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Al-enabled Business Model Innovation for the Healthcare Industry

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Master of Science Thesis TRITA-ITM-EX 2022:290
KTH Industrial Engineering and Management
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Abstract

Recent developments in the field of Artificial Intelligence (AI) drive businesses to introduce digitally advanced products, services, processes, and mechanisms to various markets (Kraus et al. 2022; Parida et al. 2019). In this manner, the healthcare sector proves as a propitious industry for successful Al-application (Jiang et al. 2017; Yu et al. 2018). However, expected business gains cannot be achieved through the sole integration of Al-systems into healthcare products, processes and/ or services (Aström et al. 2022; Lee et al. 2019). To appropriately operationalise and commercialise Al-based offerings, so-called Al-solution-specialists are urged to change, adapt, and modify their prevailing business models (BMs) (Frank et al. 2019; Kiel et al. 2017). This study addresses the mentioned research gap by providing a thorough investigation of relevant literature and conducting a qualitative research methodology. By the means of guideline-based, structured interviews, data from seven cases on Al-based business models in the healthcare sector were collected. With our findings we propose one theoretical framework on healthcare-specific Al-enabled BM modifications and one model on generalised Al-based value chain activities. In this way, we deliver insights into how Al is utilised in healthcare firms and how it is ultimately integrated into firm operating models - highly contributing to current literature. Further, our proposed frameworks serve as blueprints supporting practitioners in successfully creating, delivering, and capturing value stemming from Al-based technologies. Finally, being limited in scope, we propose future research to extend the study's focus to an ecosystem-perspective and further apply a longitudinal research design to observe Al-enabled business model changes over a longer time span.

Keywords

Artificial Intelligence, Business Model, Business Model Innovation, Healthcare Industry

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Sammanfattning

Framsteg inom Artificiell Intelligens (AI) motiverar företag att introducera digitalt avancerade produkter, tjänster, processer och mekanismer till flera olika marknader (Kraus et al. 2022; Parida et al. 2019). Hälso- och sjukvårdsbranschen är en lovande marknad för applikationer av Al (Jiang et al. 2017; Yu et al. 2018). För att uppnå förväntade värdeökningar krävs dock mer än integration av Al i hälso och -sjukvårdsprodukter, -processer och/eller tjänster (Åström et al. 2022; Lee et al. 2019). Lösningsspecialister inom Al uppmanas att anpassa och modifierar rådande affärsmodeller för att på lämpligt sätt operationalisera och kommersialisera Al-baserade lösningar (Frank et al. 2019; Kiel et al. 2017). Den här artikeln behandlar forskningsluckan inom området genom en ingående litteraturstudie samt kvalitativa studier. Via strukturerade intervjuer baserade på riktlinjer samlas data från sju fall av Al-drivna affärsmodeller inom hälso- och sjukvårdssektorn. Baserat på våra resultat föreslår vi ett teoretiskt ramverk för Al-drivna förändringar av affärsmodeller inom hälso- och sjukvårdssektorn, samt en generell modell för Al-baserade aktiviteter i värdekedjan. På så sätt bidrar vi till den existerande litteraturen med inblickar i hur Al används av företag inom hälsa och sjukvård och hur Al integreras i existerande verksamhetsmodeller. Därtill agerar de presenterade ramverken som stöd för idkare i processen att skapa, leverera och fånga värde i koppling till Al-baserade teknologier. Avslutningsvis föreslår vi framtida forskning, där studiens omfattning ökas för att inkludera ett ekosystemperspektiv samt longitudinella studier med syfte att observera de långsiktiga förändringar av affärsmodeller som möjliggörs av Al.

Nyckelord

Artificiell intelligens, Affärsmodell, Affärsmodellinovation, Hälso- och sjukvårdsbranschen

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List of Abbreviations

3D Three-Dimensional

Al Artificial Intelligence

B2B Business-to-Business

BM Business Model

BMI Business Model Innovation

CEO Chief Executive Officer

CT Computed Tomography

IT Information Technology

ML Machine Learning

MRI Magnetic Resonance Imaging

NLP Natural Language Processing

R&D Research and Development

RQ Research Question

SaaS Software as a Service

SDG Sustainable Development Goal

SME Small and Medium sized Enterprises

1. Introduction

Living in an era of digital transformation, adapting to an increasingly digitalised world has become a challenge for countries, cities, industries, companies, and individuals alike (Kraus et al. 2022; Nambisan 2017; Verhoef et al. 2021). Digitalisation means a widespread integration of digital technologies into every-day life (Bouncken et al. 2021), and Artificial intelligence (AI) is perceived as a powerful digital technology enabling Industry 4.0 (Schallmo et al. 2017, Åström et al. 2022).

Amusingly, a significant hype has evolved around AI (Davenport and Ronanki 2018). Even very prominent AI researchers have given into the temptation of hypothesising about a science-fiction-like artificial super intelligence that can outcompete the human ability (Kaplan and Haenlein 2019). This, however, is nowhere in realistic sight. In fact, the most commonly used AI classifies as weak AI which does not provide any value outside its narrow and specialised field of application (Kaplan and Haenlein 2019). Nevertheless, the current AI technologies have numerous benefits for businesses and industries (Bohr and Memarzadeh 2020; Parida et al. 2019; Schallmo et al. 2017), making AI a very relevant topic to study (Kulkov 2021; Miller and Brown 2018).

Nowadays there is a gap between demands regarding the digital transformation in the marketplace and the organisational capabilities to respond to them (Kohli and Melville 2017). It is not surprising, as Al platforms vary in their scope and complexity, thus hindering the understanding and deploying of the technology (Holmström 2021). Research suggests that firms lack an understanding of how to appropriately create, deliver and capture value that arises from Al-based technologies (Valter et al. 2018). In business and industrial management fields it has been seen that even high investments in Al alone does not guarantee success (Åström et al. 2022; Lee et al. 2019; Trischler and Li-Ying 2021). To achieve company business objectives, it is crucial to understand how to adjust, modify and innovate single business model components to commercialise Al-based technologies (Burström et al. 2021, Davenport and Ronanki 2018, Kotarba 2018).

A great example industry that has experienced a continuous integration of AI technologies into daily operations is the healthcare industry (Yu et al. 2018). AI in the healthcare sector has drawn attention of both researchers and healthcare practitioners (Kulkov 2021; Miller and Brown 2018). Meanwhile, the United Nations' World Health Organisation has established an AI for healthcare focus group (Leone et al. 2021). Over time, AI has been reducing healthcare

costs, speeding up drug discovery, and generally improving patient health outcomes (Garbuio and Lin 2019), all the while creating new competitive landscapes (Leone et al. 2021).

