in know-how, like analytics, data science, software engineering and digital marketing, most firms build up required expertise through hiring domain experts (e.g., Pharmaceutics: B4; Retail: C6). However, this strategy is also associated with challenges. First, the labour supply of talents with the required knowledge is rather limited (e.g., Automotive: B1; Industrial Products B6; Retail: C6). The situation is further complicated by the fact that such talents usually require an appropriate working environment. Incumbent firms usually cannot provide that and are therefore not attractive for those talents (e.g., Automotive: B1). In addition, the work ethic and labour protection laws are incompatible with requirements of innovative talents (Industrial Products: C5). Finally, many executives also have expressed their concerns regarding the university education of talents (especially in Germany), which is not practical enough (Industrial Products: C5; Retail: B9). Firms address these challenges with the creation of Tech-Hubs in attractive areas (e.g., Tel Aviv, Shanghai or Los Angeles), where the pool of talents providing the required knowledge is much higher than in the cities of the head offices of European firms (e.g., Industrial Products: C5; Retail: B9; Retail: B10).

4.3.3 Key Partners

More and more firms see their ***customers as partners in their ecosystem*** (e.g., Automotive: C1; Retail: B10). On the one hand, customers take the role of buyers of products and services and generate revenues. On the other hand, customers increasingly turn into suppliers of data, serving as an input for improving products and services (Pharmaceutics: C3; Retail: B8; Retail: B9). However, when using customer data for specific purposes, firms need to consider industry-specific privacy policies. Additionally, it is important to consider that an increasing number of customers have the fear of becoming a transparent customer (Industrial Products: C5). Firms need to make their customers feel, that their data confidentiality is protected, and the data is only used by the specific firm for pre-defined purposes. Firms should give their customers the feeling that they can decide for what purposes their data may be used. Firms with a good data governance will have an advantage of trust in this case. Furthermore, to ensure that the customers have a good feeling about offering their data to the company, incentives should be offered to the customers (e.g., free additional services) (Automotive: C1).

Furthermore, an ***increasing number of partnerships with technology firms*** can be observed (e.g., Automotive: C1; Pharmaceutics: C3). This includes partnerships with global players, medium-sized technology firms, as well as startups. Partnering with technology firms is an appropriate approach for extending the value proposition of existing products or services or even for offering new products or services (Automotive: B1; Industrial Products: C5; Retail: C6). Technology firms can serve as a supplier of additional technologies or technological knowledge (e.g., Industrial Products: C5). Furthermore, especially global players with platform business models can provide a necessary customer interface what incumbent firms usually do not offer (Automotive: C1). A typical challenge in partnering is finding a profit-sharing model which is acceptable for both parties (Industrial Products: C5).

Partnerships with direct or indirect competitors are also increasing steadily (e.g., Retail: B8). A main goal of these partnerships is to reduce material costs. Several firms together have a greater market power than a single firm. In many industries, firms together build up platforms where they join forces (Retail: B10). However, in this case, partnering bears the risk of giving up a potential competitive advantage created by good negotiation skills. Because prices are usually negotiated individually, partnering with a firm with higher prices always means giving up a competitive advantage (Retail: B8). Therefore, companies need to be aware of their individual competitive situation.

4.4 Financial Aspects

The following Table 17 shows our findings regarding the financial aspects of a firm's business model.

BM Element	Changes	Challenges	Responses
Cost Structure	Increasing investments in innovative business areas	Potentially arising financial risks	Partnerships with peers
Revenue Streams	Emergence of additional revenue streams	Small share of total sales	Double-barreled strategy
	Emergence of additional payment models	Uncertain profitability Modification of products	Payment options should depend on the product

Table 17. Changes, challenges, and responses regarding the financial aspects

4.4.1 Cost Structure

The total costs of firms are increasingly driven by a constantly ***increasing amount of investments in innovative business areas***. Because these expensive investments in new innovative areas are highly uncertain in terms of their outcome, but unavoidable to stay competitive, related firms face financial risks (e.g., Automotive: C1; Pharmaceutics: C3). Through joint investments with other inter-industrial firms, they try to diversify this financial risk (Pharmaceutics: C3). The resulting lower investment sums enable the possibility to invest in different projects which allows a diversification of potential risks. Additionally, most investments require an internal compensation, which means that cost-saving interventions in other areas are required (Automotive: B1).

4.4.2 Revenue Streams

Executives off all examined industries agree that there are and will be ***additional revenue streams*** caused by digital transformation (e.g., Automotive: B1; Pharmaceutics: C3; Industrial Products: C5; Retail: B9). This mainly stems from the sale of additional digital products and services. However, across all examined industries, such revenue streams represent only a small share of total sales (e.g., Automotive: B2; Pharmaceutics: B5; Industrial Products: B6; Retail: B9). Thus, the additionally offered products and services only have a supporting role as of now. However, most executives agree that this share will increase in the future, even if most executives also consider that this process might take up to 10 years (e.g., Automotive: B1; Pharmaceutics: B5; Retail: C6). In order to be prepared for this moment, it is essential to continue pursuing the development of new digital products and services (e.g., Automotive: B2). Stopping investments in innovative business areas would spell doom for those companies once digital products and services determine their industries. Furthermore, it needs to be considered that the purpose of many additional digital services is not to directly generate new revenue streams, but to gather data, to improve customer relationships, or to fulfil other purposes instead of generating revenues (Retail: B9).

Not only the origin of revenue streams changes, also the structure of the underlying revenue streams changes. Across industries, ***additional payment models*** play an increasingly important role (e.g., Automotive: B1; Pharmaceutics: C3; Retail: C6). These additional payment models include pay-per-use-models, subscription models, and leasing models. Whereas subscription models are predominantly used in the consumer & retail industry (Retail: C6) and the pharmaceutical industry (Pharmaceutics: C3), pay-per-use models and leasing models are primarily represented in industries, where the products are typically relatively costly (Automotive: B1; Industrial Products: C5). Especially the pay-per-use model is also often used for additional digital services (e.g., navigation system in cars). To ensure the profitability of new payment models, firms need to evaluate which payment models should be offered for which types of products and services (e.g., Automotive: C1). Additionally, firms need to consider that especially for using the pay-per-use-model the underlying products might require a modification (e.g., a washing machine where each cycle is charged separately) (Industrial Products: B7; Industrial Products: C5).

5 Discussion

5.1 Implications for Research and Practice

The results of our case study provide several important implications for both researchers and practitioners alike. First, our study contributes to the literature of digital transformation by providing new insights to advance the scientific understanding of the impact of digital transformation on the business model of incumbent firms in traditional industries. Consistent with existing literature, our findings indicate that digital transformation has an impact on all elements of an incumbent firm's business model and thereby has the potential to (re)define a firms' value propositions(s) and to change its whole identity (e.g., Wessel et al. 2021). The findings of our study regarding the creation of new value propositions, the augmentation of physical products with new digital services, the digitization of marketing and sales channels, and the transformation of workforce and culture confirm previous findings of Porter and Heppelmann (2014), Parry and Strohmeier (2014), Barrett et al. (2015), Hansen and Sia (2015), Piccinini et al. (2015), and other researchers. However, our paper takes existing research one step further by providing a more holistic view of the impact of digital transformation on each business model element of incumbent firms across various traditional industries. Furthermore, we contribute to the existing literature by providing detailed information on how the overall impact of digital transformation on incumbent firm's business models can be accessed and conceptualized. As illustrated in Figure 21, we conceptualize the impact of digital transformation on incumbent firm's business models as (1) changes triggered by the use of digital technologies, (2) challenges resulting from changes that collide with existing organizational and/or environmental conditions, and (3) organizational responses a firm needs to adopt to address the arising challenges.

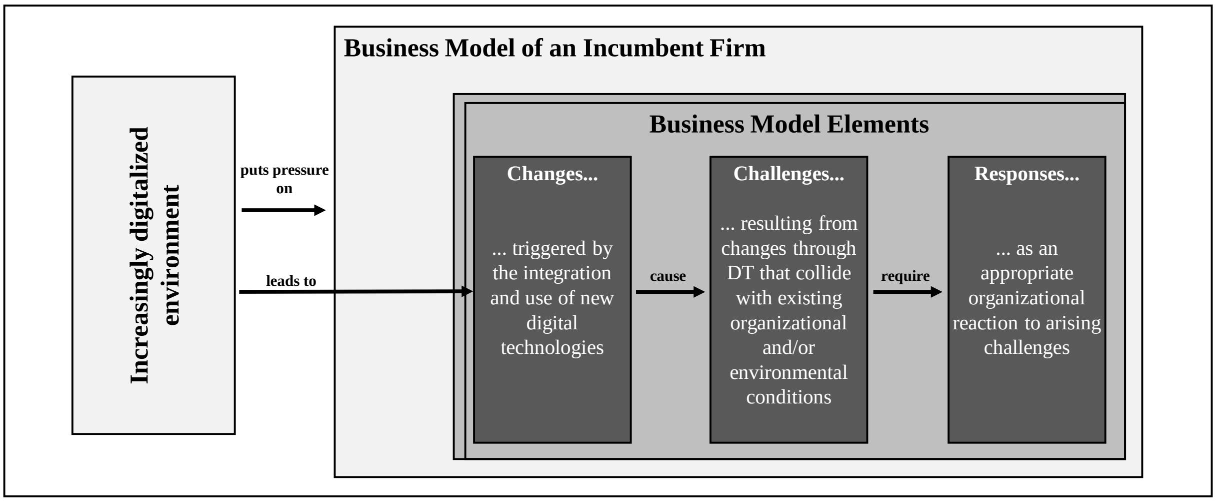

Figure 21. The impact of digital transformation on incumbent firm's business models

As illustrated in Figure 21, an increasingly digitalized environment puts pressure on existing business models of incumbent firms. To stay competitive, incumbent firms need to undergo a digital transformation and therefore need to integrate digital technologies into their existing business model. The integration and use of new digital technologies cause changes across all business model elements of incumbent firms. Consequently, no element of the business model of incumbent firms remains unaffected by the changes caused by digital transformation. Therefore, executives across industries need to consider all elements of their specific business model by driving digital transformation. Furthermore, our findings indicate that the scope of specific changes differs across the specific business model elements. Some of the identified changes are merely radical, i.e., they have a strong impact on the specific business model element, what causes bigger challenges and subsequently requires more strategic effort. However, other changes are merely incremental and do not require much attention of the top management. Furthermore, the scope of specific changes also varies across industries. Whereas all industries go through the same change process, for some industries the challenges of change are more difficult than for others.

Our findings further show that it is difficult for incumbent firms to handle the changes triggered by digital transformation. These difficulties are presented as challenges in our study and arise from changes through digital transformation that collide with existing organizational conditions (e.g., long grown corporate governance structures or outdated IT infrastructures), or environmental conditions. In general, every change within the business model elements of incumbent firms evokes at least one new challenge the affected firm must deal with. Hence, when changes within a specific business model element are envisaged, potential new challenges must also be considered. Accordingly, appropriate organizational responses are needed for achieving digital transformation and to ensure that the introduced changes have a positive effect on the future performance of a firm.

Overall, our findings also underline the great importance of the development of ambidextrous capabilities to address contrasting demands and resolve paradoxical tensions (Gregory et al. 2014), as well as agile capabilities to react rapidly to new changes and challenges caused by digital transformation. These capabilities can be a key for a successful digital transformation.

5.2 Limitations and Future Research

Despite the careful design of our study, this paper is subject to several limitations due to the nature of the applied research methodology. A major limitation concerns the external validity. Because case studies are susceptible to context, the boundary conditions and generalizability of the specific study need to be considered (Marshall 1996; Lee and Baskerville 2003). In this study, we analyzed four different traditional industries, which play a major role in the European economy. However, because these industries do not reflect all traditional industries, it is uncertain whether our results can be generalized to other traditional industries. Furthermore, we only analyzed firms with headquarters in Europe, which limits the geographical scope of our study to Europe. Overall, this study primarily argues for the generalization of the findings to incumbent firms of the four analyzed industries in the European territory. However, a question worth verifying in future studies would be whether the findings also can be generalized to other industries and other territories. Finally, this study investigated the overall impact of digital transformation and thereby did not differentiate between the use of different digital technologies. However, future research can build on this by analyzing the impact of individual digital technologies, like artificial intelligence, on the overall business model of incumbent firms. Furthermore, future research could analyze whether the use of some digital technologies has a greater impact than the use of others.

6 Conclusion

In recent years, research has already started discussing digital transformation in relation to business models. However, its focus has mainly been on specific business model elements or on specific industries. Furthermore, a clear conceptualization of the impact of digital transformation on incumbent firm's business models was missing. This study aimed to approach these research gaps by exploring the impact of digital transformation on the overall business model of incumbent firms across different industries and thereby examining the nature of this impact to provide detailed information about how this impact can be conceptualized and what it means for an incumbent firm.

The results of our study show that digital transformation causes changes in all elements of an incumbent firm's business model across all examined industries. No business model element remains unaffected by digital transformation issues. These changes, which are primarily triggered by the use of new digital technologies as a reaction to an increasingly digitalized environment, can be incremental or radical. The scope of a specific change varies across specific types of change, as well as across industries. Changes caused by digital transformation are difficult to handle for incumbent firms across all industries. This is reflected by the fact that changes through digital transformation that collide with existing organizational and/or environmental conditions cause challenges the respective firms must deal with. Consequently, appropriate organizational responses need to be prepared as a reaction to challenges that may occur.

Overall, our paper contributes to the ongoing research in the field of digital transformation by providing novel insights to advance the scientific understanding of digital transformation in incumbent firms. Additionally, due to our practical implications, the provided insights are useful for practitioners to recognize and prepare for potential challenges, which may arise from a firm's digital transformation efforts.

I.3. AI and BMI in Incumbent Firms (Study 3)

Paper Title:

Artificial Intelligence and Business Model Innovation in Incumbent Firms: A Cross-Industry Case Study

Abstract: Artificial intelligence (AI) has the potential to disrupt entire industries and thereby drives business model innovation (BMI) in incumbent firms. However, empirical research on the impact of AI on the business model of incumbent firms, as well as research on AI as a driver for BMI in these firms, is still rare. This paper aims to extend research in this field by analyzing the impact of AI on the specific elements of firms' business models. Further, it provides an analysis of the mechanisms of AI-driven BMI. By conducting in-depth case study research across four traditional industries, we contribute to the literature by providing new insights on the impact of AI on each business model element of incumbent firms. Based on these findings, we additionally present a framework explaining the processes and outcomes of BMI through AI.

Outlet: Die Unternehmung: Swiss Journal of Business Research and Practice

Citation: Metzler, D. R., Neuss, N., and Muntermann, J. 2021. "Artificial Intelligence and Business Model Innovation in Incumbent Firms: A Cross-Industry Case Study," *Die Unternehmung: Swiss Journal of Business Research and Practice* (75:3), pp. 324-339.

Keywords: Artificial Intelligence, Business Model Innovation, Digital Transformation, Incumbent Firms, Qualitative Research, Case Study Research

1 Introduction

The emergence of new disruptive technologies, like artificial intelligence (AI), is shaping businesses across industries. Especially incumbent firms are increasingly confronted with new technological innovations, changing customer needs, and newly emerging competitors with innovative business models (e.g., Svahn et al. 2017; Osmundsen and Bygstad 2020). To stay competitive in an increasingly digitized environment, these firms need to undergo a digital transformation, including the implementation of new digital technologies, to innovate their existing business models (Westerman and Bonnet 2015; Levkovskyi et al. 2020). In that regard, AI can be seen as a key technology with the potential to affect the way firms develop products and services, communicate with customers and partners, procure resources, and generate value (Agrawal et al. 2017; Davenport and Ronanki 2018).

Prior research has already started discussing AI in relation to business models. However, its scope is primarily limited to the use of AI in (individual aspects of) single business model elements. For example, Kshetri (2020) investigated the use of AI in human resource management. Stormi et al. (2018) and Lokuge et al. (2020) examined the use of AI in customer relationship management. Baryannis et al. (2019) investigated the use of AI in supply chain management. Other research in that field is limited to a selected industry sector. For example, Lee et al. (2019) examined possibilities for the development of AI-based business models in firms of the manufacturing industry. Neuhüttler et al. (2020) investigated AI as a driver for business model innovation (BMI) in smart service systems for higher-level business model pillars. Finally, Soto Setzke et al. (2020) investigated BMI in the context of digital transformation in general. Existing research, thereby, indicates that the use of AI affects firms' existing business models in many ways and can be seen as a driver for BMI. However, a holistic overview of the impact of AI on all business model elements of firms across various industries is missing. In addition, research on processes (i.e., its implementation) and outcomes (i.e., potential results) of AI as a driver for BMI is missing. This study aims to address these research gaps by shedding light on the growing role of AI within the business models of incumbent firms over a variety of industries. Incumbent firms, thereby, can be defined as firms with an established market position in a traditional industry and a traditional business model not originally based on the use of digital technologies (Metzler and Muntermann 2020). These firms were chosen as the main unit of analysis for two main reasons: (1) They play a major role in the economy of most industrialized countries and (2) the digitalization, including the implementation of new digital technologies, like AI, in these firms is different and more challenging compared to purely digital firms (Svahn et al. 2017; Osmundsen and Bygstad 2020). Against this background, we have formulated the following research questions (RQ):

RQ1: How does the use of AI impact the specific elements of incumbent firms' business models?

RQ2: How does AI drive business model innovation in incumbent firms?

To answer these questions, we conducted an exploratory multiple case study. In our data collection, we used expert interviews with senior management executives of eight incumbent firms in the following four industries: (1) Automotive, (2) Pharmaceutics, (3) Industrial Products, and (4) Consumer & Retail. These industries were chosen as all of them represent traditional industries focusing on producing and selling physical goods. Further, these industries are confronted with digitalization issues and the advent of new AI-related technologies and applications in recent years. Combined with 462 published corporate documents, we conducted a qualitative content analysis. The results of our study provide new insights on the impact of AI on each element of incumbent firms' business models. In addition, they contribute to a better understanding of the processes and outcomes of AI and its role as a driver for BMI in incumbent firms.

