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

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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.

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

**Künstliche Intelligenz und Geschäftsmodellinnovation in etablierten Unternehmen:
Eine industrieübergreifende Fallstudie**

Zusammenfassung: Künstliche Intelligenz (KI) hat das Potenzial, ganze Industrien disruptiv zu verändern und treibt damit Geschäftsmodellinnovationen in etablierten Unternehmen an. Empirische Forschung zu den Auswirkungen von KI auf das Geschäftsmodell etablierter Unternehmen sowie Forschung zu KI als Treiber für Geschäftsmodellinnovationen in diesen Unternehmen ist jedoch noch selten. Diese Arbeit zielt darauf ab, die Forschung in diesem Gebiet zu erweitern, indem die Auswirkungen von KI auf die spezifischen Elemente der Geschäftsmodelle von Unternehmen analysiert werden. Darüber hinaus werden die Mechanismen KI-getriebener Geschäftsmodellinnovation erforscht. Mithilfe der Durchführung einer detaillierten Fallstudienforschung in vier traditionellen Industrien leisten wir einen Beitrag zur Literatur, indem wir neue Erkenntnisse über die Auswirkungen von KI auf die einzelnen Geschäftsmodellelemente etablierter Unternehmen liefern. Basierend auf diesen Erkenntnissen präsentieren wir zusätzlich ein Rahmenwerk, das die Prozesse und Resultate KI-getriebener Geschäftsmodellinnovation erklärt.

Stichwörter: Künstliche Intelligenz, Geschäftsmodellinnovation, Digitale Transformation, Etablierte Unternehmen, Qualitative Forschung, Fallstudienforschung

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/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/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/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/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/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/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/Norvig* 2003; *Sharda et al.* 2021). Whereas ML is a subset of AI learning from experience and training for algorithmic pattern identification (*Russell/Norvig* 2003; *Sharda et al.* 2021), DL is a specification of ML which uses artificial neural networks to identify patterns in large amounts of unstruc-

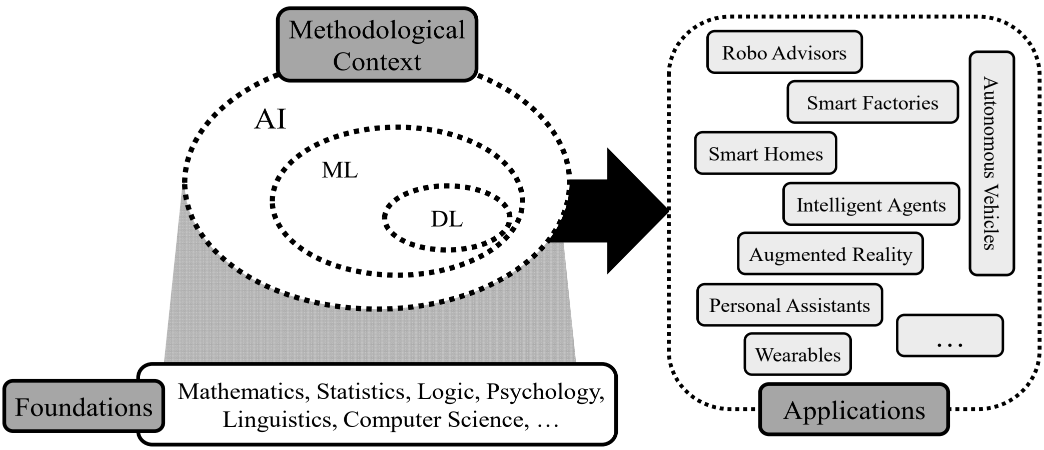

Figure 1: The Context of Artificial Intelligence

tured data (*Khamparia/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 1*).

Powered by large datasets, AI is capable of depicting human-like thinking and therefore solving problems that were solved by humans before (*Russell/Norvig* 2003; *Plastino/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 (*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/Purdy* 2018; *Brock/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/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/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/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/Pigneur* (2010). As illustrated in *Figure 2*, 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/Pigneur* 2010; *Wirtz et al.* 2016).

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/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/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