1.1. Purpose

As the business and industrial management fields lack understanding for operationalising Albased technologies (Åström et al. 2022; Burström et al. 2021) and the healthcare sector is benefitting from AI greatly (Parida et al. 2019; Schallmo et al. 2017), the purpose of this thesis is to understand the utility and use of AI-based technologies in the healthcare industry in order to close the existing research gap in the business and industrial management fields. We aim to collect data on how firms in the healthcare industry create, deliver and capture value through AI-based technologies, and expand the healthcare-specific knowledge about AI-enabled business model innovation.

1.2. Research Question

To fulfil our aims and purpose we will be answering the following three research questions:

RQ1: Which Al-use types are employed in healthcare firms?

RQ2: How do healthcare firms create, deliver, and capture value when Al-based technologies are integrated into their offerings?

RQ3: How are Al-based technologies integrated into healthcare firm operating models?

1.3. Delimitations

This study and its findings are limited to the European healthcare sector. The interviewed companies are either start-ups or SMEs, thus the findings are not directly comparable to operations of big industrial companies that serve healthcare. As part of the research study, seven companies, from three Al-pioneer countries (Sweden, France, and Germany) were analysed (UnternehmerTUM GmbH 2022). As a result, the presented findings about Al utilisation for healthcare businesses are not exhaustive. Moreover, the challenges with Altechnology implementation in healthcare, such as ethics, regulations and industry players' scepticism towards the technology, is not covered. Lastly, the authors have chosen the business model as a lens to view and investigate the use of Al technologies for value creation, delivery, and capture for stakeholders within the healthcare sector. Another unit of analysis might result in different findings and conclusions.

1.4. Sustainability

This thesis tackles subjects that contribute to three Sustainable Development Goals (SDGs) established by the United Nations General Assembly in 2015. These are:

#3 "Good Health and Wellbeing",

#8 "Decent Work and Economic Growth", and

#9 "Industry, Innovation and Infrastructure" (United Nations 2015a).

SDG #3 is to "Ensure healthy lives and promote well-being for all at all ages" (United Nations 2015b). This goal is directly contributed to by our thesis, as we provide knowledge on how Albased companies can provide benefits in healthcare. Two of the investigated cases demonstrate the ability to serve more people in need of healthcare in a shorter amount of time thanks to Al-based solutions, potentially making healthcare more available in third world countries in the future. Another of the cases allows preventing musculo-skeletal injuries in the elderly population, thus extending a healthy life to later ages.

SDG #8 aims to "Promote sustained, inclusive and sustainable economic growth, full and productive employment and decent work for all" (United Nations 2015c). Our thesis studies the utility of AI-technologies for businesses within the healthcare sector, thus providing knowledge to further investigate economic growth due to AI and the consequences of AI use.

SDG #9 extended explanation is to "Build resilient infrastructure, promote inclusive and sustainable industrialization and foster innovation" (United Nations 2015d). By studying AI incorporation into the digital economy, we directly elucidate the use of a technological innovation within a specific industry. Understanding the ways how AI is implemented within the healthcare sector can serve as a foundation to develop more resilient, inclusive and sustainable healthcare industry processes.

1.5. Thesis Structure

In the Theoretical Background section, we will summarise literature around AI, AI use in healthcare, business models (BM) and business model innovation (BMI), as well as AI integration in healthcare products, services and processes. It will establish two frameworks for AI effects on three BM components: value creation, delivery and capture. Each of the Theoretical Background subchapters is introduced by a short overview of the content covered within the subchapter. The Methods section explains the choice of method for conducting our thesis study and presents short descriptions of the analysed companies. Our Findings section

will uncover the knowledge obtained around our research questions, while Discussion will place the findings in the context of the current state of research and confirm, elaborate and extend the chosen frameworks based on the empirical data. The Conclusion will summarise the main findings, the theoretical and practical implications of them, as well as cover the limitations of the study and future research suggestions.

2. Theoretical Background

2.1. Al and Healthcare

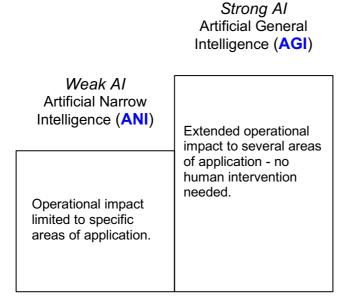
Recent research identifies Artificial Intelligence (AI) as an emerging, digitally enabling domain, strongly driving the Digital Transformation of industries and organisations (Kraus et al. 2021). In medical sciences the increased availability and collection of useful healthcare data has paved the way for successful AI-application (Jiang et al. 2017), while simultaneously creating a strong competitive environment in the current healthcare sector (Leone et al. 2021). In this sense, AI's impact on the prevailing healthcare landscape is heavily discussed both in academia and practice (Kulkov 2021; Miller and Brown 2018), leaving great confidence in its ability to significantly improve healthcare operation and delivery processes (Bohr and Memarzadeh 2020). The next two subchapters will place emphasis on the conceptualisation of Artificial Intelligence and explain its main application fields in the healthcare sector.

2.1.1. Conceptualisation and Use of Al

Al can deliver numerous benefits such as the automation and optimization of processes, the improvement of profitability and performance, as well as a significant reduction of errors (Parida et al. 2019; Schallmo et al. 2017). However, Al platforms can vary both in scope and complexity, hindering the understanding of the technology and hence its deployment (Holmström 2021).

Reflecting its nascent nature, multiple AI definitions have been coined, and for the purpose of this study we describe AI as a computer system with human-like abilities such as learning, judgement, and decision-making (Garbuio and Lin 2019; Mishra and Tripathi 2021; Taddy 2018; Zhang and Lu 2021). The potential development of AI can be divided into two evolutionary stages: 1) Weak AI, currently being the omnipresent first generation of AI, also called Artificial Narrow Intelligence. It describes AI systems, which specialise in solving a specific task - unable to generalise outside of their given application field. 2) The second not yet reached AI level is called Strong AI or Artificial General Intelligence and is characterised by the capability to apply its knowledge to several areas and within these outperform or equal human ability (Åström et al. 2022; Kaplan and Haenlein 2019). The illustration below visualises the two AI maturity levels and summarises them briefly:

Figure 1: Evolutionary stages of AI maturity.



Source: Adapted from Åström et al. 2022; Kaplan and Haenlein 2019.