This study is structured as follows: First, we provide a theoretical background of AI as a driver for innovation and the concept of BMI in incumbent firms. Second, we introduce the methodological foundations of our case study. This is followed by a detailed presentation of our findings. Within the discussion section, limitations of our study and implications for research and practice are presented. Finally, the conclusion summarizes the most important findings.

2 Theoretical Background

2.1 Artificial Intelligence as a Driver of Innovation

AI is one of the most disruptive technologies and can be seen as a key driver of innovation (May et al. 2020). Since there is no commonly accepted definition of AI, one can describe it as the representation and duplication of studied human thought processes in machines (Sharda et al. 2021). In contrast to other technologies, AI does not only enhance existing processes. Rather, it can be seen as a capital-labor hybrid production factor, underlining AI's innovative power and differentiating AI from other technologies (Plastino and Purdy 2018). AI, thereby, is based on techniques of various fields, such as mathematics, computer science, and linguistics and comprises of a variety of methods, such as machine learning (ML) and deep learning (DL) (Russell and Norvig 2003; Sharda et al. 2021). Whereas ML is a subset of AI learning from experience and training for algorithmic pattern identification (Russell and Norvig 2003; Sharda et al. 2021), DL is a specification of ML which uses artificial neural networks to identify patterns in large amounts of unstructured data (Khamparia and Singh 2019; Sharda et al. 2021).

Today, an increasing number of (business-) applications, such as intelligent agents or autonomous vehicles, are based on AI or at least contain significant AI elements (see Figure 22).

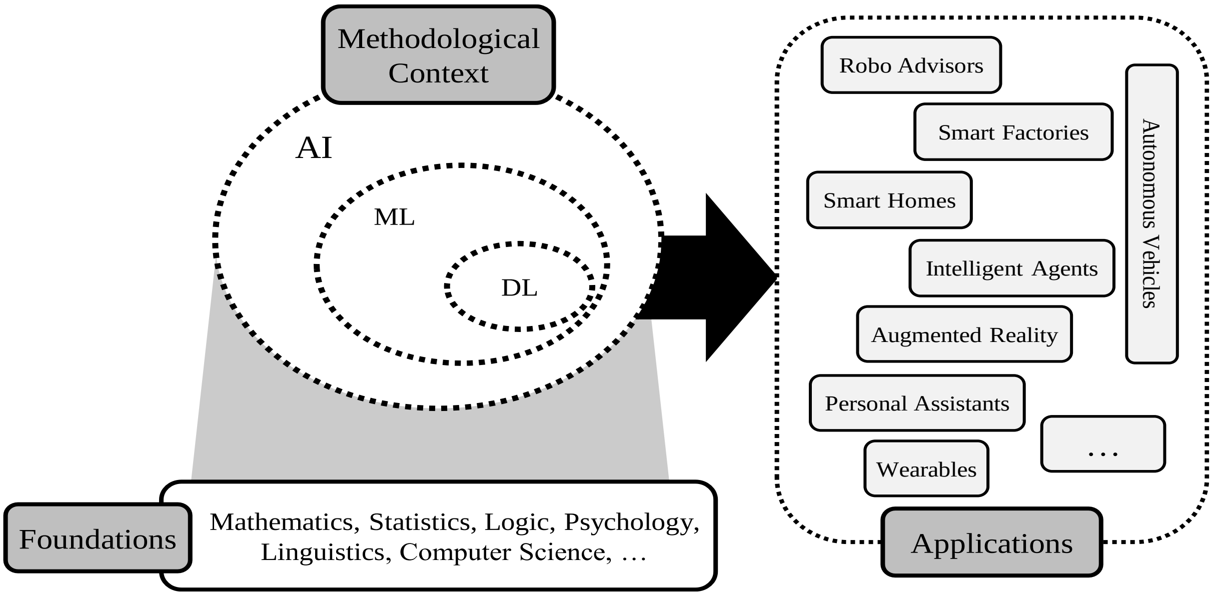

Figure 22. The context of artificial intelligence

Powered by large datasets, AI is capable of depicting human-like thinking and therefore solving problems that were solved by humans before (Russell and Norvig 2003; Plastino and Purdy 2018). The underlying AI models thereby entail three main components: (1) data, (2) algorithms, and (3) decisions or solutions and improve the data-to-insight-process (Sharma et al. 2014; May et al. 2020). As a central driver of innovation, AI has found its way to be implemented for a variety of tasks along the value chain and, thereby, disrupts entire industries by automating processes, extending the range of products and services, and augmenting the workforce (Plastino and Purdy 2018; Brock and von Wangenheim 2019). Since the term AI remains fuzzy, in this paper, we focus on AI as a technology (including its subordinated methods ML and DL) as well as on AI-based (business-) applications and applications containing significant AI elements with the aim to create business value.

Incumbent firms increasingly consider AI as a new key resource to stay competitive in an increasingly digitized environment (Brock and von Wangenheim 2019). However, to enable technological development through AI, user engagement and openness regarding the adjustment of the different elements of the existing business model is important (Baden-Fuller and Haefliger 2013). Consequently, it is important to consider the business model concept when implementing new AI technologies or applications.

2.2 Business Model Innovation in Incumbent Firms

The business model concept is widely used in research across various disciplines, including innovation management and information systems (e.g., Zott et al. 2011; Veit et al. 2014). A business model can be described as a blueprint pointing out the basic principles of how an organization creates value and how this value is transferred to stakeholders (Osterwalder and

Pigneur 2010). The business model concept, therefore, brings together business strategy and business operations. In terms of its core elements, it has been conceptualized in various ways (Zott et al. 2011). For example, Hamel (2000) divides a business model into core strategy, strategic resources, customer interface, and value network. More frequently used in research and practice is the business model canvas (BMC), introduced by Osterwalder and Pigneur (2010). As illustrated in Figure 23, the BMC structures a business model into nine elements and is characterized by its granularity, diversity, and industry-independence, making it especially suitable for this study (Osterwalder and Pigneur 2010; Wirtz et al. 2016).

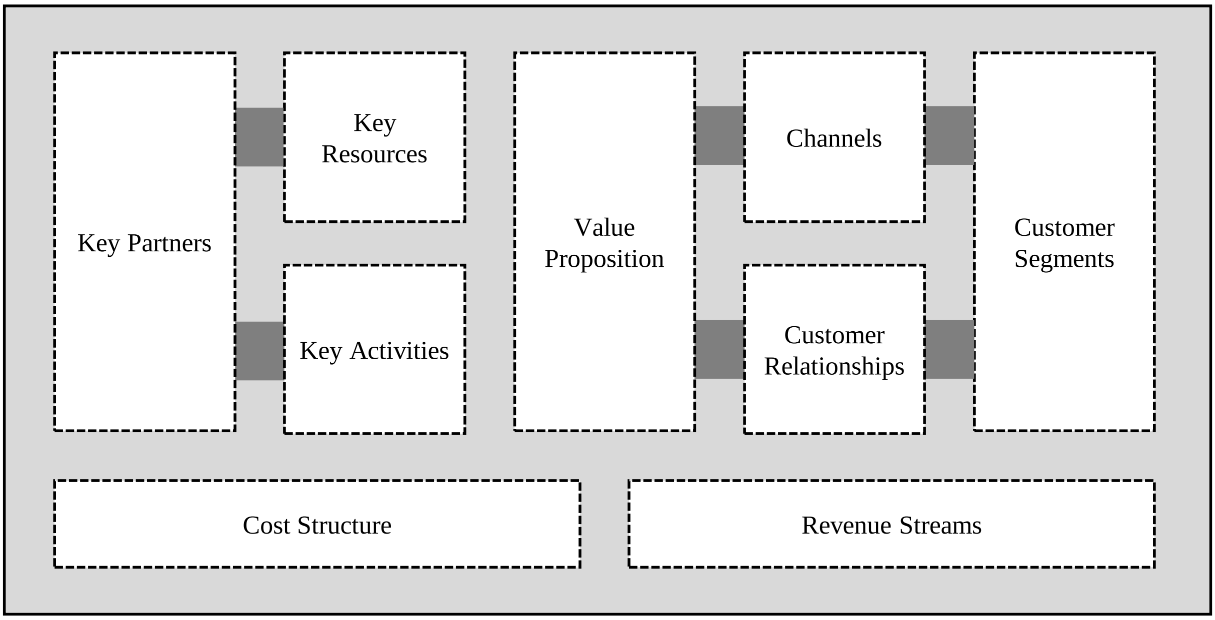

Figure 23. The business model canvas (Osterwalder and Pigneur 2010)

The implementation and use of new technologies has the potential to affect business models in manifold ways (Burmeister et al. 2016; Neuhüttler et al. 2020). Especially in order to stay competitive in an increasingly digitized environment, incumbent firms implement new technologies and thereby adapt their traditional business models as needed (Chesbrough 2007; Baden-Fuller and Haefliger 2013). Research in this field is mostly undertaken under the term BMI, which can be defined as "*designed, novel, nontrivial changes to the key elements of a firm's business model and/or the architecture linking these elements*" (Foss/Saebi 2017, p. 201; Fjeldstad and Snow 2018). Existing research in this field indicates that information systems and digital technologies play a major role in (re-)designing business models (e.g., Hildebrandt et al. 2015; Soto Setzke et al. 2020). For example, in the case of big data, research shows that internal and external data, as well as related analytic capabilities, have the potential to innovate a firm's existing business model or even to create new business models (e.g., Sorescu 2017; Ciampi et al. 2021). In addition, Burmeister et al. (2016) show that also Industry 4.0 technologies can drive BMI in firms. In that regard, organizational issues (e.g., the development of dedicated teams and interdepartmental collaboration) play a major role.

Recently, research started discussing AI in the context of business models. However, its scope is limited to the use of AI in individual aspects of single business model elements (e.g., Lokuge et al. 2020), to selected industry sectors (e.g., Lee et al. 2019), or to selected AI applications (e.g., Kshetri 2020). Overall, research concerning AI in the context of business models is still at an early stage. Until today, empirical research on the impact of AI on firms' business models in a holistic way, as well as research on processes and outcomes of AI as a driver for BMI is missing. This study aims to approach these research gaps by analyzing how AI impacts and innovates incumbent firms' business models.

3 Methodology

To answer our research questions, we conducted an exploratory case study. The case study as a research method was chosen because this study deals with a contemporary phenomenon in a real-life context where control over behavioral events is not required (Yin 2014).

3.1 Case Study Setup

In order to get a cross-industry overview of the impact of AI on incumbent firms' business models, as well as insights on AI-driven BMI, we chose a multiple case study design which allows us to strengthen findings in light of replication logic (Eisenhardt 1989b; Yin 2014). Furthermore, the evidence from multiple cases can lead to more robust conclusions by being more compelling (Herriott and Firestone 1983). Discussions with domain experts of a major international management consulting firm as part of our pre-study led us to the decision to conduct the study within four different industries: (1) Automotive, (2) Pharmaceutics, (3) Industrial Products, and (4) Consumer & Retail. These industries were chosen as all of them represent traditional industries focusing on producing and selling physical goods while also being confronted with new AI-related developments in recent years. We chose two firms for each industry as the main units of analysis. This allowed us to validate insights and to perform cross-firm comparisons. All firms meet our definition of an incumbent firm and have one prevailing business model, since the existence of competing business models within one firm could be challenging for our analysis (Markides and Charitou 2004).

Firm	Industry Sector	Field of Activity	Age in Yrs.	Total Assets (bn. €)
F01 F02	Automotive	Automotive Manufacturer Automotive Supplier	>80 >140	>400 >40
F03 F04	Pharmaceutics	Pharmaceutical Manufacturer Pharmaceutical Manufacturer	>180 >350	>9 >80
F05 F06	Industrial Products	Manufacturer of Chemicals Building Material Manufacturer	>150 >70	>8 >0,2
F07 F08	Consumer & Retail	Consumer Goods Manufacturer Consumer Goods Wholesaler	>140 >50	>30 >15

Table 18. Overview of selected firms and industries

As illustrated in Table 18, an average age of more than 100 years, combined with the respective fields of activity, indicates that all firms are pure incumbent players. Additionally, an average of more than 70 billion Euro in total assets justifies their economic relevance.

3.2 Data Collection

Our main data source consists of (1) expert interviews and (2) corporate documents. The expert interviews were conducted with one purposefully selected participant of each firm. Expert interviews were chosen as one main data source, as they provide detailed explanations, as well as personal views and focus directly on the specific case study topic (Yin 2014). All experts were senior management executives with outstanding professional competencies in specific IT areas (e.g., Chief Information Officer (CIO) or Chief Digital Officer (CDO)). Therefore, all experts were key people in the management of the digital transformation and the implementation of new technologies. Additionally, we conducted interviews with high-level consultants of a major international management consulting firm who have advised several firms of the considered industries regarding their digitalization and technology implementation activities in the past. This helped us to deepen the industry-specific insights and to obtain further information. The allocation of the interview partners to the four industries, as well as their position, can be obtained from Table 19.

Industry Sector	Firm (F) / Consulting (C)	Position of interviewed Person
Automotive	F01 F02 C01 C02	Head of Digitalization Head of Digitalization Manager Senior Associate
Pharmaceutics	F03 F04 C03	CIO CIO Partner
Industrial Products	F05 F06 C04 C05	Head of Digitalization Strategy- and Product Manager Senior Partner Senior Manager
Consumer & Retail *(Short Form: Retail)*	F07 F08 C06	CDO CIO Partner

Table 19. Overview of conducted expert interviews

The interviews used for this study are based on a semi-structured interview questionnaire. The questionnaire mainly focuses on the implementation of digital technologies, including AI, and their impact on each element of the BMC within the specific firms and industries. A semi-structured approach was chosen, as it appears more suitable when talking about sensitive issues like strategic mechanisms (Myers 2009). The interviews averaged a duration of 60–90 minutes and were digitally recorded, transcribed, and integrated into the qualitative data analysis software MAXQDA.

To extend our data basis, as well as to minimize potential response biases and the possibility of inaccuracies due to poor recall, we additionally used two document types (i.e., firms' annual reports of the reporting years 2015–2019 and firm-related news articles) as our second data source. To gather relevant news articles, we created a search string, which is specific to our RQs, and applied it on each firms' website. The number of news articles and annual reports for each firm can be obtained from Table 20.

Firm	Field of Activity	News Articles	Annual Reports
F01	Automotive Manufacturer	174	5
F02	Automotive Supplier	81	5
F03	Pharmaceutical Manufacturer	13	5
F04	Pharmaceutical Manufacturer	114	5
F05	Manufacturer of Chemicals	17	5
F06	Building Material Manufacturer	2	5
F07	Consumer Goods Manufacturer	15	5
F08	Consumer Goods Wholesaler	6	5
		422	40

Table 20. Overview of collected corporate documents

3.3 Data Analysis

The dataset was analyzed with a rigorous content analysis approach. We used a deductive approach with the BMC serving as the foundation for data analysis (Myers 2009). Based on the BMC, we developed a category system and a corresponding coding scheme. For each interview and document, we coded all aspects referring to the impact of AI on firms and linked the excerpts to the affected business model element(s). In this context, we refer to the definition of AI introduced in section 2.1 and classified all technologies and applications with the aim to represent and duplicate studied human thought processes as AI. This includes AI as a technology (including its subordinated methods ML and DL), as well as AI-based (business-) applications and applications containing significant AI elements. Afterward, we assigned a code to these excerpts that describes the specific impact on the particular business model element. To obtain a cross-industry overview and strengthen our findings in light of replication logic, the results of each industry were compared to those of the other industries. Due to great overlaps within the results, our main findings are represented as cross-industry phenomena being observable across several industries.

The rigor of our study is given through construct validity, internal validity, external validity, and reliability (Yin 2014). Multiple sources of evidence for each firm and industry were used to ensure construct validity. Additionally, data analysis was conducted by a team of two unbiased researchers. All documents were coded by each researcher independently. The results were compared, and mismatches were discussed to reach a consensus. To ensure internal validity, we used pattern-matching and explanation-building to validate the conclusions' causal relationships and inferences. Testing the findings by replicating them in various firms for each industry and across the different industries, where the theory has specified that the same results should occur, strengthens external validity. Finally, to ensure reliability, we used a case study protocol and a case study database.

4 Findings

4.1 AI-Enabled Impact on Business Model Elements

Table 21 provides a holistic overview of the AI-enabled impact on the specific BMC elements of incumbent firms. These results summarize our findings, which were generalized from cross-industry insights. Additional industry-specific insights are discussed below.

BMC Element	Ratio (%)		AI-Enabled Impact
	tot.	adj.	
Key Resources	14.4	25.2	• Development of new AI-specific competencies • Development of new AI-related research units • Improvement of technological infrastructure • Replacement of humans by AI-based robots and algorithms
Key Partners	17.5	28.0	• Formation of new AI-driven partnerships and alliances
Key Activities	25.2	41.2	• Automation and optimization of internal processes through AI • Workload reduction through AI-based human-robot collaboration • Predictive analytics for consumer need and trend anticipation
Value Proposition	28.2	48.9	• Development of AI-based or -supported products and services • Integration of AI components in existing products and services
Customer Relationships	6.6	10.5	• Use of ML-algorithms for personalization issues • AI-based automation and individualization of customer communication
Channels	3.1	5.1	• Use of AI-supported communication and sales channels
Customer Segments	0.8	1.2	• Emergence of new AI-enthusiastic customer groups
Cost Structure	8.7	13.6	• Cost savings through more cost-effective AI-supported production • Shift from HR-costs to technology- and maintenance-costs
Revenue Streams	14.4	3.6	• Emergence of new AI-enabled revenue streams

Table 21. AI-enabled impact on BMC elements

As illustrated in Table 21, the use of AI can impact all business model elements of a firm. The use of AI thereby modifies the existing business model of incumbent firms, which underlines its role as a driver for BMI. However, some business model elements seem to be more affected than others since some business model elements are less discussed in the analyzed interviews and corporate documents. The total ratio (tot.) in Table 21 indicates the percentage of our overall documents (scaled to the number of documents per company) in which the impact of AI on a specific business model element was discussed. The adjusted ratio (adj.) indicates the percentage without including documents that do not contain any coded elements. For example, text passages referring to the impact of AI on a firm's key resources were coded in 14.4 % of our overall documents (resp. in 25.2 % of the documents with codes).