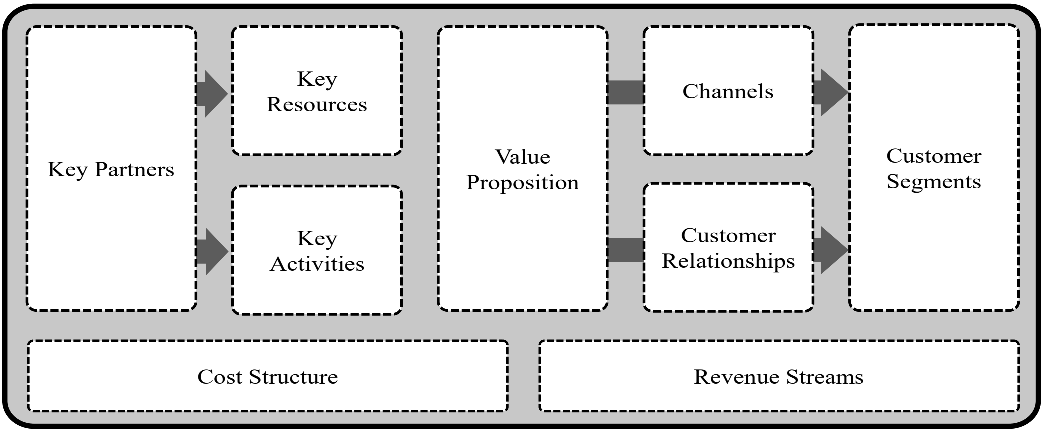

Figure 2: The Business Model Canvas (*Osterwalder/Pigneur* 2010)

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 inter-departmental 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* 1989; *Yin* 2014). Furthermore, the evidence from multiple cases can lead to more robust conclusions by being more compelling (*Herriott/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/Charitou* 2004).

Firm	*Industry Sector*	*Field of Activity*	*Age in Yrs.*	*Total Assets in bn. €*
F01	Automotive	Automotive Manufacturer	>80	>400
F02		Automotive Supplier	>140	>40
F03	Pharmaceutics	Pharmaceutical Manufacturer	>180	>9
F04		Pharmaceutical Manufacturer	>350	>80
F05	Industrial Products	Manufacturer of Chemicals	>150	>8
F06		Building Material Manufacturer	>70	>0.2
F07	Consumer & Retail	Consumer Goods Manufacturer	>140	>30
F08		Consumer Goods Wholesaler	>50	>15

Table 1: Overview of Selected Firms and Industries

As illustrated in *Table 1*, 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 2*.

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

Table 2: 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 3*.

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 3: 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 4 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.

As illustrated in *Table 4*, 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 4* 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).

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

BMC Element	*Ratio (%) tot.*	*adj.*	*AI-enabled Impact*
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	2.3	3.6	▪ Emergence of new AI-enabled revenue streams

Table 4: AI-enabled Impact on BMC Elements

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.

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.

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).

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).

Customer Relationships: AI has the potential to reshape the way how firms interact with existing and new customers. *Firms increasingly use ML-algorithms for personaliza-*

tion 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. 1 for AI applications, [is] the well-known chatbot*" (C06).

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).

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.

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).

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.

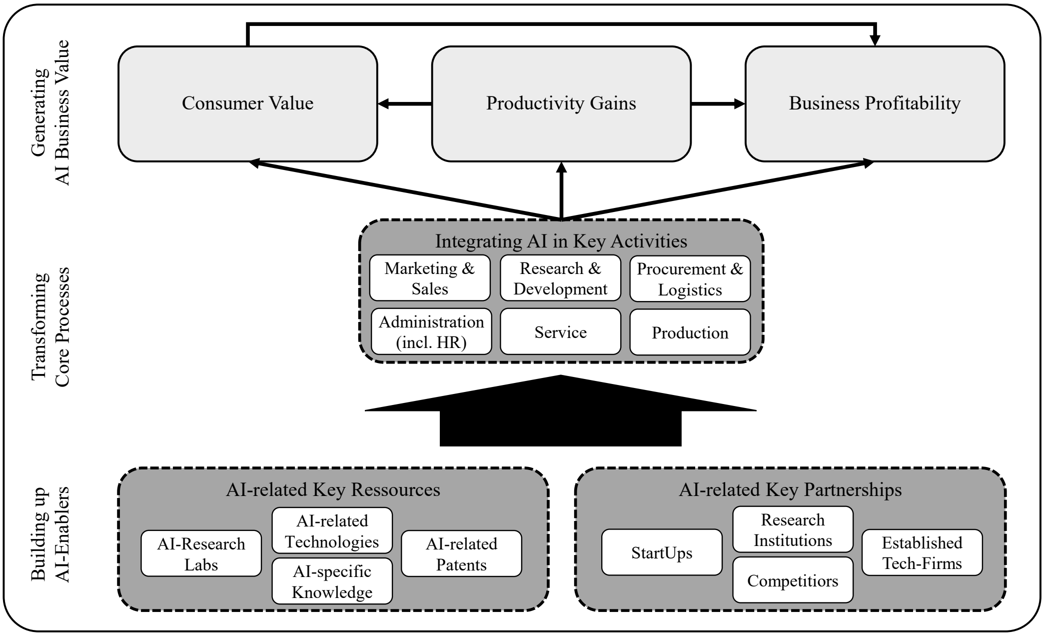

Figure 3: BMI and Value Generation Through AI

As illustrated in *Figure 3*, 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/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, we can observe the same pattern for AI (e.g., *Hildebrandt et al.* 2015; *Burmeister et al.* 2016; *Soto Setzke et al.* 2020). 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/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/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.

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