2.1.2. Al Taxonomy in Healthcare

The healthcare industry consists of firms, which are involved in the delivery, facilitation, and coordination of medical or medically related products, processes and/ or services (Investopedia 2021; Kraus et al. 2021). These can be grouped either into 1) Provision of medical services, 2) Production of medical equipment, 3) Drug development, 4) Provision of medical insurance, and 5) Delivery of healthcare to patients or combinations of these (Investopedia 2021). With digitalisation rapidly improving the field of medical science together with the healthcare industry, great demand for the development and integration of digitalised healthcare systems was created (Dicuonzo et al. 2022; Kraus et al. 2021). Hence, rising challenges and opportunities foster the use of advanced digital technologies such as Artificial Intelligence (Buch et al. 2018) - establishing the healthcare sector to one of the most promising fields of Al application (Yu et al. 2018). This aspect is also reflected in the growth rate of the European Artificial Intelligence Market, which is expected to rise to up-to approximately 44% from 2021 to 2027 (Graphical Analytics Private Limited 2021).

Al's functions applied to the healthcare industry are mainly targeted at following points: Assisting medical professionals in decision-making procedures, reducing human error in clinical practice, and making predictions regarding health risks or potential outcomes (Jiang et al. 2017; Topol 2019). In general, the integration of Al in the healthcare sector aims at processing large amounts of clinical data, extracting or computing medically relevant

information and thus, for example, supporting decision-making in the diagnosis and treatment of patients (He et al. 2019). Further, Al-based technologies can be provided with learning and self-improving capabilities, which ultimately increase their performance and accuracy based on feedback (Buch et al. 2018; Jiang et al. 2017). Considering the above-mentioned aspects, Al can be divided into seven operational types in healthcare: 0) Prevention (Yu et al 2018), 1) Diagnostics (Bohr and Memarzadeh 2020), 2) Therapy and Treatment (Mirnezami 2020), 3) Medical Imaging (Tran et al. 2020), 4) Drug Development and Molecule Modelling (Bohr 2020), 5) Al-Assisted Surgery (Witkowski and Ward 2020), 6) Al-Assisted Patient Monitoring (Jeddi and Bohr 2020), and 7) Al-Based Medical Devices (Aframian et al. 2020).

Strongly linked to these medical areas, AI can further be categorised into three fundamental use types in business, which are presented with healthcare-specific examples: 1) Assisted Intelligence, which helps to improve business processes, by amplifying the value of current activities - mostly used in medical image classifications, 2) Augmented Intelligence, which provides firms with new capabilities and altering the nature of business activities and requiring changes in the current business model - mostly seen in prevention or precision medicine, and lastly 3) Autonomous Intelligence, which is currently under development and will be able to decide human-independently and choose its own actions based on established business goals (Garbuio and Lin 2019). The feasibility of the latter is not discussed in academia and thus requires further investigation. The following figure visualises the three above-mentioned business use cases of AI and gives examples of their possible application:

Assisted Intelligence Prevention, personalisation and precision medicine

Augmented Intelligence Prevention, personalisation and precision decision-making

Figure 2: Al use types and their examples in healthcare.

Source: Own illustration based on Garbuio and Lin (2019).

2.2. Al, Business Models and Business Model Innovation

Al is perceived as one of the most promising tools to explore and exploit emerging opportunities from digitalisation (Åström et al. 2022; Obschonka and Audretsch 2020). As Albased systems not only result in product- and service-technical changes, but especially in considerable organisational transformations, challenges and opportunities, their implementation is highly linked to business models and their respective innovation (Cockburn et al. 2018; Garbulo and Lin 2019). Thus, the primary challenge for firms is to apply business model innovation and develop novel business activities that represent market traction and allow business operations to be scaled (Berman 2012; D'ippolito et al. 2019; Rachinger et al. 2018). This process is targeted at improving a company's strategic fit for successfully functioning in the "Al economy" (Kotarba 2018; Verhoef et al. 2021). The next three subchapters will give a general overview on business models and business model innovation as well as elaborate on how the operationalisation of Al affects both.

2.2.1. Conceptualisation of Business Models and Business Model Innovation

Business Models (BMs) and Business Model Innovation (BMI) have just in the last decade become influential for business research (Casadesus-Masanell and Ricart 2010; Foss and Saebi 2016). Recent reviews on business models highlight the construct's usefulness in management practice (Ritter and Lettl 2018; Schneider and Spieth 2013; Wirtz et al. 2016). However, literature has not yet reached consensus on a universally valid definition (Kraus et al. 2020). Reflecting its nascent nature, business model innovation is even less well-theorised, suggesting great need for further investigation of the phenomenon (Foss and Saebi 2018, Spieth and Schneider 2014). To not replicate previous research, we will solely place emphasis on the key theories from literature.

In general, a business model can either be considered a methodological instrument (Chesbrough 2010), a management tool for controlling and directing business activities (Schneider and Spieth 2013) or an innovation lever itself (Osterwalder and Pigneur 2010; Teece 2010). Authors like Zott and Amit (2011) represent a business model as a subject, organisation, and governance of operations, which aim at creating value by exploiting business opportunities. In this manner, academics converge on the business model's main components, including: the value proposition (Demil and Lecoq 2010), the configuration of the value chain - building the basis of economic activity and required resources to actualize the value proposition (Chesbrough 2007), and finally the value capture (Foss and Saebi 2016). Yet, academia has coined multiple descriptions regarding BMs, not agreeing on a widely accepted one as it would lack clarity and specificity (Zott and Amit 2011). Within the variety of

definitions, Teece (2010) delineates a business model as a theoretical framework, incorporating two main elements: the value creation and delivery and the value capture (Sjödin et al. 2020), strongly emphasising the interaction between these value blocks within an organisational unit (Schneider and Spieth 2013). In this context, Kim (2021) highlights that the business model's architecture does not consist of a trivial list of its components, but rather describes the functional relations among these underlying mechanisms. These linkages can differ in their degree of interdependence and their connection to the firm's environment (Ritter and Lettl 2018).

Changes in the business model's architecture or its individual elements, which can arise from external or internal factors, can be referred to as business model innovation (Foss and Saebi 2016, Kim 2021). As attention regarding the phenomenon has highly increased both in practice and academia (Bouwman et al. 2018), its conceptualization becomes vital for this study. Previous research on business model innovation has strongly focused on investigating its antecedents, its moderators, and its effects (Foss and Saebi 2016, Schneider and Spieth 2014), establishing it to a complex object of interest. Its noncumulative nature results in a lack of construct clarity and classification (Zott and Amit 2011, Spieth and Schneider 2014). Overall, business model innovation considers the transformation, reconfiguration and change of a whole system of products, processes, services, technologies, or innovation flows (Bouncken et al. 2021). While some authors (see Wirtz et al. 2016) view the concept as the result or outcome of the rearrangement of business model components, others (see Evans and Johnson 2013) perceive it as a process - emphasising its dynamic character.