4.1.1 Key Resources

The development and use of AI technologies and applications requires the *development of new AI-specific competencies*. Employees need to acquire new skills and new talents need to get hired (e.g., F01; F04; F05). In this context, an automotive manufacturer plans to invest several billion euro in the development of AI competencies (F01). Furthermore, *firms increasingly invest in the development of AI-related research units* or integrate AI research groups in similar departments like data labs or innovation hubs (e.g., F01; F03; F04; F07). For example, one firm established a "*central competence center [...] for artificial intelligence and machine learning [where] IT experts are working together with universities, research centers, and startup companies to make use of [...] AI*" (F01). Moreover, to meet the technological requirements for using AI, *firms improve their technological infrastructure*, especially by upgrading the internal IT infrastructure and moving systems and applications to cloud platforms (e.g., F01; F03). While the IT infrastructure is constantly being expanded and new jobs in the field of AI are being created, *the human as a key resource gets increasingly replaced by AI-based robots and algorithms*, especially for monotonous and recurring tasks (e.g., F01; F04). Overall, the investments in the development of new competencies, new research units, improved technological infrastructure, and machine labor are key foundations for developing and integrating AI in a firm's key activities.

4.1.2 Key Partners

Most incumbent firms lack important resources regarding the development and use of AI. To close this gap, *firms form new AI-driven partnerships and alliances*. Firms organize hackathons, develop acceleration programs, or invest in startups to benefit from their AI expertise (F02; F04; F05; F07). Furthermore, incumbent firms increasingly collaborate with competitors and research institutions, such as universities or research centers, especially to expand their AI-specific research and development (R&D) capabilities (e.g., F01; F02; F04; F05). In that regard, a firm within the automotive industry started a project where "*international manufacturing companies and research institutions want to [...] accelerate the development of autonomous driving – especially when it comes to artificial intelligence*" (F01). Finally, firms also partner with incumbent tech-firms to create synergies by combining industry- and technology-specific knowledge (e.g., F04; F05). Overall, the formation of new partnerships is another key foundation for developing and integrating AI technologies and applications in a firm's key activities.

4.1.3 Key Activities

The use of AI to *automate and optimize processes and workflows* is of great importance for firms across all considered industries. However, the focus is still different. Firms of the automotive and industrial products industry primarily focus on automating and optimizing procurement, production, and logistics processes. For example, they implement automated procurement systems (F01), safe-guarding systems for production processes (F01), or intelligent human-robot collaborations (F01; F02). Pharmaceutical firms mainly focus on implementing AI in R&D activities, for example, in the development of software and algorithms for smart drug discovery (F04) or material research (F04). Finally, the firms of the consumer & retail industry primarily focus on automating and optimizing marketing and sales activities, as well as logistic activities (e.g., by implementing inventory drones, warehouse robots, self-driving trucks, or packaging robotics) (F07; F08). Additionally, firms across all industries use AI in marketing- and sales activities to *analyze trends and customer needs through predictive analytics and smart algorithms.* The aim is to better meet customer needs by personalizing products and services, as well as improving the customer service (e.g., F01; F04; F08). For example, in one firm "*AI and algorithms are used to analyze the shopping behavior of customers and to forecast sales trends, which allows [...] to develop targeted offers*" (F08).

4.1.4 Value Proposition

The implementation of AI technologies and applications in incumbent firms' key activities enables the *development of AI-based or -supported products and services*. The automotive industry develops smart autonomous cars and smart mobility services (e.g., AI-supported driver communication assistants). Even car parts get equipped with AI-supported sensors (e.g., smart tires continuously checking tire pressure) (F01; F02). Within the pharmaceutical industry, AI allows smart nutrition recommendation services, automated disease diagnostics, and infection recognition, as well as more general smart health treatment services (F03; F04). In addition to the development of completely new products or services, the *integration of AI components in existing products and services* offers additional value to customers. Examples include smart hairstyle prediction software for hairstylists (F07), smart home devices for automated mosquito control (F07), and smart shading based on AI-supported sunlight sensors (F06).

4.1.5 Customer Relationships

AI has the potential to reshape the way how firms interact with existing and new customers. *Firms increasingly use ML-algorithms for personalization issues*. This includes the personalization of the customer support, bonus programs, and other marketing campaigns (F08). Furthermore, the use of AI enables an *automation and individualization of customer communication*. Most firms offer smart assistants to improve and personalize communication and realize cost savings through the elimination of telephone- and chat-support (e.g., F02; F04; F08). In that regard, one consultancy expert stated that "*No. one for AI applications, [is] the well-known chatbot*" (C06).

4.1.6 Channels

The use of *AI to improve marketing and sales channels* is primarily of great importance within the consumer & retail industry. For example, firms implement smart point-of-sale systems and AI-based barcode technologies for individual pricing in their stores (F07; F08). One firm recently launched a smart self-checkout system and "*via AI, [they] can recognize what's in a caddy with an image recognition software. [...] Cameras [...], combined with the situation that we also weigh the caddy, allows us to determine what is actually in the caddy, with a hit rate of over 99 %*" (F08). However, also other industries use AI applications, like AI-supported mobile applications and online platforms to improve their communication and sales channels (e.g., F01; F04).

4.1.7 Customer Segments

Especially, the development of new AI-based or AI-supported products and services with novel and innovative functions, as well as the integration of AI in existing products, leads to the *emergence of new AI-enthusiastic customer groups*. However, changes within this business model element were rather rarely mentioned in contrast to other elements.

4.1.8 Cost Structure

Integrating AI in a firm's key activities allows shaping the cost structure, primarily through *more cost-effective production* and optimized internal processes. Nearly all considered firms use AI for process automation and optimization (e.g., F01; F03; F05; F07). Exemplary AI applications are "*autonomous vehicles [in the production line] that can [...] address high cost and shortage of labor and enable efficiency gains*" (F07) or software for process transparency and early notification of supply bottlenecks (F02; F07). A firm within the consumer & retail industry even uses "*AI to optimize free trade agreements and save costs*" (F07). Overall, these cost savings lead to an improved financial situation. Additionally, a *shift from HR costs to technology and maintenance costs* shapes incumbent firms' cost structure. Thereby, the replacement of employees through AI-based robots, especially in the production line, allows a fast and automated workflow, while employees can focus on more challenging tasks (F01; F03; F07).

4.1.9 Revenue Streams

The *sales of new AI-enabled or AI-supported products and services lead to the emergence of new revenue streams.* The sharp increase in demand for smart products and services opens additional revenue streams for those firms offering such products or services (F02; F06). Additionally, the AI-enabled extension of existing products and services leads to higher sales prices through an added value and thereby to new revenue streams (F05; F06).

4.2 BMI and Value Generation Through AI

Based on our findings regarding the impact of AI on firms' business models, we developed a framework explaining the processes and outcomes of AI as a driver of BMI.

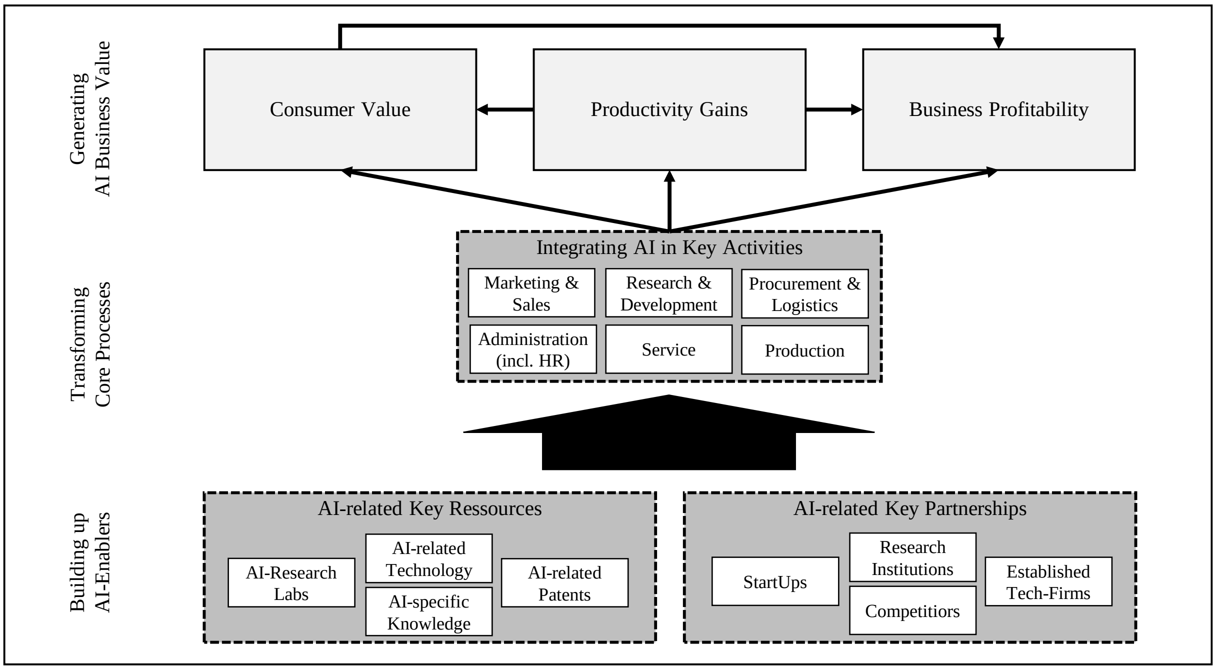

Figure 24. BMI and value generation through AI

As illustrated in Figure 24, successful AI-driven BMI is a process starting with the building of AI-enablers. This comprises the development of AI-related key resources and AI-related key partnerships. Modifications within these business model elements serve as the main foundation to enable the development and integration of AI in a firm's key activities. Depending on the specific industry, different key activities are the focus of transformation. Through an appropriate integration of AI technologies and applications in a firm's key activities, the course will be set for the generation of added business value. Thereby, in line with the definition of "IT business value" (Hitt and Brynjolfsson 1996), the term "AI business value" not only relates to a financial component, but rather relates to added consumer value (e.g., through an improved customer interface and new or improved products and services), productivity gains (e.g., through an automation and optimization of internal processes), and increased business profitability (e.g., through cost savings and new revenue streams).

AI-driven BMI should be seen as a continuous process where a firm should continuously rethink the appropriateness of its key resources and key partnerships. As AI is a relatively new technology and new applications are regularly available, firms should constantly rethink the role and appropriateness of their key resources and key partnerships and, if necessary, adapt or extend them.

5 Implications, Limitations, and Future Research

The results of our study provide several important implications for both researchers and practitioners alike. Our study contributes to the existing literature by providing novel insights on how the emergence of AI impacts and innovates the business models of incumbent firms. Whereas existing literature already found that digital technologies in general and specific technologies like big data and industry 4.0 play a major role in (re-)designing business models (e.g., Hildebrandt et al. 2015; Burmeister et al. 2016; Soto Setzke et al. 2020), we can observe the same pattern for AI. Furthermore, in line with existing literature, we show that organizational issues play a major role in technology-driven BMI (e.g., Burmeister et al. 2016) and all elements of an incumbent firm's business model can be affected (e.g., Metzler and Muntermann 2020).

In our study, the BMC elements key resources and key partners are particularly strong affected, possibly due to incumbent firms' great backlog demand regarding digitalization issues (Sebastian et al. 2017). In order to implement AI within their key activities, these firms need to build up key competencies in this area in advance. Also, the key activities of the investigated firms get increasingly reshaped through the integration of AI technologies and applications in order to increase the consumer value, the productivity, and the business profitability. Thereby, the scope of the use of AI differs across the examined industries. The financials of the analyzed firms are rather affected by changes in the cost structure (e.g., through the intelligent automation of processes) than by changes within the revenue streams. Changes within the customer segments were rather less mentioned by the investigated firms. This might be because firms with changed value propositions only meet the changed expectations of existing customer segments instead of the expectations of completely new customer segments.

Despite the careful design of our study, this paper is subject to some limitations, especially concerning external validity. As case studies are susceptible to context, the boundary conditions and generalizability of the specific study need to be considered (Lee and Baskerville 2003). Therefore, the findings of our case study can primarily be generalized to incumbent firms within the four analyzed industries in the European territory. However, future research can build on this by verifying whether our findings can be generalized to other industries and territories. Additionally, whereas this study aims at providing exploratory research on the use of AI in incumbent firms, future research could investigate differences between incumbents and non-incumbents. Another possible future research direction concerns the value generation potential of AI. In this study, we found that an appropriate integration of AI in a firm's key activities provides the potential for the generation of AI business value. However, the term AI business value need not necessarily mean a financial component and we also do not compare the added value with additional costs arising from AI integration. Future research could address this gap by conducting quantitative-empirical studies regarding the advantageous analysis of AI investments.

6 Conclusion

This explorative research aimed to analyze the impact of AI on the business models of incumbent firms in a holistic way, as well as the processes and outcomes of AI as a driver for BMI. To gain insights, we conducted a multiple case study in incumbent firms across four traditional industries. With our results, we show how each element of the BMC is affected by AI. Based on our findings, we further present a framework explaining the processes and outcomes of AI as a driver of BMI. Our major insights are: (1) AI has an impact on all elements of the BMC in incumbent firms and thereby drives a modification of the existing business models of firms in terms of BMI. (2) Due to high backlog demand, incumbent firms need to expand their technological competencies to integrate AI-based technologies and applications into their key activities to subsequently benefit from AI. (3) AI can lead to business value in incumbent firms in terms of added consumer value, productivity gains, and increased profitability.

I.4. Managing DT at the Business Unit Level (Study 4)

(Not included in this document due to copyright)

Paper Title:

Managing Digital Transformations at the Business Unit Level: An Exploratory Case Study of a Global Finance Function

Abstract: With its far-reaching implications for businesses and the global economy, digital transformation has become a highly relevant topic for executives and researchers alike. The formulation and execution of digital transformation strategies is vital to stay competitive in an increasingly digitalized world. Existing research strongly focuses on digital transformation strategy formulation and execution at an organizational level. However, digital transformation does not only have to be managed at an organizational level, but also at the business unit level. Therefore, by conducting a single case study in a large pharmaceutical manufacturing firm, we shed light on digital transformation strategy formulation and execution in a highly relevant business unit which further represents an important business model function: the finance function. Our contributions are dichotomous. First, we provide a comprehensive overview of the digital transformation process of a global finance function, including the presentation of specific process steps, transformation outcomes, as well as drivers and barriers. Second, this paper is the first that analyzes the formulation and execution of digital transformation strategies at a business unit level. In that regard, we show that digital transformation strategies are not only formulated at an organizational level, but also at a business unit level.

Outlet: Redacted in this version

Citation: Metzler, D. R., Muntermann, J., and Wittig, B. 2022. “Managing Digital Transformations at the Business Unit Level: An Exploratory Case Study of a Global Finance Function,” *Under Review*.

Keywords: Digital Transformation, Digital Transformation Strategy, Incumbent Firms, Finance Function, Qualitative Research, Case Study Research

II. Research Area:
Digital Transformation and Corporate Communication

The article in the second research area takes over another very important perspective. In this research area, the role of digital transformation in external communication tools of firms is investigated. In that regard, the research paper analyzes the role of the chief digital officer concerning the external communication flow of a firm's digital transformation endeavors. It highlights a high correlation between the existence of a chief digital officer and the amount of digital transformation-related signals in firms' external communication tools. The paper addresses the following research questions:

> **Research Question II.1:** How does CDO presence impact the volume of digital transformation-related signals in external communication tools?
>
> **Research Question II.2:** How does the volume of digital transformation-related signals differ across communication tools with different degrees of regulation?

II.1. CDOs and DT-Related Signaling (Study 5)

Paper Title:

The Role of CDOs in Signaling Digital Transformation Endeavors: An Analysis of Firms' External Communication Tools

Abstract: As part of their digital transformation, firms increasingly appoint Chief Digital Officers (CDOs). Existing research suggests that CDOs are appointed to drive and coordinate digital transformation activities and communicate digital transformation-related topics to stakeholders. However, the specific role of the CDO as a mediator between a firm and its external stakeholders, such as investors, remains unclear. Relying on signaling theory, we investigate whether CDO presence impacts digital transformation-related signaling in firms external communication tools. Indeed, our results show a strong positive association between CDO presence and the volume of digital transformation-related signals. Therefore, it can be assumed that CDO presence has the potential to contribute to reducing digital transformation-related information asymmetries between firms and external stakeholders. However, since our results show that less regulated communication tools are more likely to be used for digital transformation-related signaling than highly regulated ones, the reliability of such signals remains questionable.

Outlet: International Conference on Information Systems (ICIS) 2021

Citation: Metzler, D. R., Bankamp, S., Muntermann, J., and Palmer, M. 2021. "The Role of CDOs in Signaling Digital Transformation Endeavors: An Analysis of Firms' External Communication Tools," in *Proceedings of the 42nd International Conference on Information Systems,* Austin, TX, United States.

Keywords: Digital Transformation, Chief Digital Officer, External Corporate Communication, Signaling Theory, Quantitative Research, Natural Language Processing

1 Introduction

With rapid advancements in the development and improvement of digital technologies, firms must increasingly address the challenges of digitalization. Thereby, digitalization and associated technological innovations lead to disruptions within industries and markets and to rapidly changing organizational environments (Bharadwaj et al. 2013; Verhoef et al. 2021). To stay competitive in an increasingly digitalized society, firms need to evolve and adapt to the changing business landscape, making digital transformation crucial for firms to survive and remain competitive (Bharadwaj et al. 2013; Vial 2019; Firk et al. 2021). In recent years, an increasing number of firms have recognized the need for digital transformation and its potential opportunities. In that regard, firms increasingly consider digital transformation a critical success factor and invest in new technologies and associated capabilities (Sebastian et al. 2017).

As digital transformation becomes a high-level imperative for firms and their stakeholders, it has turned into a high precedence concern on the leadership level (Hess et al. 2016). The leadership, comprising the board of directors and the rest of the top management team, is vital to a firm's digital transformation. It is responsible for driving and coordinating the strategic direction of an organization, including the decision on how to address digital transformation (Luciano et al. 2020). In addition, the top management team is responsible for communicating digital transformation-related topics with important stakeholders, such as investors (e.g., Singh and Hess 2017). In that regard, an increasing number of firms appoint the position of the Chief Digital Officer (CDO) to the top management team as a centralized digital transformation responsibility with the aim to drive and coordinate digital transformation and to communicate digital transformation-related topics with stakeholders (e.g., Péladeau et al. 2017; Singh and Hess 2017; Kunisch et al. 2020; Singh et al. 2020).

Existing research on CDOs writes from different perspectives. In that regard, Kessel and Graf-Vlachy (2021) found that CDO-related research can primarily be distinguished in three different research streams: (1) Antecedents of CDO presence, (2) The CDO in the organization, and (3) Consequences of CDO presence. Whereas research on antecedents of CDO presence and the CDO in the organization is already advanced, research on the consequences of CDO presence is somewhat underrepresented in the existing literature (Kessel and Graf-Vlachy 2021). Thereby, most of the existing research concerning the consequences of CDO presence deals with the impact of CDOs on innovation performance (e.g., Leonhardt et al. 2018; Reck and Fliaster 2018; Reck and Fliaster 2019) or on financial performance (e.g., Zhan and Mu 2016; Drechsler et al. 2019; Berman et al. 2020; Firk et al. 2021) (Kessel and Graf-Vlachy 2021). However, although Singh and Hess (2017) found that an appointed CDO is responsible for communicating digital transformation-related topics with stakeholders, the specific role of the CDO as a mediator between a firm and its external stakeholders, such as investors, is still scarcely investigated. In that regard, the reduction of potential information asymmetries between firms and external stakeholders could be a potential side effect of CDO presence. From a signaling perspective, Drechsler et al. (2019) show that firms use the announcement of CDO appointments as a form of strategic signaling to investors. However, since digital transformation activities of firms are bound to risk and uncertainty (e.g., Hess et al. 2016; Sebastian et al. 2017; Moker et al. 2020), related information are highly relevant to evaluate the future prospects of a firm. Therefore, firms need to further send digital transformation-related signals to external stakeholders to reduce potential information asymmetries. Overall, we assume that digital transformation-related signaling does not only include the announcements of CDO appointments.

Research on digital transformation-related signaling is still rare. It especially remains unclear whether those firms appointing a CDO are more likely to conduct digital transformation-related signaling, especially in their external communication tools. If so, it could be assumed that CDO presence can be seen as an indicator for better digital transformation-related signaling and that CDO presence has the potential to reduce digital transformation-related information asymmetries between firms and external stakeholders. Due to the high relevance of digital transformation for the future competitiveness of firms and the resulting high relevance of digital transformation-related information for its stakeholders, especially investors, this research gap should be closed. We approach this research gap by analyzing whether the presence of a CDO can be associated with a higher volume of digital transformation-related signaling in firms' external communication tools. In addition, in order to investigate the reliability of digital transformation-related signaling, we further analyze potential differences between communication tools with different degrees of regulation. Against this background, we formulate the following research questions (*RQs*):

RQ1: How does CDO presence impact the volume of digital transformation-related signals in external communication tools?

RQ2: How does the volume of digital transformation-related signals differ across communication tools with different degrees of regulation?

To answer these research questions, we derive two hypotheses from the literature and analyze the relationship between CDO presence in a firm's top management team and digital transformation-related signaling in external communication tools. Thereby, the volume of these theme-specific signals is measured by the relative frequency of digital transformation-related sentences within the main external communication tools firms use to communicate with external stakeholders and reduce potential information asymmetries. To calculate the frequency of digital transformation-related sentences, we used the dictionary of digital terms developed by Chen and Srinivasan (2019), which we further extended by keywords related to digital technologies and digitalization in general. Our study focuses on the constituents of the S&P 500 equity index from 2007 to 2020. Based on insights from existing research on digital transformation and CDOs, we assume that firms appointing a CDO to their top management team pay increased attention to digital transformation activities. In addition, the appointed CDO should further drive digital transformation and digital transformation-related communication and thereby further bring digital transformation to a firm's focus. Overall, this should result in an increase in the volume of digital transformation-related signals. In that regard, we distinguish between highly regulated communication tools (10-K reports) and less regulated communication tools (conference calls). Both communication tools are highly relevant, but they differ significantly in their degree of regulation and subsequently in their reliability, which may impact how firms use them to communicate digital transformation-related information and how relevant they are for external stakeholders, especially investors.

We contribute to the existing literature concerning the consequences of CDO presence in manifold ways. Our study holds important implications for firms deciding whether to appoint a CDO or not and stakeholders deciding which firms are more inclined to signal digital transformation-related activities and where to search for digital transformation-related signals. Our results show that firms with a CDO in their top management team are accompanied by a significantly higher volume of digital transformation-related signals in their external communication. However, we further show that the increase in the volume of digital transformation-related signals in less regulated communication tools is significantly higher than in highly regulated communication tools which questions the reliability of such signals.

To provide sound theoretical foundations and gain valuable insights regarding our research questions, this paper is structured as follows: Starting with the theoretical foundations, we introduce the role of the CDO in the digital transformation journey as well as the role of signaling in corporate communication. Secondly, we introduce the methodological foundation of the conducted study. Thirdly, we present the findings of our analysis. Fourthly, in the context of a discussion, the limitations of our study and implications for future research and practice are presented. Finally, the conclusion summarizes the most important findings.

2 Theoretical Foundations

2.1 The CDO as the Centralized Digital Transformation Responsibility in Firms

The emergence of new digital technologies has a transformational impact on today's society. In a business context, digital technologies can reconfigure the way firms operate their business, communicate with stakeholders (e.g., customers and partners), and compete within markets (Bharadwaj et al. 2013; Hess et al. 2016). The changes that digital technologies bring to a firms' business model, resulting in changed products, the automation of processes, or changed organizational structures, can be described as digital transformation (Hess et al. 2016). Firms need to undergo a digital transformation to stay competitive in an increasingly digitalized market environment and thereby adapt their current business models, organizational structures, strategy, and internal culture (e.g., Matt et al. 2015; Eden et al. 2019; Metzler and Muntermann 2020).

For this reason, the process of digital transformation can be seen as one of the most relevant topics on the agenda of executives across industries (Hess et al. 2016).

Existing research indicates that a firm's leadership team and especially its top management team play an important role in the strategic change processes of firms, such as the digital transformation (Singh et al. 2020). Since digital transformation involves a fundamental transformation of the entire organization, including the need for adapting mindsets and skillsets, leadership is a crucial factor in the process of digital transformation (Westerman et al. 2014a). In order to adapt the top management team for the digital era and subsequently drive digital transformation, an increasing number of firms appoint new technology-related C-level roles to the top management team. This, for example, includes the chief information officer, Chief Innovation Officer, Chief Data Officer, Chief Strategy Officer, and the Chief Digital Officer. Chief Information Officers are in charge of IT support and IT deployment, Chief Innovation Officers are in charge of corporate in general without a specific digitalization focus, Chief Data Officers are responsible for the data management and data analytics, and Chief Strategy Officers are responsible for managing and executing strategy processes. Finally, the Chief Digital Officer can be described as the key position of highest responsibility for digital transformation in firms. The CDO is responsible for driving digital transformation activities, digital mobilizing the entire firm, initiating firm-wide collaboration, and communicating digital transformation-related topics with stakeholders (e.g., Singh and Hess 2017).

Not all firms appoint a CDO to the top management team to drive digital transformation. For example, various management boards believe that an already existent CIO is sufficient to fulfill this task. However, in that regard, Singh and Hess (2017) mention that, due to the complexity of digital transformation, it is challenging for a CIO to manage the digital transformation in addition to the original responsibilities of the CIO. Therefore, a CIO might not be the best choice for managing a firm's digital transformation. Other opportunities include, but are not limited to, giving the digital transformation responsibility to the CEO (Hess et al. 2016) or divisional or functional heads (Björkdahl 2020). Overall, existing research does not find a consensus on whether the appointment of a CDO to the top management team is an adequate decision concerning digital transformation issues. Therefore, it remains unclear whether the appointment of a CDO is an essential success factor in the process of digital transformation (e.g., Leonhardt et al. 2018). However, when appointing a CDO to the top management team, it is essential that the CDO and other C-level positions work closely together. For example, the CIO provides the foundation for digital transformation by delivering the necessary agile IT capabilities for more flexibility and digital innovation (Haffke et al. 2016). Furthermore, the CIO is also responsible for implementing the changes in the infrastructure and platforms. Therefore, it is essential that the CIO and the CDO work closely together while the CIO acts as an IT specialist and the CDO as the digital transformation specialist (Haffke et al. 2016; Singh and Hess 2017). Moreover, as the most senior manager, the CEO needs to back the digital transformation and assure that framing the digital transformation successfully supports the CDO in engaging and inspiring the entire organization, especially middle management. Therefore, also the CEO needs to work closely with the CDO and support the digital vision and activities (Westerman et al. 2014a).

The decision to appoint a CDO to the top management team depends on various internal and external factors (Kessel and Graf-Vlachy 2021). Most firms appoint a CDO as a response to realizing that the current top management team lacks managers with appropriate skills. In addition, CDOs are most common in firms with a focus on intangible assets. In firms focusing on tangible assets, CDOs are not that frequently presented (Firk et al. 2021; Kessel and Graf-Vlachy 2021). Another common trigger of appointing a CDO is market competition. In markets with highly digital-savvy competitors, firms appoint CDOs as a reaction to their peers (e.g., Haffke et al. 2016; Singh and Hess 2017; Firk et al. 2021; Kessel and Graf-Vlachy 2021).

Exiting research on CDOs has further dealt with the required characteristics and skillsets of CDOs. In that regard, it was found that a good CDO needs a mixture of technology-related skills (e.g., general IT competencies), a digital mindset (e.g., a digital visionary spirit), and more general skills (e.g., change management expertise) (Singh and Hess 2017). Additionally, existing literature derived various CDO-typologies regarding their specific role within the leadership team. For example, Singh and Hess (2017) proposed three different CDO types: (1) Entrepreneur CDOs, (2) Digital Evangelist CDOs, and (3) Coordinator CDOs. The Entrepreneur CDO mainly focuses on digital innovation, complementing the existing IT infrastructure and drive innovation by developing, exploring, and exploiting digital technology. The Digital Evangelist CDO focuses on spreading the digital strategy throughout the organization to motivate and inspire employees for the digital transformation. Finally, the Coordinator CDO drives high-level coordination and alignment throughout the organization and creates synergies across the firm. However, all CDO-typologies have in common that they agree on the fundamental idea of implementing a CDO: setting up a position in the top management team that drives and coordinates a firm’s digital transformation journey (e.g., Singh and Hess 2017; Tumbas et al. 2017).

Appointed to a firm’s top management team, a CDO drives and coordinates the digital transformation with the responsibility of formulating an overarching digital transformation strategy and making digital transformation a strategic priority (Westerman et al. 2014a; Haffke et al. 2016; Singh and Hess 2017; Singh et al. 2020). This includes introducing new digital technologies, driving a digital culture, and accelerating the digital transformation process (Singh and Hess 2017; Singh et al. 2020). In addition, the CDO is responsible for coordinating digital initiatives and the associated change management within a firm, mediating between different organizational units, working against organizational barriers, and communicating digital transformation-related topics with stakeholders (Singh and Hess 2017; Tumbas et al. 2017; Tumbas et al. 2018). However, it remains unclear whether these actions are also visible and valuable in the communication with external stakeholders, especially investors. In that regard, CDO presence could be associated with a higher volume of digital transformation-related signals that would, at best, reduce potential information asymmetries between a firm and its external stakeholders.

2.2 Signaling Theory and the Reduction of Information Asymmetries Through External Corporate Communication

Information asymmetries frequently occurs between a firm's management (possessing more information) and different stakeholder groups, especially investors (possessing less information). In that regard, the principal-agent theory explains contractual relations between parties with mismatched goals in the presence of uncertainty and asymmetric information (Pavlou et al. 2007). The principal (e.g., investor) commissions the agent (e.g., manager) to perform tasks on her or his behalf (e.g., management of the firm). In this case, the agent has more precise information than the principal due to her or his specific role and related activities, making the agent's assessment more difficult. Situations can arise in which the agent does not act in accordance with the principal's utility function but only maximizes her or his own utility. (Grossman and Hart 1983) show that this situation can reduce investor's welfare.

In order to reduce information asymmetries and minimize potential welfare losses, firms capitalize on signaling. The so-called signaling theory primarily addresses situations where two different parties have asymmetric information concerning a specific topic (Spence 2002; Connelly et al. 2011). In his seminar work on job market signaling, Spence (1973) shows how job applicants can reduce information asymmetries to hamper the selection ability of prospective employers (Connelly et al. 2011). Generally, signaling theory explains how the party with more information (e.g., management), the sender, chose signals to communicate that information. The other party (e.g., investor), the receiver, should interpret this signal (Connelly et al. 2011). How useful and effective a signal is for a potential receiver is determined by signal reliability (Connelly et al. 2011), which can be described as the extent to which a signal can be perceived as trustworthy. One of the most common signaling tools for firms are external communication tools, including 10-Q-reports, 10-K-reports, and conference calls. These tools include information about financials as well as information about current strategic topics, including digital transformation. Although all these communication tools are highly relevant, they are characterized by a different degree of regulation and standardization. On the one hand, 10-Q-reports and 10-K-reports are documents required by the SEC quarterly (10-Q) or yearly (10-K). These documents contain financial statements, disclosures, internal controls, and management discussions and analyses (SEC 2021a; SEC 2021b). The management has to report all material information, including qualitative information (Cannon et al. 2020). In addition, the 10-K reports are audited by external auditors (SEC 2021a; SEC 2021b). Overall, it can be concluded that 10-K reports are highly regulated and standardized documents for corporate disclosure. The content in these documents can be classified as highly trustworthy. On the other hand, also other less regulated tools are used to communicate with external stakeholders. For example, conference calls are quarterly telephone-based meetings where firms inform investors and analysts about current topics concerning their business development. These conference calls play a unique role, as they take place in connection with the quarterly earnings announcements and thus provide an essential form of corporate disclosure (Huang et al. 2018). In contrast to 10-K reports, conference calls are not one-sided communication, but company representatives also have to respond spontaneously to questions raised by analysts or others. Thus, compared to highly regulated 10-K reports, conference call transcripts are much less standardized and non-audited documents. The trustworthiness concerning its content, therefore, is not necessarily secured.

Existing research shows that firms use signaling to reduce potential information asymmetries with external stakeholders concerning various topics (e.g., Moker et al. 2020). Since digital transformation activities of firms are bound to risk and uncertainty (e.g., Hess et al. 2016; Sebastian et al. 2017; Moker et al. 2020) and related information highly relevant to evaluate the future prospects of a firm, external stakeholders, such as investors, try to gather a lot of information in order to reduce potential information asymmetries (Moker et al. 2020). Especially a firms' central corporate communication tools are suitable for stakeholders to look out for visible signals of firms (Moker et al. 2020). In that regard, Brown et al. (2004) showed that conference call activity is negatively related to information asymmetry and Fu et al. (2012) show that information asymmetry is reduced when the frequency of financial reporting increases.

Related research shows that the presence of a chief data officer is associated with a higher frequency of big data-related signaling in annual reports (Kralina 2018). Concerning CDOs, Drechsler et al. (2019) found that firms use public announcements of CDO appointments as strategic signaling to investors. However, it remains unclear whether CDO presence is also associated with a higher quantity of digital transformation-related signaling and whether this information is relevant for external stakeholders with regard to potential information asymmetries.

2.3 Hypothesis Development

Existing research agrees that digital transformation is a highly relevant topic concerning the future competitiveness of firms (e.g., Westerman et al. 2014a). In order to drive and coordinate digital transformation activities, firms increasingly appoint CDOs to their top management team (e.g., Singh and Hess 2017; Tumbas et al. 2017; Singh et al. 2020). In that regard, it can be assumed that those firms appointing a CDO to their top management team pay particularly increased attention to digital transformation activities. A high strategic priority of digital transformation, paired with the fact that digital transformation activities are bound to risk and uncertainty, holds the risk of information asymmetries between a firm and its external stakeholders. In order to reduce potential information asymmetries, these firms can increase their digital transformation-related signaling. Since an appointed CDO is responsible for communicating digital transformation-related topics with external stakeholders, it should further be recognizable that CDOs increase the strategic priority of digital transformation in external communication. Overall, these circumstances should be visible in digital transformation-related signaling in firms' external communication tools. Existing research underscores these assumptions. For example, Kralina (2018) shows that the appointment of a special position (i.e., chief data officer) to the top management team can be associated with increased signaling in the area of responsibility of this person (i.e., big data activities) (e.g., Kralina 2018). Based on these assumptions, we derive the following hypothesis 1 (*H1*):

H1: CDO presence can be associated with a higher volume of digital transformation-related signals in firms external communication tools.