Founded on Teece's (2010) business model definition, Zott and Amit (2011), suggest that business model innovation can either be: 1) The integration of new business model activities, 2) The adoption of new linkages between already existing activities, or 3) The replacement and substitution of business actors and stakeholders. In line with this, business model modifications can take place in the value creation logic by entering new industries, in the value capture mechanisms by offering novel pricing models and/ or in the general "firm model" by redefining organisational boundaries and adopting an ecosystem perspective (Giesen et al. 2007; Sjödin et al. 2020). Accordingly, Foss and Saebi (2016) define business model innovation as the "designed, novel, nontrivial changes to the key elements of a firm's business model and/ or the architecture linking these elements." (pp. 216).

2.2.2. Al, Value Creation and Value Delivery

As the core of the business model, the *value creation* dimension encompasses all offerings directed at realising the firm's value proposition (Chesbrough 2010; Demil and Lecoq 2010). In general, it is defined by a set of activities, which build the value chain, and aims at targeting identified customer needs (Foss and Saebi 2018). Extending product- and/ or service-portfolios through Al-fuelled systems results in several benefits for companies and their respective customers (Burström et al. 2021). Further, the value creation mechanism describes how different capabilities and resources are allocated and combined to generate added value within its respective value chain network (Urbinati et al. 2019).

On the firm's side, Al-based technologies contribute to the development of Al capabilities, which support the automation and optimization of value chain activities (Cockburn et al. 2018). Through the application of data mining techniques Al analyses vast amounts of data, detecting patterns and predicting unforeseen events (Cheah and Wang 2017), which then support decision-making processes and gradually improve their outcomes (Kiel et al. 2017). In this sense, Al algorithms examine and interpret extensive masses of data and generate previously unavailable information, which reduces uncertainty to a greater extent and provides market insights with higher accuracy (Åström et al. 2022; Mishra and Tripathi 2021). Ultimately, this contributes to increased efficiency, cost and error reduction regarding value creation operations and improved firm performance (Cockburn et al. 2018; Lee et al. 2019). On the customer's side, literature suggests that the output will not be perceived with greater value (Burström et al. 2021), questioning how added value is generally generated for end-users. However, through the Al-enabled extension of products and/ or services, new target segments together with emerging, operational customer needs can be identified (Chalmers et al. 2020; Parida et al. 2018).

Further, Al-applications affect the *value delivery* dimension, as back-end operations are directly connected to customer activities (Burström et al. 2021; Kiel et al. 2017). In this way, market insights - generated by Al operations in the value creation logic - align back-end processes with front-end needs (Cheah and Wang 2017; Lee et al. 2019). Thus, routines for product- and/ or service-deliveries progress continuously through Al-enabled monitoring and control - resulting in higher supervision of maintenance processes as well as product and service flows (Åström et al. 2022; Chalmers et al. 2020).

2.2.3. Al and Value Capture

The implementation of AI into current products, processes and/ or services profoundly builds on value chain processes which are strongly linked to the firms pricing models and their cost structure (Cockburn et al. 2018). In general, the *value capture* mechanisms describe all business operations, which ensure economic returns arising from the value creation logic (Chesbrough 2010). As AI serves as a catalyst for the development of new products and/ or services, novel revenue sources can be discovered, and cost efficiency increased (Urbinati et al. 2019). Furthermore, through the integration of AI-applications, existing revenue streams are improved through the better use of resources and more transparent stakeholder relationships are established (Burström et al. 2021). Despite AI's recognized positive influence on value creation operations through cost reduction, authors like Sjödin et al. (2020) suggest that AI infrastructures and their maintenance come with comparably high costs.

2.3. Theoretical Frameworks

Current technological developments such as AI pressure healthcare firms to develop and incorporate numerous digital activities into their every-day business and medically related practices (Bouncken et al. 2021; Kraus et al. 2019; Minas and Triantafillou 2020). Furthermore, these organisations increasingly rely on products, services, processes, and operations, which are built on AI-based technologies and their respective configuration (Burström et al. 2021; Frank et al. 2019). In this manner, healthcare companies are forced to reshape *all* value operating modules (Berman 2012; Bouwman et al. 2018), including AI-based technologies into their value creation logic and into their value network across all value chain mechanisms (Dmitriev et al. 2014, Li 2020). The next two subchapters present two theoretical models. The first one concentrates on general, industry-unspecific AI-related business model changes, while the second model explains how AI-fuelled systems are integrated into healthcare value chains.

2.3.1. General Al-related Changes in Business Models

Implemented throughout a product- and/or service-portfolio, Al provides multiple possibilities to create, deliver and capture value from novel offerings and new revenue streams generating strong competitive advantages for various companies (Lee et al. 2019; Sjödin et al. 2021). Despite being an emerging research field, academia agrees on general, **industry-unspecific** Al-related changes. To give a holistic view, the table below will summarise the earlier mentioned (see subchapters 2.2.2 and 2.2.3) business model modifications stemming from Al:

Table 1: General Al-related changes in each BM element.

BM Component	General Al-related Changes		
Value Creation	 Generation of new market insights Automation and optimization of value chain activities Increased efficiency and reduced errors Identification of new target segments and customer needs 		
 Alignment of back-end to front-end needs Improved monitoring and control mechanisms Supervision of maintenance processes, product- and process flows Improvement of delivery routines 			
 Reduced costs and increased firm performance Improved existing revenue streams Identification of new revenue sources 			

Source: Adapted from Åström et al. 2022; Burström et al. 2022; Kiel et al. 2017; Sjödin et al. 2021; Urbinati et al. 2019.

2.3.2. Al Integration in Healthcare Value Chains

Al-based systems applied in healthcare can support diagnosis and therapy selection, predict health risks and classify diseases (He et al. 2019). Additionally, Al provides added value for a diverse set of stakeholders throughout a firm's value chain (Burström et al. 2021; Teece 2018). Literature identifies several benefits for the healthcare industry, such as the automation and optimisation of business operations as well as medical routine tasks, the decrease of diagnostic and therapeutic errors, the improvement of work effectiveness and cost reduction (Alloghani et al. 2020; Dicuonzo et al. 2022; Parida et al. 2019; Laudien and Pesch 2019). With the establishment of the role of Al-solution-specialists, a great shift in responsibility and value aspects for each stakeholder is portrayed (Yu et al. 2018). Thus, the classical model of patient-physician-interaction drastically changes (Topol 2019). Yet, regardless of its specific operational area, the Al-healthcare firm's value chain activities can be summarised into a generalised process. Here, Al-systems most noticeably make use of machine learning (ML) algorithms (Alloghani et al. 2020). Being among the fundamental implementations of Al (Garbuio and Lin 2019), ML describes an algorithms' capability to improve its performance by learning from data and is mainly used for making predictions, classifications, data clustering, and reducing dimensionality (Zhang and Lu 2021). In the case of unstructured data, obtained in the form of written or spoken language, Natural-Language-Processing (NLP) techniques are applied to derive useful information and supplement already structured data (Jiang et al.