As already discussed in the theoretical background, there exist differences between external communication tools. Whereas highly regulated communication tools (i.e., 10-K reports) mainly contain strictly defined content, less regulated tools (i.e., conference calls) include information on current topics where the specific information needs of analysts and other stakeholders can be addressed. In that regard, signal reliability is an important issue. On the one hand, from the argument of signal reliability, regulated communication tools would be more appropriate if firms want to signal that they really engage in digital transformation. Since such communication tools are more trustworthy and reliable, their signals are more useful for their receivers. Thus, if firms really put much effort into digital transformation activities, which implies that their signals are meaningful and provable, they would choose these more reliable communication tools for digital transformation-related signaling. However, on the other hand, if digital transformation is more of a cheap talk; that is the firms like to talk about it but not do any substantially with digital transformation, firms would primarily rely on less regulated communication tools to talk about digital topics. Overall, both, firms that strongly engage in digital transformation, as well as firms for those digital transformation is more of a cheap talk, can engage in digital transformation-related signaling in less regulated communication tools. However, only those firms really engage in digital transformation can also engage in digital transformation-related signaling in highly regulated communication tools. In the end, it can be assumed that the volume of signals differs across different communication tools. Only those firms really engaging in digital transformation can use digital transformation-related signaling in highly regulated communication tools, and only CDOs in such firms can further accelerate this signaling. Based on these assumptions, we further derive the following hypothesis 2 (*H2*):

H2: The impact of CDO presence on the volume of digital transformation-related signals in non-regulated communication tools is higher than in regulated ones.

To test our hypotheses, we measure the volume of digital transformation-related signals in different external communication tools of the analyzed firms. In that regard, we use the relative amount of digital transformation-related sentences in two of the most important external communication tools: (1) 10-K reports and (2) conference calls.

Since the CDO appointment is an endogenous and not a random event, firms make a conscious decision to make a CDO appointment. This endogeneity problem makes it difficult to make statements about the causal effect of CDO appointments since an unobserved third variable and not the CDO appointment itself could drive the results. We aim to minimize this problem by selecting an appropriate research methodology. The following section describes our methodological approach to test the derived hypothesis and subsequently answer our research questions.

3 Methodological Approach

To analyze the impact of CDO presence within a firm's top management team on the volume of digital transformation-related signals, we conduct an empirical study comprising several sequential steps. In the first step, we utilize natural language processing techniques to calculate the relative frequency of digital transformation-related sentences (DIGITAL RATIO) in a firm's major external communication tools. The sentence-based ratio should prevent the use of numerous topic-specific words in a short section of the text, biasing the results as it could happen with a word-based ratio. However, as part of the validity check, we can confirm that the results of this study do not change when the digital ratio is calculated at the word level. The DIGITAL RATIO serves as our proxy to measure the volume of digital transformation-related signals. It is calculated for the selected firms' 10-K reports and conference calls. Indeed, not every digital transformation-related sentence has to be a conscious and deliberate signal in the sense of signaling theory. For example, it may be the case that certain content (especially in 10-K reports) must be reported due to regulatory requirements. Although this kind of communication can reduce information asymmetries, it would lack the conscious decision of the signaler that is at the heart of signaling theory. Since it is hardly possible to decide which sentences were sent conscious and deliberate in the sense of the theory, we cannot make a differentiation and consider all sentences as signals in the sense of the signaling theory.

To determine the relative frequency of digital transformation-related sentences in these documents, we use the dictionary of digital terms developed by Chen and Srinivasan (2019) and extend it with other important digital technology-related and other digitalization-related word groups and keywords. The existing dictionary comprises a selection of relevant digital technology-related word groups (i.e., the word groups Big Data, Cloud, Artificial Intelligence, and Machine Learning) with a selection of relevant keywords for each word group and a selection of other digitalization-related keywords. Since this sample of word groups and keywords does not represent a sufficient universe of digital transformation-related issues, we extend the existing dictionary by adding word-groups concerning other important digital technologies. Thereby, we primarily focus on SMACIT technologies (Sebastian et al. 2017) and add the word groups “Social Media,” “Mobile,” and “Internet of Things.” Furthermore, we extend the existing word groups with similar and alternative words. The final dictionary of digital terms can be found in the appendix. Researchers are invited to use and extend the existing dictionary for future research projects. A sentence is classified as digital transformation-related if it contains at least one entry (word or n-gram) from the applied dictionary. In that regard, we use a search that is not case-sensitive. If relevant, we also consider different wordings (e.g., virtual agent / virtual agents). In the appendix, the words for which we consider different endings are indicted by the wildcard character “*.” We calculate the DIGITAL RATIO of a document by dividing the digital transformation-related sentences by the total number of sentences in the document.

In order to determine the extent to which CDO presence affects the volume of digital transformation-related signals, we estimate equation (1) , representing a panel regression in which the firms are observed several times during the observation period. This panel structure is particularly suitable for investigating an event’s effect (in this case, first-time CDO appointments) on the dependent variable (Wooldridge 2015).

$$\begin{aligned} &DIGIAL\ RATIO[CC; 10\ K]_{t,i} = \alpha_0 + \alpha_1 CDO_{t-1,i} + \alpha_2 INTANGIBLES_{t-1,i} \\ &+\alpha_3 MTB_{t-1,i} + \alpha_4\, ln(TOTAL\ ASSETS)_{t-1,i} + \alpha_5 ROA_{t-1,i} + \alpha_6 LEVERAGE_{t-1,i} \\ &+\alpha_7 RETURN_{t-1,i} + \alpha_8\, ln(1 + DIGITAL\ M\&A)_{t-1,i} + \alpha_9 RELATED\ CxO_{t-1,i} \\ &+\alpha_i + \alpha_t + \varepsilon_{t,i} \end{aligned} \tag{1}$$

The dependent variable DIGITAL RATIO is calculated separately with respect to the conference calls [CC] and the annual reports [10 K] on a firm (i) year (t) level. In order to answer RQ2, the digital Ratios will be examined separately for each document type. The main variable of interest is the binary variable CDO which is set to 1 for all firm-year combinations with an acting CDO in the respective year and firm and 0 in all other cases. We further incorporate common control variables into the equation that could influence the volume of digital transformation-related signals. We follow Firk et al. (2021) and use intangible assets (excluding goodwill and scaled by net sales) to assess whether the business model is more focused on knowledge (intangible assets) or on tangible assets (e.g., production of raw materials). We use the market-to-book ratio (MTB) to account for the firm’s valuation, the natural logarithm of total assets to account for firm size, return on assets (ROA) to account for profitability, the leverage ratio (LEVERAGE) to account for the capital structure and the annual stock return (RETURN) to account for current stock market performance. In addition, we use the variable DIGITAL M&A to account for the acquisition of digital knowledge through inorganic growth (Hanelt et al. 2021b). The variable is calculated by the number of digital M&A transactions the company has conducted as an acquirer during the respective year. We define an M&A transaction as digital if the target’s business description or the purpose text of the deal contains at least one entry of the dictionary that is also used for the DIGITAL RATIO. Since it is not only the CDO who could potentially engage in digital-transformation-related signaling, we also consider the board’s composition with respect to other technology-related C-level roles as discussed in the theoretical background (section 2.1). The variable RELATED CxO is 1 in all firm-years where the board has a chief information/technology/innovation/data or strategy officer and 0 in all other cases. We further utilize firm fixed effects (α_i) to control for all time-invariant firm characteristics (e.g., industry) (Wooldridge 2015) and year fixed effects (α_t) to account for period-specific characteristics (e.g., increased awareness of the relevance of digitalization activities over time). This comprehensive set of controls reduces the problem of endogeneity of a CDO appointment in our research design. Finally, we use lagged independent variables (lagged by one year) to mitigate the potential problem of reversed causality.

4 Datasets and Descriptive Statistics

To get a basic understanding of the main variables used in this study and to present first interesting insights concerning our data, we present our different datasets and descriptive statistics. As a sample, we use all firms that were part of the U.S. equity index S&P 500 at any time during the period from January 1, 2007 to December 31, 2020. The selection of the S&P 500 allows a relatively broad sample and also good data availability. Since the trend towards appointing CDOs started around 15 years ago (Singh and Hess 2017), the period under review covers the main phase of CDO appointments in firms. The resulting sample includes a total number of 810 firms and thus theoretically 11,340 firm-year observations (810 firms x 14 years). Not all 810 firms existed during the whole period (e.g., due to liquidations and mergers). This reduces the number of observations we consider for our analysis.

For our research approach, we use three distinct datasets. The first dataset comprises information about board positions. Our main variable (CDO), as well as the control variable Related CxO, is drawn from this dataset. The process of gathering the CDO data comprises several sequential steps. In the first step, we combine the data of the three databases (1) Boardex, (2) Amadeus, and (3) Crunchbase and extracted all current and former senior executives for those firms included in our sample. Afterward, we identify relevant CDO positions. In that regard, we build on recommendations of existing research (e.g., Kunisch et al. 2020). Therefore, we classify all senior executives with the term “digital” in their role title as potential CDOs. According to Kunisch et al. (2020), this procedure ensures considering those CDOs with similar roles but different role titles. In the next step, we check all resulting potential CDOs and eliminate clear non-CDOs. This, among others, include divisional CDOs, subsidiary CDOs, Chief Data Officers, and CIOs. Finally, to extend our dataset, we also browsed professional websites, online-based executive platforms, firm websites, and press releases with regard to those firms included in our sample. The final sample of CDOs solely contains top management positions responsible for the digital transformation activities within their specific firm. Our approach identifies 213 CDOs across 152 firms of the total 810 firms included in our sample. For the control variable Related CxO, we used the role titles from the Boardex and Amadeus databases.

The second dataset includes the textual data used to explore the scope of digital transformation-related content in firms' external communication tools. This dataset includes 10-K reports and transcriptions of conference calls for those firms included in our sample. We extract 10-K reports from the SEC Edgar database, and the conference calls stem from the Refinitiv Thomson ONE database. We choose these data types as they represent highly relevant external communication tools that give insights into ongoing and completed strategic issues. Both data types aim to reduce potential information asymmetries and therefore contain a vast amount of information that enables a deeper insight into the firms' corporate strategy and, therefore, are suitable for our study (e.g., Bowman 1984; Brown et al. 2004; Kloptchenko et al. 2004; Lee and Hong 2014). Whereas 10-K reports are highly standardized annual reports whose publication is legally prescribed, conference calls are carried out several times a year (usually each quarter) to inform investors and analysts about a firm's business development. In contrast to other annual reports, 10-K reports are generally more detailed but lack graphical elements. From the 10-K reports, we extract the text passages for further analysis. We remove any tables and figures. From the conference calls transcripts, we separated the content from the metadata. For the subsequent analysis, we use the conference calls' presentations as well as the Q&A sessions. We remove extremely short sentences of less than 20 characters, as a manual review of the text sections has shown that these are mostly very short statements from conference call participants without meaningful content (e.g., "Ok, thank you."). We use the extracted textual data from both sources to calculate the DIGITAL RATIO as described in the methodology section.

To obtain a first understanding of the data used, we combined both datasets (i.e., CDO information and text in external communication tools) to show how the CDO RATIO and the DIGITAL RATIO evolved over time.

As illustrated in Figure 27, the CDO presence across the considered firms has increased strongly during the observation period. In line with existing literature, we can observe that before 2010, CDOs were only very sporadically present in our sample. However, at the end of our observation period, in 2020, a CDO is present in about one-fifth of the analyzed firms. In addition, also the DIGITAL RATIO across the 10-K reports and conference calls has increased strongly over time. In that regard, our data indicates that the average DIGITAL RATIO of the conference calls is significantly higher than the average DIGITAL RATIO of the 10-K reports.

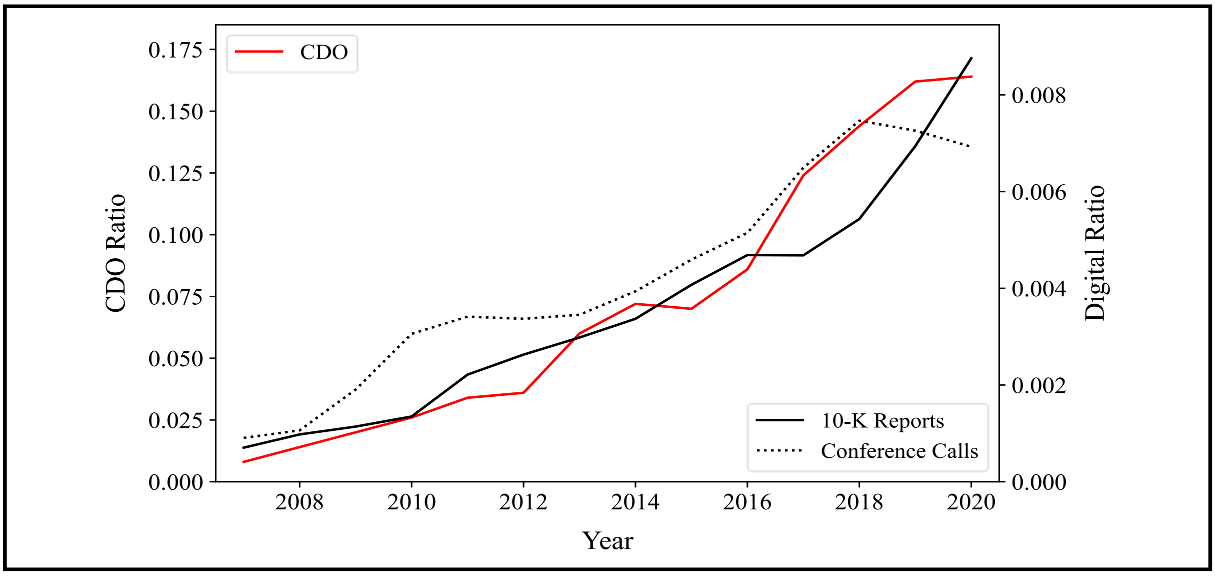

Figure 25. CDO presence and digital transformation activities within S&P 500 over time

Since existing research indicates industrial differences in the frequency of CDO appointments, we also investigate the CDO RATIO and the DIGITAL RATIO per industry. The relevant information is shown in Figure 28. The chart on the left side illustrates the CDO RATIO per industry and its development over the years 2007, 2014, and 2020. The chart on the right side illustrates the average DIGITAL RATIO over the entire study period per industry and communication tool (10-K reports vs. conference calls).

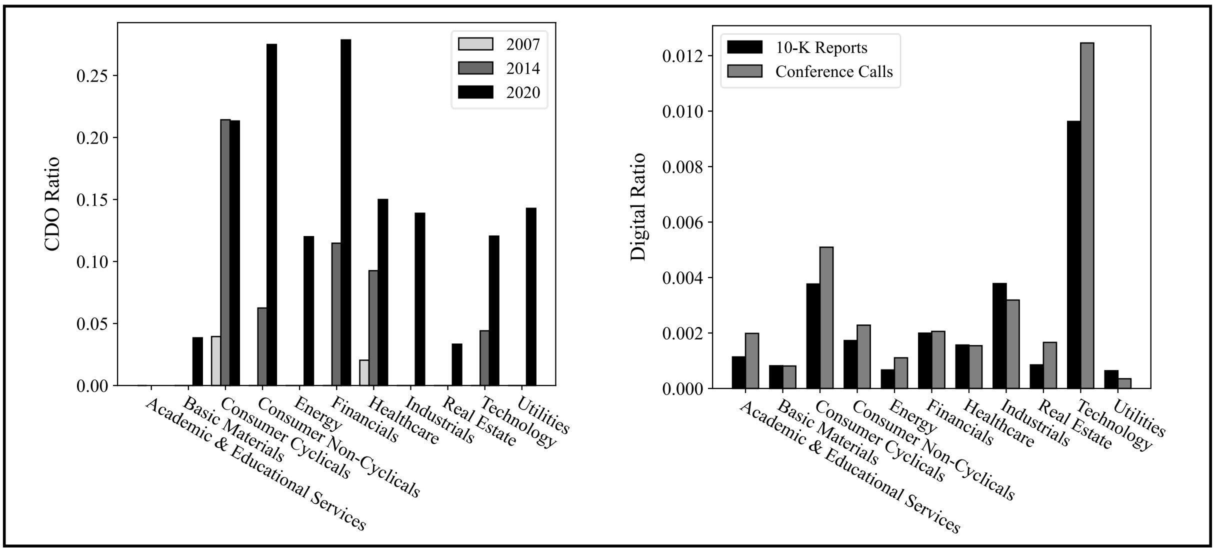

Figure 26. CDO ratio and digital ratio across industries and communication tools

In line with existing literature (e.g., Firk et al. 2021; Kessel and Graf-Vlachy 2021), our data shows that the proportion of firms with a CDO in their top management team in firms with a high focus on intangible assets (e.g., Financials) is higher than in firms with a high focus on tangible assets (e.g., Basic Materials). The DIGITAL RATIO measured in 10-K reports and conference calls also varies considerably among different industries. It is not surprising that the DIGITAL RATIO of firms within the technology sector is the highest of all industries. This can be justified because these firms focus on developing and selling technology-based products and services. As a result, they have a high technology focus in their reporting. Consumer cyclical firms and industrial firms have a relatively high DIGITAL RATIO as well. Firms of the basic materials industry and the utility industry have the lowest average DIGITAL RATIO. Finally, another interesting finding in this dataset is that the average DIGITAL RATIO in conference calls is higher than in 10-K reports. This might be due to the fact that 10-K reports only allow little flexibility, whereas conference calls also include a larger share of more spontaneous content. Further, since the content conference call documents is not highly regulated, this could indicate that digital transformation is more of a cheap talk for many firms.

The third dataset includes the control variables gathered from Refinitiv DataStream (accounting and price data) and SDC (M&A data). Table 26 shows the descriptive statistics for all variables. We only include a firm-year observation in our analysis if all variables from equation (1) are available (10-K report, conference calls transcripts, and control variables). We further drop singleton observations (firms with only one observation during the observation period) as they do not add within-firm variation to our analysis. This reduces the total number of firm-year observations for the subsequent analysis to 6,456.

	N	**Mean**	**SD**	**P(0.01)**	**P(0.99)**
DIGITAL RATIO [CC]	6,456	0.0047	0.0100	0.0000	1.0507
DIGITAL RATIO [10-K]	6,456	0.0039	0.0078	0.0000	1.0415
CDO	6,456	0.0649	0.2464	0.0000	1.0000
INTANGIBLES	6,456	0.1667	0.4313	0.0000	1.783
MTB	6,456	2.6742	59.7569	-40.2000	45.9900
TOTAL ASSETS (M)	6,456	41,267	142,956	475.685	731,781
ROA	6,456	0.0697	0.0867	-0.2299	0.2990
LEVERAGE	6,456	0.6177	18.1205	-12.7548	17.1008
RETURN	6,456	0.1545	0.4173	-0.6859	1.4572
DIGITAL M&A	6,456	0.0694	0.3500	0.0000	2.0000
RELATED CxO	6,456	0.7103	0.4536	0.0000	1.0000

Table 22. Descriptive statistics

To better understand how the utilized variables are interrelated, we calculate the pairwise correlations (Pearson correlation). The results can be obtained from Table 27.

Variables	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**	**(9)**	**(10)**	**(11)**
(1) DIGITAL RATIO [CC]	1										
(2) DIGITAL RATIO [10-K]	0.68*	1									
(3) CDO	0.14*	0.11*	1								
(4) INTANGIBLES	0.02*	0.04*	0.02*	1							
(5) MTB	0.01	0.02	0.01	0.01	1						
(6) TOTAL ASSETS (M)	-0.01	0.01	0.06*	-0.01	-0.01	1					
(7) ROA	0.10*	0.10*	-0.02	-0.09*	0.01	-0.09*	1				
(8) LEVERAGE	0.01	0.01	0.01	-0.01	0.48*	-0.02*	-0.01	1			
(9) RETURN	0.05*	0.04*	-0.01	-0.01	0.03*	0.04*	0.10*	-0.01	1		
(10) DIGITAL M&A	0.33*	0.29*	0.04*	0.01	0.01	0.03*	0.06*	0.01	0.01	1	
(11) RELATED CxO	0.06*	0.08*	0.08*	-0.01	0.01	0.02*	0.04*	0.01	-0.01	0.07*	1

* significance at the 0.05 level

Table 23. Correlation matrix

A significant positive correlation between CDO presence and DIGITAL RATIO can be observed, which could indicate a positive relation between CDO presence and the volume of digital transformation-related signals in external corporate communication. The correlation matrix also shows that a higher DIGITAL RATIO is associated with a higher return on assets and higher stock returns. This could be interpreted as communication about digital transformation measures that positively impact profitability (if increased communication is associated with increased digital transformation activities) and investors' assessment. The reversed direction could also be possible, so that particularly profitable firms invest their resources, especially in such activities, and communicate it to the capital market. There is also a positive correlation between firm size and CDO presence which is also as expected because larger firms typically have a larger board (Eisenberg et al. 1998) and are therefore more likely to implement more specific positions such as that of a CDO. Finally, we see higher Digital Ratios for firms that engage in DIGITAL M&As and that have RELATED CxOs in their top management team.

5 Empirical Results

In order to evaluate the impact of CDO presence on the volume of digital transformation-related signals, we make use of the underlying data's panel structure. The analysis is divided into two parts. In the first part, we consider only first-time CDO appointments, while in the second part, the entire set of observations is utilized by the panel regression.

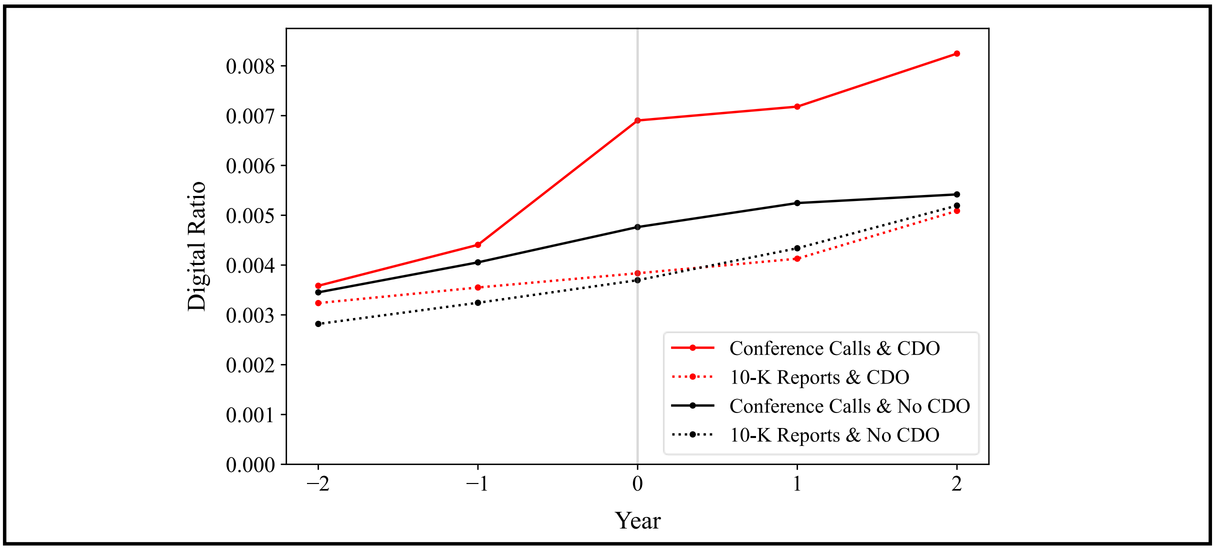

Figure 27. Digital transformation activities around CDO appointments

First, we only look at the cases of first-time CDO appointments for which we can observe the two years before and the two years after the appointment. For this, the firm must exist for the entire five years, and data on CDO presence, conference call transcripts, and 10-K reports must be available for each year. This results in a total of 81 first-time appointments we can utilize. Thereby, our analysis focuses on the transition from a firm without CDO presence to a firm with CDO presence. The results of this analysis can be obtained from Figure 29.

The red lines in Figure 29 show how the DIGITAL RATIO changes over time relative to the first-time CDO appointment. The year 0 marks the year in which the CDO is appointed. The black lines serve as references and show how the DIGITAL RATIO developed in the conference calls and the 10-K reports among those firms that did not appoint a CDO during the entire observation period. The temporal structure of the CDO groups and the reference groups are matched. For the conference calls (solid line), we observe an almost identical DIGITAL RATIO in the two years before the appointment. However, in the year of the CDO appointment, the DIGITAL RATIO rises sharply, while the reference firms only follow the overall trend. In the two years after the CDO appointment, the DIGITAL RATIO are again relatively parallel, but those of the firms with a CDO are on a much higher overall level. This suggests that the CDO has triggered an increase in the volume of digital transformation-related signals in conference calls. Based on 10-K reports (dotted line), no such effect can be observed. The two graphs are thus relatively similar over the entire period under consideration. Again, this could indicate that digital transformation is more of a cheap talk for many firms. Firms indeed increase their digital transformation-related signaling after CDO appointments, however, mostly in less regulated communication tools with lower signal reliability. Further, in 10-K reports firms have only little flexibility, whereas conference calls also include a larger share of spontaneous content and Q&A sessions.

The findings derived from Figure 29 provide a first indication that H1 and H2 can be confirmed. Thereby, the confirmation of H1 is mainly driven by the conference calls. To provide statistical evidence, we make use of a research approach in which all 6,456 firm-year combinations are utilized and not only the limited time periods surrounding first-time CDO appointments as in the previous analysis. Due to the larger number of observations and the numerous control variables, this analysis allows more precise statements about the effects of CDOs on digital transformation-related signaling. The results are shown in Table 28.

	[1] DIGITAL RATIO [CC]	[2] DIGITAL RATIO [10-K]	[3] DIGITAL RATIO [CC]	[4] DIGITAL RATIO [10-K]
CDO	0.0053***	0.0035***	0.0031**	0.0009*
	(10.51)	(9.05)	(2.54)	(1.80)
INTANGIBLES			-0.0016**	-0.0011**
			(-2.12)	(-2.19)
MTB			0.000001	0.000001
			(1.15)	(1.51)
ln(TOTAL ASSTES)			0.0014**	0.0013***
			(2.10)	(2.96)
ROA			0.0010	0.00004
			(0.43)	(0.02)
LEVERAGE			-0.000002	-0.000003
			(-0.48)	(-1.08)
RETURN			0.0003	0.0002
			(0.69)	(1.29)
ln(1+DIGITAL M&A)			0.0030***	0.0025**
			(3.22)	(2.43)
RELTATED CxO			-0.0003	-0.0007*
			(-0.32)	(-1.72)
Intercept	0.0043***	0.0037***	-0.0085	-0.0075*
	(33.90)	(37.12)	(-1.43)	(-1.93)
N	6,456	6,456	6,456	6,456
Fixed Effects	No	No	Firm & Year	Firm & Year
Clustering	No	No	Firm	Firm
Adj. R^2	0.017	0.012	0.628	0.718

* p<0.1, ** p<0.05, *** p<0.01; t statistics in parentheses

Table 24. Panel regression

Models [1] and [2] are standard OLS regressions. Thus, they do not consider the panel structure of the underlying data. However, they show that CDO presence has a positive effect on the DIGITAL RATIO. Models [3] and [4] correspond to equation (1) specified in the methodology section. Also, based on these regression models, it can be seen that CDO appointments have a significant positive effect on the DIGITAL RATIO in the conference calls (p=0.010). The effect with respect to the 10-K reports is almost significant (p=0.072) but with less than a third of the magnitude compared to the effect on conference calls. Thus, H1 and H2 can be confirmed. Both models account for multiple control variables, firm fixed effects, and year fixed effects. Furthermore, we use heteroskedasticity-robust standard errors that are clustered on the firm dimension. The regression coefficient of 0.0031 for the conference calls also shows an economically significant effect size, considering that the mean value across all years and firms is only 0.0047 and that even if only the firms that introduce a CDO later in the observation period are considered, the mean DIGITAL RATIO is only 0.0055 in the year before the CDO is appointed. The CDO effect thus corresponds to an increase of 56.36% in the DIGITAL RATIO of conference calls. The results clearly confirm that CDO presence is associated with an increase in the volume of digital transformation-related signals and that this signaling primarily takes place via less regulated communication tools (i.e., conference calls). Interestingly, we do not see a significant effect of RELATED CxO positions on digital transformation-related signaling, which emphasizes the specific role of CDOs concerning digital transformation.

6 Discussion

6.1 Theoretical and Practical Implications

This paper enhances existing literature in the research stream "Consequences of CDO presence" in manifold ways. Our analysis shows that CDO presence is continuously increasing across S&P500 firms which underlines the high relevance of CDOs for firms. Further, it underlines the strategic importance of dealing with the decision on appointing a CDO or not. Our data indicates that CDO presence and digital transformation-related signaling in external communication tools vary across industries. In line with existing literature, we show that CDO presence in firms focusing on intangible assets is higher than in firms with tangible assets (e.g., Firk et al. 2021; Kessel and Graf-Vlachy 2021).

Consistent with existing studies, we show that the appointment of a particular position in the top management team can be associated with increased signaling in the area of responsibility of this person (e.g., Kralina 2018). In our case, we show that CDO presence leads to a higher volume of digital transformation-related signals within firms' main external communication tools (i.e., firm's 10-K reports and conference calls). Thus, CDO presence is associated with a higher volume of digital transformation-related signals in a firm's corporate communication tools. In addition, our results indicate significant differences between the volume of digital transformation-related signals in highly regulated communication tools (i.e., 10-K reports) and less regulated ones (i.e., conference calls). Conference calls contain a relatively higher amount of such signals. Concerning signal reliability, it can be assumed that digital transformation is more of a cheap talk for many firms. These firms like to talk about it but do not substantially engage in digital transformation activities. In that regard, CDO presence indeed reinforces digital transformation-related signaling. However, mostly associated with relatively low signal reliability. Overall, it remains questionable if the increased signaling through CDO presence is suitable for reducing potential information asymmetries. Another potential reason for the predominant use of non-regulated communication tools, is that 10-K reports are highly standardized documents in which firms have only little flexibility. This makes it more difficult for firms to address current issues as quickly as possible. Second, conference calls also include a large share of spontaneous content. In such conference calls, firms have the possibility to present and discuss current issues. In addition, in conference calls, external analysts and other persons can ask questions that can increasingly be related to digitalization activities. Therefore, it can be assumed that digital transformation-related signaling works easier through less regulated communication tools. However, again, this bears the risk that such less regulated communication tools are not as trustworthy as more regulated communication tools. Consistent with these results, we also found considerable variation among the different document types concerning the increase of the scope in digital transformation-related content as a direct reaction to the first-time appointment of a CDO. Whereas we can observe a sharp increase in digital transformation-related content in conference calls as a reaction to CDO appointments, the increase in 10-K reports does not exceed the overall trend. This also might be due to the highly regulated and standardized nature of 10-K reports. Overall, these results indicate that less regulated communication tools (i.e., conference calls) are more likely to be used to address digital transformation-related topics. Investors searching for information concerning firms' digital transformation activities, therefore, are more likely to find such information in less-regulated communication tools. However, at the same time, these communication tools are accompanied by lower signal reliability. Thus, it could be that firms rather just referencing digital technologies and digital transformation in order to impress the investors instead of implementing these technologies.

For firms, our study can support the decision-making process when facing the question of appointing a CDO to the top management team or not. Our study suggests that appointing a CDO to the top management team is an excellent option for firms that are at least interested in improving their digital perception with regard to external stakeholders. Nevertheless, our study does not replace a systematic decision-making process. Firms should also consider their specific requirements and determine their individual needs.

Finally, although our results confirm hypothesis 2, that the impact of CDO presence on the quantity of digital transformation-related content in less regulated communication tools is different than in highly regulated communication tools, these results are questionable from a regulatory point of view. On the one hand, firms have to report all material information, including qualitative information, in a 10-K report. Indeed, digital transformation-related topics are material information as the degree of digitalization impacts the future competitiveness of firms. However, on the other hand, digital transformation-related topics play a rather subordinate role in 10-K reports.

6.2 Limitations and Future Research

Besides the careful design of our research approach, this study is subject to some limitations. First, our study only considers S&P500 firms. Therefore, our results can only be generalized to large US-based firms. Future research could build on this by verifying whether our results can be confirmed in other countries and for small and medium-sized enterprises (SMEs). In addition, we only assessed two specific communication tools (i.e., conference calls and 10-K reports). These are the very important communication tools of firms to get in touch with investors and other stakeholders. However, these sources still only represent a selection of relevant communication tools of firms. Future research could adopt this methodology and could, for example, also analyze firms' websites and other publicly available sources.

The volume of digital transformation-related signals in documents is measured based on a dictionary, which allows a high degree of transparency and replicability for future research. However, machine learning techniques may extract such content with a higher degree of accuracy (e.g., Huang et al. 2014). Further, although we already extended the existing dictionary of digital words, future research could extend it even further, e.g., by adding more digital technology-related word-groups.

One of the most ubiquitous problems in research on firm's management teams concerns endogeneity. Decisions on the structure of the top management team are typically made consciously and in particular based on strategic considerations. As a result, our results may not be causally driven by the CDO. Our results (increased relevance of digital transformation activities) and the appointment of the CDO could also be driven simultaneously by a third variable that is not considered. At the same time, the CDO presence could have no causal impact on the scope of digital transformation-related communication. For this reason, our results can only indicate an association between the presence of a CDO and the relevance of digital transformation activities in firms. While we control for numerous possible factors through the use of firm and year fixed effects as well as control variables that could drive our results, we cannot derive flawless causality based on our study design. This leads to the possibility that the results could be affected by the phenomenon that firms with a higher strategic focus on digital transformation naturally engage more in digital transformation activities (independent of the presence of a CDO). Future research is encouraged to further improve this approach in order to minimize endogeneity issues further.

Our study indicates that CDO presence is associated with a higher volume of digital transformation-related signals quantitatively. Future research could build on this by verifying whether there also is a causal effect between these variables. Further, our study assumes that this higher quantity of digital transformation-related signaling, i.e., higher information quantity, goes along with higher information quality, reducing potential information asymmetries. However, it remains unclear whether the presence of a CDO really has a positive impact on the quality of digital transformation-related signaling and thereby has the power to reduce potential information asymmetries. Future research could build on this by qualitatively analyzing the content of digital transformation-related signaling of firms with a CDO vs. firms without a CDO. Finally, future research could also investigate whether a higher quantity of digital transformation-related signaling has an impact on specific information asymmetry proxies (e.g., bid-ask spreads), financial performance, and capital market parameters.

7 Conclusion

Existing CDO-related research indicates that firms appoint CDOs to the top management team intending to drive and coordinate digital transformation activities and communicate digital transformation-related topics with stakeholders (e.g., Péladeau et al. 2017; Singh and Hess 2017; Kunisch et al. 2020; Singh et al. 2020). However, until now, it remained unclear whether those firms appointing a CDO are more likely to conduct digital transformation-related signaling, especially in their external communication tools, and whether a CDO appointment is an appropriate instrument to increase a firm's external visibility and to handle investor relations concerning digital transformation. With this study, we approached this research gap by analyzing the impact of CDO presence on the volume of digital transformation-related signals in firms' external communication tools.

Our empirical results indicate that CDO presence leads to an increase in the discussion of digital transformation-related topics in firms' external communication tools. This increase in the volume of digital transformation-related signals can be observed directly after a CDO appointment. In addition, we show that this effect is mainly driven by the impact on less regulated communication tools (i.e., conference calls). Overall, our results highlight that the presence of a CDO in the top management team can be associated with a higher volume of digital transformation-related signals in a firms' external communication tools. Therefore, it can be concluded that a CDO is an appropriate instrument to increase a firms' external visibility and to handle investor relations concerning digital transformation. However, concerning signal reliability, investors and other external stakeholders need to evaluate whether a firm actually engages in digital transformation or if it is more of a cheap talk.