2017). The latter can again be fed into ML algorithms (Lee et al. 2019), assisting in decision-making processes (He et al. 2019). The following figure exemplifies a simplified Al-based value chain where Al-guided clinical data processing results in medical activities, such as diagnosis, treatment, or prognosis:

Clinical Activities

Data

Unstructured Data

NLP techniques

ML algorithms

1) Diagnosis
2) Treatment
3) ...

Legend

Generation

Output

Input

Figure 3: Al-based Value Chain for Healthcare.

Source: Adapted from Alloghani et al. 2020.

Although the integration of Al-systems offers several benefits for healthcare stakeholders (Parida et al. 2019), previous research shows that even high investments into Al-programs and projects have *not* resulted in the expected business gains (Åström et al. 2022; Lee et al. 2019). In this context, the importance of business model innovation arises, as the successful implementation and operationalisation of Al-based systems into healthcare practices demands the adjustment or modification of existing value creation, delivery, and capture mechanisms (Kiel et al. 2017; Kulkov 2021). Otherwise, Als positive effects on healthcare's operation and delivery processes and corresponding business gains cannot be achieved (Åström et al. 2022; Sjödin et al. 2020) - risking Al to become an end rather than a lever for technological and organisational change (Dicuonzo et al. 2022). This highlights the research gap.

3. Research Design

3.1. Choice of Methodology

Previous research falls short in understanding how healthcare companies operationalise Albased products, processes and/ or services *and* commercialise these through their corresponding business models (Kulkov 2021; Valter et al. 2018). Thus, this study will answer the following three research questions:

RQ1: Which Al-use types are employed in healthcare firms?

RQ2: How do healthcare firms create, deliver, and capture value when Al-based technologies are integrated into their offerings?

RQ3: How are Al-based technologies integrated into healthcare firm operating models?

With the theoretical understanding in the respective field of interest being rather scarce (Mishra and Tripathi 2021), the following thesis applies a qualitative, exploratory methodology approach (Baxter and Jack 2008). Compared to other (descriptive and explanatory) research methods (Saunders et al. 2007), this approach was found most suitable for the thesis's purpose, as exploratory studies aim at clarifying a subject's nature and generate new valuable insights (Robson 2002).

To appropriately answer our second research question, it is indispensable to clearly state and justify the BM and BMI definitions applied in this study. Being highly accepted and widely used in academia, we follow Teece's (2010) BM description - strongly focusing on the main components: value creation and delivery and value capture. Founded on Teece's (2010) view, we comply with Zott and Amit's (2011) BMI definition, as it includes a broader perspective on what can be considered innovation. Thus, we adopt the "multiple-change view" of BMI, which refers to two different situations: 1) The transition from one business model to another within an already established company or 2) The creation of an entirely new business model in a new venture (Chesbrough 2007; Osterwalder and Pigneur 2010).

As Business Models consider aspects such as different value flows, their respective interaction, and the functional relations among these (Casadesus-Masanell and Ricart 2010), they are complex systems (Foss and Saebi 2016). Thus, to appropriately conduct our study, we reviewed various deductive and inductive research strategies (Saunders et al. 2007), such as action research (Coghlan and Brannick 2005), grounded theory approach (Glaser and Strauss 1967) and case study methodology (Eisenhardt 1989). The latter was found to be

well-suited for the investigation of business models (Yin 2018), as case studies portray detailed, empirical, specific phenomena within their real-life, social context (Yin 2009) and they strongly focus on the dynamics presented within single situations (Baxter and Jack 2008; Eisenhardt 1989). Yet, each case and thus each investigated business model represents a separate unit of analysis (Eisenhardt and Graebner 2007; Miles and Huberman 1994). Based on each individual case, correlations and patterns between certain scenarios can be determined (Eisenhardt and Graebner 2007). To ensure a stronger empirical basis, more robustness and higher reliability for our article (Baxter and Jack 2008; Yin 2009), we conduct a multiple case study consisting of seven cases.

3.2. Data Collection and Data Sampling

The empirical data was collected through structured, guideline-based expert interviews (Eisenhardt and Graebner 2007) which were carried out in digital form via video calls. An adapted business model framework according to Teece (2010), consisting of the main components: the value creation and delivery as well as the value capture, served as the basis for the interview structure. Specific questions emerging from renowned papers published in highly ranked journals (see Chesbrough 2007; Demil and Lecoq 2010; Teece 2010) were created and assigned for each business model component. Further, inquiries regarding Alrelated topics which emerged from our literature review were added.

To guarantee a high level of the study's quality, the firms and their representatives were selected beforehand based on three inclusion criteria. First, the to-be explored enterprises must operate in the current healthcare sector. Second, the companies must integrate AI-based technologies into their products and/ or services and already sell these to the market and create turnover. Third, the interview partners must be classified as experts. In this context, the expert status is ascribed by the researchers (Meuser and Nagel 2009) and is attributed to a person's occupational field of activity (Bogner et al. 2009). As such, we identified experts as professionals who hold specific knowledge about AI-based products and/ or services as well as about organisational structures, processes, and the business model of their firm (Littig 2008). A total of 90 firms, limited to five countries (Sweden, Norway, Netherlands, France, and Germany) which established themselves as pioneers in the given research field (UnternehmerTUM GmbH 2022), were contacted. Seven of these, from Sweden, France, and Germany, were interviewed between the 28th of March 2022 and the 6th of April 2022. Table 2 summarises the company- and interviewee-specific information of each case.

To follow the highest ethical standards, while conducting each interview, all participants were rightfully informed about the study's purpose and the intended use of their personal and/ or company-specific data in advance. Prior to each digital interview, all study members were asked for consent in recording the meetings and given the right to review all collected information. Additionally, the final version of the thesis is shared with all interviewees. To ensure reliability of the data obtained (Eisenhardt 1989), the case study methodology was extended through a secondary analysis approach (Yin 2018). For this purpose, the companies' websites were examined, and the findings added to the corresponding business model component. Moreover, the interview structure was rigidly followed and held unchanged - enhancing the acquired data's' credibility and transferability (Baxter and Jack 2008).

Table 2: List of interviewed healthcare firms.