C. Contributions

In this last part (C) of this cumulative dissertation, the main contributions of the two different research areas are presented. This part aims to reiterate the contributions of each research paper and research area and to relate these contributions to the pre-formulated research questions. This includes a presentation of the most relevant findings, theoretical and practical implications, specific limitations, and suggestions for future research.

The first research area focuses on the impact of digital transformation and specific digital technologies on the overall business model and specific business model elements of firms. This research area outlines the current state of research in the field of digital transformation-driven business model innovation (Metzler and Muntermann 2021, **paper I.1**), assesses the impact of digital transformation on the overall business model of incumbent firms (Metzler and Muntermann 2020, **paper I.2**), describes the role of artificial intelligence as a driver for business model innovation in incumbent firms (Metzler er al. 2021a, **paper I.3**), and provides insights on the process of digital transformation strategy formulation and execution within the finance function of an incumbent firm (Metzler et al. 2022, **paper I.4**).

The second research area focuses on corporate communication in the context of digital transformation. Metzler et al. (2021b, **paper II.1**) provide insights on the role of the chief digital officer in communicating digital transformation-related information with external interest groups of firms.

The individual research articles of each research area contribute to the ongoing research on digital transformation by providing a holistic and multi-faceted view of the impact of digital transformation strategy formulation and implementation on the business model of firms and their corporate communication.

1 Summary of Findings

In this section, the findings of the two research areas (including five research articles) are summarized and synthesized. For this purpose, the research questions of each research area are restated. Afterward, a summary of the most important findings concerning each research question is presented. An extended discussion of the findings can be found in each of the individual research papers of this cumulative dissertation.

1.1 Research Area I: Digital Transformation and Business Model Innovation

The first research area aims at providing a holistic overview of the impact of digital transformation and specific digital technologies on the overall business model and specific business model elements of firms.

The first paper of this dissertation aimed to structure the existing literature in the field of digital transformation-driven business model innovation. The associated research questions and the main findings of this paper are illustrated in Table 29.

Summary of Paper I.1	
Title	Digital Transformation-Driven Business Model Innovation – Current State and Future Research Directions
Research Question(s)	How can existing research on digital transformation-driven business model innovation be systemized and what are major insights? What are worthwhile future research directions concerning digital transformation-driven business model innovation?
Main Contribution	Development of a research framework on digital transformation-driven business model innovation and presentation of the current state of research and future research avenues.

Table 25. Summarized overview of paper I.1

The results of Metzler and Muntermann (2021, **paper I.1**) provide meaningful answers to the above stated research questions. First of all, by conducting a systematic literature review (Webster and Watson 2002), the paper provides an organizing framework that conceptualizes and systemizes digital transformation-driven business model innovation. In that regard, the paper suggests that research on digital transformation-driven business model innovation can be divided into four different transformation aspects: antecedents, processes, outcome, and evaluation. Further, some of the analyzed articles refers to conceptual foundations concerning digital transformation-driven business model innovation. Most research focuses on the processes and the outcome of digital transformation-driven business model innovation. However, research concerning the evaluation of digital transformation-driven business model innovation is rather underrepresented.

In a second step, the paper provides an overview of potential future research opportunities for each of the different transformation aspects. The results show that although research concerning the processes and outcomes is rather advanced than research regarding the other transformation aspects, there are still many research gaps left in all research perspectives.

The second paper in the first research area dives deeper into the impact of digital transformation on the existing business models of incumbent firms. This paper's underlying research question and main findings are illustrated in Table 30.

Summary of Paper I.2	
Title	The Impact of Digital Transformation on Incumbent Firms: An Analysis of Changes, Challenges, and Responses at the Business Model Level
Research Question(s)	How does digital transformation impact the overall business model of incumbent firms in traditional industries?
Main Contribution	Development of a framework explaining the impact of digital transformation on the overall business model of in-cumbent firms, including a presentation of changes, challenges, and responses for each business model element.

Table 26. Summarized overview of paper I.2

To answer the above stated research question, in Metzler and Muntermann (2020, **paper I.2**), a multiple case study across different incumbent firms in different traditional industries was conducted. To advance scientific research in that field, this paper is the first that provides an all-embracing holistic view of the impact of digital transformation on the overall business model of incumbent firms across various industries. The findings of the paper suggest that digital transformation has an impact on all business model elements. This counts for incumbent firms across all considered industries. For example, digital transformation drives an individualization of products and services, digitization and personalization of customer communication, the use of data as a new key resource, and the emergence of new revenue streams.

Further, the paper contributes to the ongoing scientific discussion concerning digital transformation by providing a first conceptualization of the impact of digital transformation on incumbent firm's business models as (1) changes (induced by integrating digital technologies), (2) challenges (as a result of a collision between digital transformation-driven changes and existing environmental or organizational conditions), and (3) responses (as potential reactions to such challenges).

A similar approach, but with a significantly different research goal, was used in Metzler et al. (2021a, **paper I.3**). Instead of analyzing the impact of digital transformation as a whole, in this paper, the impact of one of the most innovative digital technologies, artificial intelligence, on the business model of incumbent firms was analyzed. The underlying research question and the main findings are summarized in Table 31.

Summary of Paper I.3	
Title	Artificial Intelligence and Business Model Innovation in Incumbent Firms: A Cross-Industry Case Study
Research Question(s)	How does the use of AI impact the specific elements of incumbent firms' business models? How does AI drive Business Model Innovation in incumbent firms?
Main Contribution	Provision of insights on the impact of artificial intelligence on existing business models and development of a framework explaining the role of artificial intelligence in innovating existing business models of incumbent firms.

Table 27. Summarized overview of paper I.3

As a result of analyzing multiple expert interviews coupled with corporate news articles and annual reports, this paper first assesses the impact of artificial intelligence on each business model element of incumbent firms across various industries (Metzler et al. 2021a, **paper I.3**). Similar to the study in Metzler and Muntermann (2020, **paper I.2**), artificial intelligence also finds applications across all business model elements. However, artificial intelligence mainly impacts the business model elements' value proposition (e.g., for personalization issues), key activities (e.g., for automating and optimizing processes), key resources (e.g., through replacing humans with robots), and key partners (e.g., through forming new artificial intelligence-driven partnerships). Business model elements regarding the customer interface (customer relationships, channels, customer segments) and financial aspects (revenue streams, cost structure) are rather less affected by implementing and using artificial intelligence.

In a second step, a framework explaining the processes and outcomes of value generation through the use and implementation of artificial intelligence in existing business models is presented. As a first step, firms need to build up enablers for implementing and using artificial intelligence. This comprises the build-up of artificial intelligence-related key resources (e.g., technology and knowledge) and artificial intelligence-related partnerships (e.g., with research institutions and startups). Afterward, core processes can be transformed through the integration of artificial intelligence in firms' key activities (e.g., marketing and sales or production). Finally, the intelligent integration of artificial intelligence can lead to an increase in customer value, productivity gains, and an increase in business profitability.

A final view on the implications of digital transformation for business models is represented in the next paper. In contrast to the aforementioned studies, this paper focuses on digital transformation strategy formulation and execution in relation to one specific business model element instead of the overall business model: the finance function. The research question behind this approach and the main contribution can be taken from Table 32.

Summary of Paper I.4	
Title	Managing Digital Transformations at the Business Unit Level: An Exploratory Case Study of a Global Finance Function
Research Question(s)	How does an incumbent pre-digital firm digitally transform its finance function and what are the drivers, barriers, and outcomes of this process?
Main Contribution	Conceptualization of the process of digital transformation strategy formulation and execution at the business unit level and presentation of insights on drivers, barriers, and outcomes of digital transformation in a global finance function.

Table 28. Summarized overview of paper I.4

By conducting a single case study within a European pharmaceutical manufacturer, Metzler et al. (2022, **paper I.4**) indicate that digital transformation strategies are not only formulated at an organizational level but also at a business unit level and digital transformations at a business unit level can trigger digital transformations at an organizational level. The study further indicates that digitally transforming a global finance function can be seen as an iterative process comprising three major steps: digital strategizing, digital implementation, and digital follow-up. This process is driven by several internal and external drivers.

Digitally transforming a global finance function offers a high potential to improve the overall business, especially through an increase in the quality and efficiency of financial processes. This is shown by presenting the main outcomes of digitally transforming a global finance function. However, digitally transforming a global finance function is also accompanied by several technological and cultural challenges that need to be considered by the transforming firm's management. These challenges are presented as five specific barriers.

Overall, the studies in this research area underline the high impact new emerging digital technologies and digital transformation have on existing business models. The studies show that digital transformation as a whole, but also transformative digital technologies, like artificial intelligence, shape and reconfigure existing business models and business model elements. However, the studies further show that the process of digital transformation, either on the business model level or the business unit level, is accompanied by several technological and cultural challenges that have to be considered by the transforming firm's management.

1.2 Research Area II: Digital Transformation and Corporate Communication

The second research area concerns the corporate communication of firms regarding their digital transformation endeavors. Gathering information concerning the formulation and implementation of a firm's digital transformation strategy is especially important for investors to evaluate the future prospects of a firm. The chief digital officer is predestined to play an important role in this process. Against this background, two research questions were formulated in Metzler et al. (2021b, **paper II.1**). The research questions and the main contribution can be taken from Table 33.

Summary of Paper II.1	
Title	The Role of CDOs in Signaling Digital Transformation Endeavors: An Analysis of Firms' External Communication Tools
Research Question(s)	How does CDO presence impact the volume of digital transformation-related signals in external communication tools? How does the volume of digital transformation-related signals differ across communication tools with different degrees of regulation?
Main Contribution	Provision of insights on the role of the chief digital officer in communicating digital transformation endeavors and reducing digital transformation-related information asymmetries.

Table 29. Summarized overview of paper II.1

Metzler et al. (2021b, **paper II.1**) address the above stated research questions by conducting an empirical study in which natural language processing techniques were used to analyze 10-K reports and conference calls concerning their digital transformation-related content. The results of a conducted panel regression show that CDO presence is associated with a higher volume of digital transformation-related content in 10-K reports and conference calls. Whereas the general volume of digital transformation-related content in 10-K reports and conference calls is very similar, the positive association between CDO presence and the volume of digital transformation-related content in conference calls is about three times higher than in 10-K reports. Since conference calls are rather less regulated, the signal reliability is questionable, and the receivers of such signals have the task of evaluating whether the digital transformation-related content really comprises insightful information on digital transformation endeavors or not.

In addition, the results of this study show that CDO presence in the top management team of firms and also the digital transformation-related content in firms' external communication tools (i.e., in 10-K reports and conference calls) has increased significantly over the last few years. This is especially true for firms in industries specializing in intangible assets (e.g., technology, financial), which increasingly appoint CDOs and communicate about their digital transformation endeavors. This underlines the increasing relevance of digital transformation for firms.

1.3 Synthesis: Implications of Digital Transformation for Business Models and Corporate Communication

Although in this cumulative dissertation the individual research articles are divided into two different research areas, all research articles and both research areas are strongly connected.

The findings in the first research area indicate that firms are strongly engaged in digital transformation activities. In that regard, digital transformation and the implementation and use of specific digital technologies, such as artificial intelligence, have a huge impact on transforming firms' business models and business model elements. This impact goes along with complex challenges and risks firms have to deal with, but also with chances to improve the competitive position within a market.

High risk, on the one hand, and high potential, on the other hand, lead to the fact that digital transformation is associated with high uncertainty. Appropriate management of digital transformations can play a decisive role in competition and can determine whether firms improve their competitive position or even disappear from the market. Therefore, every firm that undergoes a digital transformation needs to assign digital transformation responsibilities, for example, by appointing a chief digital officer. In addition, to make meaningful assessments of the future prospects of a firm, it is important for investors to gather as much information on firms' digital transformation endeavors as possible.

The findings within the second research area indicate that the strong engagement of firms in digital transformation activities is also reflected in a strong increase in digital transformation-related information in firms' external communication tools. Further, the results of the second research area show that the presence of chief digital officers is associated with an even higher increase in this digital transformation-related information flow. However, since this mainly applies to rather less regulated communication tools (i.e., conference calls), it is questionable, whereas this increase in digital transformation-related communication has the potential to reduce or even minimize potential information asymmetries between a firm and its stakeholders, especially investors.

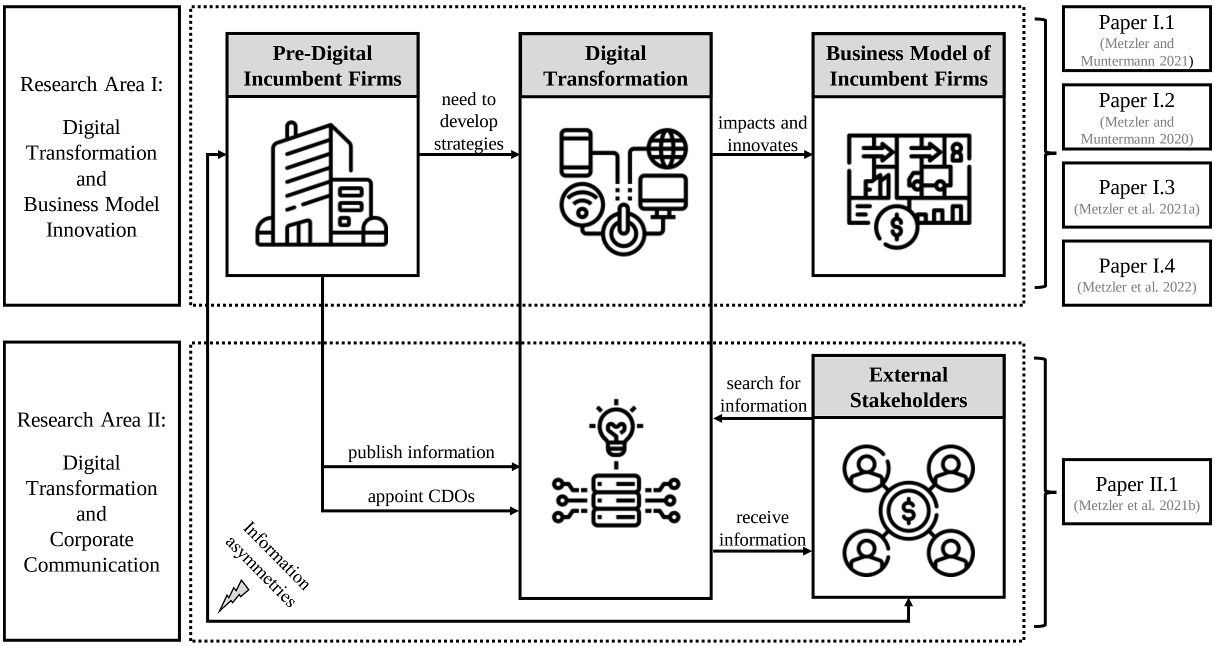

Figure 28: (Inter-)relations between research areas in this dissertation

2 Implications

In this section, the most important implications for each research area are presented. The implications of both research areas are grouped into implications for research and implications for practice. An extended discussion of the implications for research and practice can be found in each of the individual papers of this cumulative dissertation.

Overall, the studies of this cumulative dissertation contribute to the ongoing scientific discussion on digital transformation in manifold ways, which has been called for in various scientific articles (e.g., Vial 2019; Hanelt et al. 2021a; Verhoef et al. 2021). Thereby, the specific studies draw on the existing knowledge on digital transformation to further advance the scientific understanding of digital transformation in the context of business models and corporate communication from different perspectives.

2.1 Research Area I: Digital Transformation and Business Model Innovation

Implications for Research: The first implication of this research area concerns the high relevance of research on digital transformation in relation to business models. In that regard, Metzler and Muntermann (2021**, paper I.1**) underline the actuality of this research stream. The research paper confirms the statements of existing research concerning the high impact of digital transformation on business models (e.g., Fitzgerald et al. 2013; Hanelt et al. 2015; Loebbecke and Picot 2015; Hess et al. 2016; Klos et al. 2017; Schallmo et al. 2017; Vial 2019; Böttcher and Weking 2020; Li 2020; Rof et al. 2020; Caliskan et al. 2021). Further, the study introduces the concept of digital transformation-driven business model innovation and derived a framework that shows how research in this field can be systemized. The identified research articles all agree that digital transformation has a huge impact on business models, which is primarily reflected in reconfigurations of existing business models or the development or emergence of new business models. Although research on digital transformation-driven business model innovation has gained increasing importance over the last years, the findings of the study additionally indicate that research in this field is still in its infancy with much potential for future research to advance scientific knowledge across all identified transformation aspects. Future research, therefore, is encouraged to further conduct studies on digital transformation-driven business model innovation in order to further advance this growing field of research.

Whereas Metzler and Muntermann (2021, **paper I.1**) already indicate that research on digital transformation-driven business model innovation is highly relevant and that digital transformation has a huge impact on existing business models, the findings of Metzler and Muntermann (2020, **paper I.2**) confirm these suggestions. Additionally, the study introduces a framework conceptualizing the impact of digital transformation on firms' business models. This framework helps to better understand what the "impact of digital transformation on business models" really means. In that regard, the findings of the study further indicate that the impact of digital transformation differs between specific business model elements. Whereas the changes due to digital transformation in some business model elements are rather radical, others are merely incremental. This, of course, also influences the implications of the specific impact. In addition, the scope of the specific impact varies across industries. For some industries, specific impacts are more challenging than for other industries. Overall, whereas other research articles mostly focused on specific business model elements and/or specific industries, Metzler and Muntermann (2020, **paper I.2**) went a step further by providing a holistic and all-embracing view on the impact of digital transformation on the overall business model of incumbent firms across various industries.

Not only does digital transformation as a whole impact and innovate existing business models. The findings of Metzler et al. (2021a, **paper I.3**) indicate that the development and use of the specific digital technology artificial intelligence also have the power to impact all elements of incumbent firms' business modela. Further, the study underlines the power of artificial intelligence in driving business model innovation. Whereas existing literature already indicated that specific technologies like industry 4.0 and big data have the potential to (re-)design business models, Metzler et al. (2021a, **paper I.3**) observed the same pattern for artificial intelligence. Interestingly, the study indicates that the aim of using artificial intelligence and the application areas differ significantly across industries. Further, the study shows that the use of artificial intelligence especially impacts the business model elements' key resources and key partnerships. A potential reason for this is that most incumbent firms have a great backlog demand regarding digital transformation (Sebastian et al. 2017). The customer segments and channels, on the other hand, seem to be rather less affected by implementing and using artificial intelligence. Also, the revenue streams seem to be rather less affected although the value propositions are rather strongly affected by integrating artificial intelligence in existing products or developing new products based on artificial intelligence.

Another important theoretical implication in this research area is that firms do develop not only digital transformation strategies for the overall organization, but also for specific functional business units. In that regard, Metzler et al. (2022, **paper I.4**) found that the case firm of the study formulated an independent, but well-aligned, digital transformation strategy for their global finance function. As digital transformations in general, also this process can be seen as an iterative process (Chanias et al. 2019). Additionally, the study shows that digitally transforming the finance function leads to changes in organizational structures, a shift in employee profiles, employee replacement by intelligent systems, and increased process quality and efficiency. In that regard, digitally transforming the finance function plays an important role in improving the overall business through the intelligent implementation of new digital technologies.

Implications for practice: The research articles in this research area are very practice-oriented. The implications for practice are therefore highly versatile. The framework developed in Metzler and Muntermann (2021, **paper I.1**) helps practitioners to identify important topics to discuss when digitally transforming their business (models). Further, practitioners can find the most relevant literature in the field of digital transformation-driven business model innovation in this paper.

The findings of Metzler and Muntermann (2020, **paper I.2**) suggest that managers of firms need to consider all elements of their business model when formulating or executing digital transformation strategies. Practitioners must be aware that digital transformation affects all elements of their firm's business model. Based on the findings in Metzler and Muntermann (2020, **paper I.2**), executives can anticipate specific challenges arising from business model changes and can elaborate appropriate responses to these challenges. Further, they can compare their already planned or executed responses with the suggested responses of Metzler and Muntermann (2020, **paper I.2**) and make further adjustments if necessary. As discussed in the theoretical implications, the impact of digital transformation differs between specific industries and between specific business model elements and can be either radical or incremental. Executives should especially keep in mind the industry they relate to and keep an eye on the business model elements on which digital transformation has a rather radical impact.

A wide range of potential application areas for artificial intelligence can be taken from Metzler et al. (2021a, **paper I.3**). Practitioners can use the findings of this paper to screen the potential, usefulness, and impact of artificial intelligence across all business model elements. Further, the framework on business model innovation and value generation through artificial intelligence can be used as a blueprint for planning the implementation and use of artificial intelligence in existing business models.

The findings of Metzler et al. (2022, **paper I.4**) can encourage practitioners to keep a special eye on the finance function as part of digital transformation. Further, the study indicates that it can be useful to develop individual digital transformation strategies for specific functional business units, which should be well-aligned with the digital transformation strategy and other organizational strategies of the overall organization. Further, the study gives strategic support on how to plan and implement this transformational process through the exemplary showing of the whole process of digital transformation strategy formulation and execution of the global finance function of one large incumbent firm. In addition, the elaborated barriers can help to early identify and react to potential challenges and risks in digitally transforming a global finance function.

2.2 Research Area II: Digital Transformation and Corporate Communication

Implications for research: The results of this research area contribute to the literature on the management and outcomes of digital transformation and the consequences of CDO presence. The first implication in this research area concerns the high relevance of research on chief digital officers and corporate communication. The findings in Metzler et al. (2021b, **paper II.1**) show that the number of chief digital officers in firms, as well as the digital transformation-related content in firms' external communication tools, has continuously increased over the last years. The high number of chief digital officers and the high amount of publicly available digital transformation-related content in communication tools hold the potential for meaningful future studies (especially due to a large amount of publicly available data).

The findings in Metzler et al. (2021b, **paper II.1**) confirm existing studies regarding the fact that the presence of special CxO positions can be associated with an increased signaling activity in the specific area of responsibility (e.g., Kralina 2018). In Metzler et al. (2021b, **paper II.1**), the presence of a chief digital officer is associated with an increased signaling activity in the area of digital transformation. However, since the increase in digital transformation-related signals can primarily be observed in less regulated conference calls, the signal reliability remains questionable. It can be assumed that some firms like to talk about digital transformation but do not really engage in it. The firms may just reference digital transformation issues or digital technologies to impress external stakeholders, such as investors, instead of really engaging in various digital transformation activities.

Finally, as part of its methodological approach, the study enhances the dictionary of digital terms by Chen and Sinivrasan (2019). Other researchers can use the advanced dictionary to investigate similar or other phenomena or even further develop the dictionary.

Implications for practice: The study in this research area holds important implications for practitioners, especially for senior executives of firms and external stakeholders, such as investors. First, senior executives can use the findings in their decision-making processes regarding chief digital officer appointments. Executives can learn from the findings that the presence of a chief digital officer has the potential to increase the visibility of firm's digital transformation endeavors in their external communication tools. Therefore, firms can see chief digital officer appointments as something similar to a marketing instrument. In addition, external stakeholders, especially investors, can benefit from the findings. In that regard, the findings show that investors will find more digital transformation-related information in the communication tools of firms with a chief digital officer. Further, investors will find such information in conference calls rather than in 10-K reports. Finally, investors should be aware of the fact that information in conference calls is not as reliable as information in 10-K reports.

3 Limitations

Each specific study of this cumulative dissertation is subject to limitations. In the following, the major limitations grouped into the two specific research areas are presented. An extended discussion of the limitations can be found in each of the individual papers of this cumulative dissertation.

3.1 Research Area I: Digital Transformation and Business Model Innovation

The results of the literature review in Metzler and Muntermann (2021, **paper I.1**) should be interpreted while keeping in mind several decisions made during the research process, which impacted the development process. First, concerning the literature search, the developed search string was only applied to the title, abstract, and keywords and not to the full text of articles. Applying the search string to the full text of potentially relevant articles could ensure that relevant articles that do not use specific keywords in their title, abstract, or keywords are also considered. In addition, the developed search string could be further advanced. This could be done by adding more business model-related keywords (e.g., the nine business model elements of the business model canvas (Osterwalder and Pigneur 2010)). In that regard, the impact of specific technologies on the business model of firms was left out of consideration. However, the implementation of specific digital technologies, such as artificial intelligence, can also be seen as part of digital transformation.

The literature review in Metzler and Muntermann (2021, **paper I.1**) considers all articles published in peer-reviewed journals or conference proceedings. However, specific rankings do not play a role in this literature review. A further restriction of the literature with regard to ranking criteria could positively influence the quality of the literature selection and thus also the quality of the results. Finally, as in most literature reviews, the development of the specific concepts is subject to subjectivity.

The case studies in Metzler and Muntermann (2020, **paper I.2**), Metzler et al. (2021a, **paper I.3**), and Metzler et al. (2022, **paper I.4**) are also subject to several limitations. A major limitation of all conducted case studies has to do with the external validity. Case studies, in general, are susceptible to context. The goal of case studies is not to achieve statistical generalization (i.e., extrapolating probabilities) but rather an analytic generalization (i.e., expanding and generalizing theories) (Yin 2014). Therefore, for each case study, the specific boundary conditions and the generalizability need to be considered (Marshall 1996; Lee and Baskerville 2003). The results of each case study are only completely reliable for the specific cases under investigation. A generalization is at most possible for (nearly) similar firms in (nearly) similar industries and (nearly) similar geographical regions. However, the results can not be generalized to other industries or geographical regions. The results further do not necessarily apply to firms with other internal or external conditions or management mechanisms. For example, Metzler and Muntermann (2020, **paper I.2**) indicated significant industry differences concerning the impact of digital transformation on business models, which underlines the importance of considering the generalizability of each case study.

The main source of evidence across all conducted case studies is expert interviews. Major weaknesses of interviews are the possibility of response biases and reflexivity (the interview partner gives the answers the researcher wants to hear) (Yin 2014). Further, not all points of view from all relevant persons can be queried. To cushion these issues somewhat, in all case studies, additional documents (e.g., annual reports and news articles) were analyzed. However, the beforementioned issues cannot be solved completely.

Finally, all conducted case studies were analyzed through different qualitative coding techniques. These qualitative coding techniques involve the risk of subjectivity. To minimize this risk, all analyses were conducted by a team of researchers. By performing a dual coder approach, the involved researchers checked for intercoder reliability in each of the specific case studies. However, the subjectivity in this research method cannot be completely ruled out.

3.2 Research Area II: Digital Transformation and Corporate Communication

Methodological and theoretical limitations are present in Metzler et al. (2021b, **paper II.1**). Regarding the natural language processing techniques used in this study, it should be noted that machine learning techniques may lead to better results, especially concerning the degree of accuracy (e.g., Huang et al. 2014). Further, the dictionary used in this study is not exhaustive and some digital technologies are omitted. In addition, the words listed in the dictionary should not necessarily occur in the context of digital transformation within the analyzed documents. Therefore, all sentences marked as “digital transformation-related” do not necessarily deal with digital transformation activities.

Another major limitation has to do with the endogeneity issue. Since structural decisions concerning the management team are typically made based on consciously strategic considerations, the results of Metzler et al. (2021b, **paper II.1**) could be driven simultaneously by a third variable (or even more variables) that is not considered and not (only) causally driven by the chief digital officer. Although the study considers various control variables and additionally controls for firm and year fixed effects, flawless causality cannot be ensured. Therefore, the results can only be seen as a positive association between chief digital officer presence and the relevance of digital transformation activities in firms which is measured by the volume of digital transformation-related signals.

Similar to a major limitation in research area 1, in Metzler et al. (2021b, **paper II.1**), the limited generalizability should also be considered. Since the study only considers US-based firms, the results cannot be reliably transferred to other geographical regions.

Finally, the study only indicates that the presence of a chief digital officer is associated with a higher degree of digital transformation-related signaling in a quantitative manner. However, it remains questionable if this also goes along with higher information quality. Only if this is the case, the presence of a chief digital officer may have the potential to reduce digital transformation-related information asymmetries.

4 Future Research

In the process of answering the specific research questions of each research area, new questions arose in each study that can be answered in future research. In this section, the most promising future research directions are presented for each research area. An extended discussion of potential future research directions can be found in each of the individual papers of this cumulative dissertation.

4.1 Research Area I: Digital Transformation and Business Model Innovation

The first study of research area one introduced the concept of digital transformation-driven business model innovation and reviewed the existing literature in that field. As already discussed, the literature search in Metzler and Muntermann (2021, **paper I.1**) includes limitations regarding search string development and search string application. Thus, future research is encouraged to further extend and perfect the literature review by advancing the developed search string and applying the search string to the full text of potentially relevant articles. The search string could, for example, be advanced by adding words for each specific business model element based on the business model canvas (Osterwalder and Pigneur 2010). In addition, to increase the quality of the final list of literature, future research could consider specific journal rankings as an additional inclusion criterion. Appropriate rankings are, for example, the “Financial Times 50” ranking or the “Verband der Hochschullehrer*innen für Betriebswirtschaft e.V. (VHB)” ranking. Further, the study by Metzler and Muntermann (2021, **paper I.1**) mainly reviews the existing literature with the aim of analyzing the current state of research in a content-related manner. However, future research could additionally focus in more detail on theoretical lenses and research methods used in the relevant articles. Finally, within the selection process of relevant literature, the impact of specific technologies on the business model of firms was left out of consideration. However, the implementation of specific digital technologies, such as artificial intelligence, can also be seen as part of digital transformation. Therefore, future research should think about extending the scope of such a literature review, for example, by adding some technology-specific keywords to the search string.

With regard to the elaborated organizing framework in Metzler and Muntermann (2021, **paper I.1**), the study revealed promising future research directions for each concept of the organizing framework. Future research is encouraged to approach these open research questions. This, for example, includes the questions of how the different concepts of business model innovation are related to digital transformation, how specific IT and dynamic capabilities create a competitive advantage concerning digital transformation-driven business model innovation, and how an appropriate (re-)evaluation process of digital transformation-driven business model innovation should look like.

Since the case studies in Metzler and Muntermann (2020, **paper I.2**), Metzler et al. (2021a, **paper I.3**), and Metzler et al. (2022, **paper I.4**) are limited concerning their generalizability, future research is encouraged to transfer these studies to other firms, industries, and geographical regions. For example, it would be interesting to compare results from a new study in Asia or the USA with the existing results counting for Europe. In this context, similarities and differences could be revealed.

Since the findings in Metzler and Muntermann (2020, **paper I.2**) indicated significant industry-specific differences concerning the impact of digital transformation on business models, future research could build on this by focusing more precisely on these differences through industry comparisons.

As discussed in the implications section, Metzler et al. (2021a, **paper I.3**) indicated that, due to a potentially great backlog of demand for incumbent firms regarding digitalization, the use of artificial intelligence especially requires adjustments in the business model elements' key resources and key partnerships. Future research could further investigate this issue by analyzing the concrete background behind this phenomenon.

Overall, future research is encouraged to investigate the background behind the fact that some business model elements are rather more affected by digital transformation issues than others. Further, since the studies by Metzler and Muntermann (2020, **paper I.2**), Metzler et al. (2021a, **paper I.3**), and Metzler et al. (2022, **paper I.4**) solely focus on incumbent pre-digital firms, future research is encouraged to investigate differences between incumbent firms and non-incumbent firms, for example, to identify specific strength and weaknesses in handling digital transformation issues.

4.2 Research Area II: Digital Transformation and Corporate Communication

The results in Metzler et al. (2021b, **paper II.1**) indicate a strong positive association between chief digital officer presence and the volume of digital transformation-related signals. However, as usual for research on firms' management teams, the study is accompanied by endogeneity issues that could not be solved completely. Future research could build on our study and find an appropriate way to further minimize or even eliminate concerns concerning endogeneity.

As already discussed in the limitations, not all sentences marked as “digital transformation-related” necessarily refer to digital transformation activities. Thus, the accuracy of the dictionary approach could be improved. This, for example, could be done by using machine learning techniques in combination with a manual pre-processing part where researchers could subsequently label those sentences marked as “digital transformation-related.”

As already discussed in the implications section, the dictionary of digital terms by Chen and Srinivasan (2019) was already enhanced in Metzler et al. (2021b, **paper II.1**). However, future research could further develop the dictionary by adding more digital technology-related word groups, other digitalization-related word groups, and adding more words to each word group.

Whereas the results of Metzler et al. (2021b, **paper II.1**) indicate an association between chief digital officer presence and digital transformation-related signaling in a quantitative manner, future research is encouraged to investigate whether the presence of chief digital officers also leads to an increase in the quality of digital transformation-related signaling (i.e., in terms of information quality). This could be done by qualitatively analyzing the digital transformation-related content in firms’ external communication tools. Only if the presence of chief digital officers leads to an increase in the information quality and quantity can it be assumed that the presence of a chief digital officer has the potential to reduce digital transformation-related information asymmetries between firms and investors. Finally, in this context, future research could also investigate whether an increase in the quantity of digital transformation-related signaling can be associated with an improvement in specific financial indicators (such as financial performance), specific capital market parameters (such as trading volume), and specific information asymmetry proxies (such as the bid-ask spread).

As discussed in the implications section, the results in Metzler et al. (2021b, **paper II.1**) show that CDO presence and the volume of digital transformation-related content in firms’ external communication tools differ significantly between industries (especially between industries with a focus on tangible assets and industries with a focus on intangible assets). Whereas this study can only make assumptions concerning the reasons behind this phenomenon, future research could investigate this phenomenon in more detail.

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Appendix

Appendix A:
Dictionary of digital words for the paper Metzler et al. (2021b, paper II.1)

Word Groups	Relevant Key Words	
Social Media	social media	web 2.0
	web 3.0	
Mobile	smart mobility	ewallet* / e-wallet*
	app	epayment* / e-payment*
	mobility	electronic wallet*
	smartphone*	electronic payment*
	self driving	wearable*
Analytics	analytics	data scien*
	big data	data mining
	smart data	business intelligence
Cloud	cloud platform*	cloud deployment*
	cloud based	distributed cloud*
	cloud computing	
Internet of Things	internet of things	industry 4.0
	iot	smart manufacturing
	internet of everything	smart production
	enterprise 4.0	
Artificial Intelligence	artificial intelligence	virtual agent*
	ai	virtual assistant*
	ai related	chatbot*
	autonomous tech*	augmented realit*
	intelligent system*	extended realit*
	computer vision	smart device*
	neural network*	robotic process automation
	virtual machine*	rpa
	virtual realit*	
Machine Learning	biometric	image recognition
	deep learning	facial recognition
	machine learning	speech recognition
	natural language processing	voice recognition
	nlp	sentiment analysis
Blockchain	blockchain	cryptocurrency*
Digitalization	digiti*	digital marketing
	digitali*	digital business*
	digital transform*	digital platform*
	digital revolution	agile
	digital strateg*	

Appendix B:
Overview of author contribution ratios for papers included in this dissertation

Paper (Citation)	Publication Status	Outlet (Research Type)	Authors	Contribution (In Percent)
I.1 (Metzler and Muntermann 2021)	Published	PACIS 2021 (Literature Review)	**Metzler** Muntermann	**95%** 5%
I.2 (Metzler and Muntermann 2020)	Published	ICIS 2020 (Case Study)	**Metzler** Muntermann	**85%** 15%
I.3 (Metzler et al. 2021a)	Published	Swiss Journal of Business Research and Practice (Case Study)	**Metzler** Neuss Muntermann	**70%** 20% 10%
I.4 (Metzler et al. 2022)	Working Paper	Redacted (Case Study)	**Metzler** Muntermann Wittig	**85%** 10% 5%
II.1 (Metzler et al. 2021b)	Published	ICIS 2021 (NLP)	**Metzler** Bankamp Muntermann Palmer	**45%** 45% 5% 5%