A application within the company****	6) Al-Assisted Patient Monitoring	 Therapy and Treatment Drug Development and Molecule Modelling ALAssisted Patient Monitoring A-Based Medical Devices 	3) Medical Imaging 5) Al-Assisted Surgery	Diagnostics Drug Development and Molecule Modelling	3) Drug Development and Molecule Modelling	0) Prevention3) Medical Imaging6) Al-Assisted Patient Monitoring7) Al-Based Medical Devices	Prevention Diagnostics A-Based Medical Devices
Company type***	Start-up	Start-up	SME	Start-up	Start-up	Start-up	Start-up
Size Compai (people) type***	4	25	34	21	10	2-10**	œ
Size (peop	2020	2018	2012	2017	2019	2012	2019
Country	France (Paris) 2020	France (Nice)	Germany (Munich)	Germany (Saarbrücken)	Germany (Dresden)	Sweden (Stockholm)	Sweden (Malmö)
Interviewee name Interviewee position Country	Al Chatbot Expert and Co-Counder	Margoux Kerhouse Business Developer	Technical Product Manager	CEO and Founder	CEO and Co-Founder	CEO and Founder	CEO
Interviewee name	Thomas Gouritin	Margoux Kerhouse	Julia Rackerseder	Nicklas Linz	Joachim Haupt	Glenn Bilby	Tomas de Souza
Company offerings*	Post-operative Thomas Gouritin Follow-Up Assistant	Digital Twin for Personalized Medication	Consulting, Research and Development in Advanced Medical Image Computing Technologies and Computer Vision	Speech Biomarkers Nicklas Linz	Knowledge-Based Structure Ananlysis for Drug Discovery	Human Movement Analysis	Clinical assessments for precision mental healthcare
Company name	Asispo	Exact Cure	lm Fusion	KI:elements	PharmAl	Qinematic	Word Diagnostics (Ablemind)

Sources: *From the respective company websites: Exactcure (2020), PharmAl GmbH (2021), WordDiagnostics AB (2022), Ki:elements (2022), Qinematic (n.d), ImFusion (2018), ASISPO (n.d).
**LinkedIn: The LinkedIn profiles of the respective firms were retrieved May 23, 2022.

***Company type sources: Start-up definition from: European Commission (2020) SME definition from: European Commission (n.d)

3.3. Data Analysis

Each conducted interview was audio-recorded as well as fully transcribed and can be viewed upon request. To appropriately analyse the collected data, we selected the qualitative content analysis approach according to Mayring (2000). In the first step, we identified content-related aspects and developed categories (Mayring 2019), following a mixed deductive-inductive approach (Mayring 2019; Stamann et al. 2016). The main categories were derived theorybased from the adapted business model framework by Teece (2010), while subcategories were generated inductively - stemming directly from the collected empirical data (Schreier 2014). Hence, for the formation of new subgroups, we followed the strategy of subsumption (Kuckartz 2014; Mayring 2010). Next, the gathered data set was thoroughly described by the means of these established (sub-)categories (Mayring 2019). Additionally, the content analysis was extended with a secondary analysis of the companies' websites, thus the accumulated data could be supplemented, expanded, and, if necessary, corrected (Kuckartz 2014; Stamann et al. 2016), resulting in triangulation of primary and secondary data. Following this method, the expert's statements could be verified, therefore providing stronger validity and reliability of data (Yin 2009). In this manner, the credibility measure of the data gathered and analysed could be improved, enhancing the quality of our thesis (Kuckartz 2014). Subsequently, arising from the (sub-)categories built, all individual cases and thus all respective business models were compared with each other, aiming at deducing, and presenting commonalities and differences. Lastly our obtained empirical data was used to test and supplement the theoretical framework of general, industry-unspecific Al-related changes in BMs, presented in subchapter 2.3.1, and to validate and extend the theoretical model of the "Al-based Value Chain" (see subchapter 2.3.2.).

4. Findings

4.1. Al Use for Healthcare Firms and in Healthcare Processes

All of the interviewed companies, also referred to as *Al-solution-specialists*, conduct value chain activities that incorporate one or more Al-based technologies. It was observed that all seven companies operate in a business-to-business (B2B) setting, while one of the companies works in a business-to-healthcare setting and another one in a business-to-research setting. The customers of the firms are healthcare professionals, pharmaceutical, insurance and biotechnology companies, as well as researchers. For simplicity the customers will be generalised as *healthcare-providers*. The interviews revealed that thanks to Al technologies the sampled companies achieve automatization, optimisation and enhancement of healthcare processes and treatment outcomes. These will be covered in the following three subchapters.

4.1.1. Automation

The clearest automation example was seen with Asispo, as the company offers a chatbot that allows performing patient follow-up after dental surgeries with minimal involvement of humans. The alternative to the Asispo chatbot are nurses and/or doctors calling the patients one by one which leads to a large investment of time and inability to follow-up all of the patients due to lack of human resources.

"Today almost half of our French patients that underwent surgery and went back on the same day are never contacted back the day after the surgery. For doctor Wolfeler and his team it represented 6 to 8 hours per week to come back to every patient taking incoming calls, emails, texts and often on personal phone, so it's quite time consuming and 80% of the time it's the same kind of advice." Thomas Gouritin, Co-Founder at Asispo, 2022

To automate medication plan prescription and follow-up, Exact Cure digital platforms allow monitoring patients' treatment efficiency and drug side-effects. Qinematic has fully automated human movement measurement with 3D cameras and provides data analysis to support decision-making regarding management of musculoskeletal issues. Meanwhile, Word Diagnostics' solution allows collecting patient medical history with reduced time investment from the doctors. In all of these cases the repetitive tasks are performed by the Al-based systems, thus saving time and effort from healthcare professionals while improving the care received by the patients.

"This new method [..] needs to be used when the clinician and the patient meet for the very first time because there's a lot of time spent on trying to get to know the patient and trying to learn about their medical history to be able to do a good assessment. It takes a lot of time but it's also introducing a lot of bias into the system." Tomas de Souza, CEO of Word Diagnostics, 2022

4.1.2. Optimisation

Besides automating healthcare processes, the above-mentioned companies optimise these processes as well. More patients can be served in a shorter amount of time with the Al-enabled solutions from Asispo, Exact Cure, Qinematic and Word Diagnostics. Additionally, the quality of care is improved due to medical advice personalisation, medication plan optimisation per individual, standardising human movement measurements and assessment, as well as reducing personal bias in mental health assessments, respectively.

PharmAI and KI:elements were identified to optimise drug discovery and drug development processes. KI:elements allows facilitating and reducing expenses of clinical trials by assisting in participant selection and trial outcome determination. Meanwhile, PharmAI offers a service that allows speeding up and simplifying the initial stages of drug discovery research.

"[..] that's what our customers really like. They can cut down a process where they normally had to test some 10,000 molecules in the lab taking like 12 months. With our technology they can do it in two months." Joachim Haupt, CEO and Co-Founder of PharmAI, 2022

ImFusion optimises medical image analysis by Al-supported advanced image registration, segmentation, modelling and reconstruction.

4.1.3. Enhancement

Lastly, almost all of the assessed *Al-solution-specialists* provide enhanced outcomes for various activities in healthcare by enabling capacities that were not possible before the introduction of AI technologies. Examples of this are the ability of Exact Cure to offer compilation of vast amounts of scientific literature to model drug treatments for individual patients and aiding creating personalised treatment plans. KI:elements offer new speech-based digital biomarkers for assessing neurological and psychiatric conditions, while ImFusion and Qinematic expressed that new medical insights are generated by AI-technologies due to their ability to process data in a way that a human cannot.

"We're using machine learning algorithms to then analyse the way that people move because it's a lot of information, it's nearly impossible to do statistically. You need to use machine learning." Glenn Bilby, CEO and Founder of Qinematic, 2022

For both Qinematic and Word Diagnostics, Al allows to detect early signs of musculoskeletal problems and mental illnesses, respectively, thus making it possible to prevent the issues from worsening and resulting in more laboursome treatment than if addressed early. ImFusion enables visual assistance in surgeries and allows gaining new research insights by offering integration of medical images from various sources acquired in advance and in real time. Finally, Al and the presently available computing power allows PharmAl to compute propensities of trillions of atoms and to find fitting compounds faster than by performing tedious laboratory experiments.

4.2. Al-related Effects in Value Creation

In order to create value for customers and users the interviewed companies rely on various activities, resources and capabilities.

Several *Al-solution-specialists* use natural language in the form of speech or text as a starting point for their Al-related activities. Asispo, Exact Cure, KI:elements and Word Diagnostics all use Al technologies that can process natural language (NLP). This allows the companies to convert the speech and written text variables into data that can be further input to ML algorithms. The output from ML provides information to support patient recovery or other clinically valuable insights. Asispo uses the output to provide matching answers to patient questions post-surgery. KI:elements generate predictive models and risk scores based on speech biomarkers for different medical conditions that are useful for running clinical trials. Meanwhile, Word Diagnostics uses the ML output to assess the mental health state of a patient based on their spoken and written answers to questions. In the case of Exact Cure, NLP is applied to mine data from scientific articles on their drug of choice. This includes both textual and mathematical/ pharmacometric data. After manual data validation, it is input to ML algorithms to aggregate data, which is followed by drug meta-model creation.

PharmAI, ImFusion and Qinematic use structured data that doesn't require NLP to perform their AI-related activities. PharmAI processes readily available 3D protein structures from online libraries and small molecule chemical data to generate relevant features that are fed into ML for computing molecule propensities. ImFusion uses medical images generated by various means (ultrasound, MRI, CT) and then uses ML to perform advanced image analysis

and allow aligning images from various sources and 3D tissue navigation. Qinematic acquires their own data in the form of 3D videos. The vast amount of image data is labelled, and biomechanics reports created to be able to analyse the human movement with ML.

Most *Al-solution-specialists* perform several non-Al-based activities in their value creation process additionally to the Al-related activities. For Asispo the main such activities include designing a patient's post-operative journey, onboarding patients to the digital platform, sending patients prompts to collect their recovery feedback and returning personalised answers and advice. For Exact Cure non-Al-based activities include selection of the drug to be modelled, verifying the ML-created drug meta models, and integrating the models into client's operations architecture. For ImFusion it is important to learn what their clients' needs are and to define appropriate solutions and ways of working with a client that they can contract. KI:elements' non-Al-based activities include consulting and participating in voice-based technology innovation in pharmaceutical companies, as well as doing research together with the customers. Qinematic enables sharing personalised exercise prescription videos between physiotherapists, doctors, nurses, gym instructors and their patients/clients. Finally, Word Diagnostics' main non-Al-based activities include running demos of their solution and discussing the implementation of it in healthcare provider practices.

The main resource for all interviewed firms are their employees with very field- and operationsspecific expertise and/ or software development skills. To give a few examples, Exact Cure mentioned expertise in IT development, pharmacy, biomathematics, pharmacometrics and project management, while KI:elements stated clinical knowledge, expertise in data collection, signal processing, NLP and pharmaceutical-related business knowledge as crucial capabilities for running their business.

Other resources required for the interviewed *Al-solution-specialists* are data-sets for training Al algorithms, customer inputs, model validation systems, server hosting, chatbot development framework (in case of Asispo), healthcare certifications, partnerships for evaluating the developed solutions via studies, legal and financial services.

4.3. Al-related Effects in Value Delivery

Three of the analysed case studies, namely Asispo, KI:elements and Word Diagnostics, use direct selling to potential customers as the main value delivery channel. For ImFusion, KI:elements and PharmAI an important marketing channel is attending scientific conferences to connect with their future partners and customers. These three *AI-solution-specialists* rely

heavily on their capabilities in biomedical research and attract their potential customer's attention when receiving research grants. Asispo, ImFusion and PharmAI rely on the network of the company founders and employees to spread the word about their offerings and to find new customers. Similarly, Exact Cure relies on their partners and clients in the pharmaceutical industry to reach their end users. Word Diagnostics named inbound marketing as a relevant delivery channel for their company.

Many of the interviewed companies are start-ups with a small number of employees (below 10 or around 20), and it was stated that these companies don't have an active marketing function within the company. Asispo is an exception as they have a digital marketing campaign in the pipeline. Meanwhile, most of the interviewed companies keep a modest presence on the social media platform *LinkedIn* to post about their activities and publications, as well as use *LinkedIn* for building their brand.

4.4. Al-related Effects in Value Capture

As expected from the findings about the main resources and capabilities within the interviewed firms, all except one *Al-solution-specialist* stated their personnel as the main expense. The other costs are mostly secondary.

"We obviously have a lot of computers but that's a one time thing. [We] bought some robots recently because we now have a robotic module group but that's not too bad. I want to say people, people are expensive." Julia Rackerseder, Technical Product Manager at ImFusion, 2022

"The most expensive part salary-wise internally will be developing new models, so basically the R&D team [..] This is the most time, the most resources." Margoux Kerhouse, Business Developer at Exact Cure, 2022

The exception here was Asispo for which the main expenses are text message service to reach their users, IT services and hosting that are outsourced, and certifications for hosting health data.

Other *Al-solution-specialists* had costs for office rent, legal fees, infrastructure and equipment for data processing, computing and data storage. Qinematic stated that the main costs for their company have been the upfront development of technology, and maintenance of their

technology and medical device compliance are costs as well. KI:elements mentioned that a small fraction of their budget is used for marketing.

The main model to capture value was different for almost every interviewed company. Meanwhile, a dominance of software licensing and subscription fees in different forms was observed.

"We work for pharmaceutical companies and we licence our speech technology into their clinical trials [..] It's a much easier model because we deal with one payer which is a large company. It's a single contract. Much easier than distributing it through health insurance or anything else." Nicklas Linz, CEO and founder of KI:elements, 2022

The main revenue stream is a licensing fee for the technology for KI:elements and a licensing fee for a software as a service (SaaS) solution for Word Diagnostics. Qinematic has a subscription fee based on the amount of usage, and Asispo a subscription fee per surgeon using their offerings. Exact Cure has an annual licence fee for drugs on the market and a fixed service fee to develop new drug models for clients in pharma, and a price per patient for insurance companies. PharmAI currently charges a service fee for their work and is transitioning to a SaaS model similar to what Word Diagnostics has. For ImFusion the major revenue stream is selling research and development (R&D) project hours and R&D work on a fixed-term basis. Besides this, ImFusion gains revenue from product sales, licensing and runtime licensing fees, as well as from research grants. Research funding is a significant income stream for KI:elements and PharmAI as well.

5. Discussion

5.1. Al Taxonomy for Healthcare Businesses (RQ1)

This study shows that the analysed *Al-solution-specialists*, integrate numerous different Alfuelled systems into their current products, processes and/ or services. By having done this, the companies have automated, optimised and enhanced the existing healthcare processes. In line with recent research, the examined Al-technologies can be assigned to the first Al evolutionary stage: Artificial Narrow Intelligence (Kaplan and Haenlein 2019), as the incorporated Al systems are limited to solving specific tasks, such as processing and computing vast amounts of clinical or medically relevant data (Åström et al. 2022; He et al. 2019). Further, the investigated Al-technologies can be categorised into the two main use types: 1) Assisted Intelligence and 2) Augmented Intelligence (Garbuio and Lin 2019). In our

cases, companies utilising the Assisted Intelligence strongly focus on routine-tasks, such as patient follow-up after ambulatory surgeries and medication prescription, and segmentation and reconstruction for medical image processing. Meanwhile, enterprises using Augmented Intelligence deliver high accuracy in diagnosis, tailor-made treatment or generate of new medically relevant insights. However, our empirical data reveals that the interviewed healthcare firms incorporate different Al-use-types into single offerings. Thus, contrary to current literature, our findings rather suggest a mixed-approach of Al-integration - blurring the lines between distinct technology use-type categorisations.

5.2. Healthcare-specific Al-enabled Changes in Business Models (RQ2)

In accordance with recent research our findings clearly demonstrate that the extension of healthcare products, processes and/ or services through AI, ultimately leads to several related changes in the firm's value operating models (Berman 2012; Bouwman et al. 2018). The next paragraphs will present the healthcare-specific AI-related changes occurring in the examined firm's business models - strongly focusing on the value creation, delivery, and capture mechanisms.

Generally, the Al-firms value creation logic can be divided into firm- and customer-oriented activities with the former concentrating on AI refining current business-operations, while the latter relates to Al-based revenue and growth operations (Cockburn et al. 2018; Teece 2018). In this way, through firm-oriented activities Al-solution-specialists develop specific Alcapabilities, which automate and optimise their value chain activities (Cockburn et al. 2018) resulting in significant cost reductions and high increase in efficiency (Dicuonzo et al. 2022). Yet, Al-based activities affecting a firm's revenue or growth operations are perceived with added value by customers (Burström et al. 2021). In this manner, our empirical data clearly manifests Al as an enabler of innovative healthcare activities - which were previously unattainable. As ML algorithms process, compute, analyse and interpret extensive amounts of clinical or medically relevant data - new, previously unavailable information can be generated (Åström et al. 2022; Mishra and Tripathi 2021). Our findings show that new medically related knowledge and/ or healthcare market insights are created (Cheah and Wang 2017). Accordingly, radical improvements of clinical outcomes and the decrease of diagnostic errors are achieved (Laudien and Pesch 2019). In this way, through the integration of Al into the value creation mechanisms, healthcare-providers are offered support in medical decisionmaking, personalised, technologically advanced solutions, and greater outcomes in daily, clinical tasks.

In accordance with literature, Al-fuelled operations from the value chain activities align backend processes with front-end needs in the *value delivery* dimension (Cheah and Wang 2017; Lee et al. 2019). Our findings additionally suggest a direct connection to the customers' clients. In this manner, *Al-solution-specialists* simultaneously create a better understanding for *healthcare-provider's* needs (Chalmers et al. 2020; Parida et al. 2018), *and* for their customer's patient's health-status. Additionally, routines for healthcare delivery processes are continuously monitored and controlled - leading to improved product, process, and service flows (Åström et al. 2022; Bohr and Memarzadeh 2020).

Being deeply founded on the corresponding value chain activities (Chesbrough 2010), Al leaves its mark in the *value capture* dimension. With reference to recent research our empirical data shows that Al-extended product- and/or service- portfolios result in improved revenue streams (Burström et al. 2021) - mainly derived from licensing or subscription models. As Al functions as an enabling technology and catalyst for further innovative business activities it triggers the discovery of novel revenue and cost reduction sources (Urbinati et al. 2019). Contrary to literature, our findings undoubtedly state that most *Al-solution-specialists* are not faced with high costs regarding Al infrastructure or computing power (Sjödin et al. 2020), but rather great personnel expenses.

The table below will summarise the above-mentioned healthcare-specific Al-enabled business model changes - marking the differences to the industry-unspecific theoretical model from subchapter 2.3.1. in **bold**:

Table 3: Al-enabled changes in each BM element for healthcare.

BM Component	Al-enabled Changes for Healthcare		
Value Creation	 Generation of new healthcare market insights and medically relevant knowledge Automation and optimization of value chain activities Improvement of clinical outcomes and decrease of therapeutic errors 		
Value Delivery	 Back-end processes directly linked to healthcare-provider and patients Improved understanding of healthcare-providers needs and patient's health status Improved monitoring and control for healthcare delivery processes 		
Value Capture	 Improved existing revenue streams Identification of new revenue sources Cost reduction of value chain activities Cost increase for Al-related personnel 		

Source: Own Illustration.

5.3. Extended Healthcare Firm Operating Model with Al Integration (RQ3)

Al-solution-specialists offer comprehensive Al-solution packages to different healthcare-providers, resulting in a generalisable Al-based value chain. Although we heavily comply with the theoretical model "Al-based Value Chain for Healthcare" (subchapter 2.3.2), adapted from Alloghani et al. (2020), our analysed case material extends and supplements previous research by offering a broader view. With the addition of certain steps and their more in-depth description, we present the "Extended Al-based Value Chain for Healthcare":

First, the *healthcare-providers* - in this scenario the customers of Al-healthcare firms comprised of pharma companies, medical professionals, hospitals, or other healthcare stakeholders - either place an order or get approached by the *Al-solution-specialist*. Normally, thereupon follow weeks or months of consultancy and training before the Al-based offerings are integrated into the *healthcare-providers*' systems.

In the second step, data is either generated and collected through clinical activities or results from previous medical research and is gathered from scientific papers or other available databases. Regardless of how information is created and accumulated, data either occurs in a structured or unstructured form. The former can directly be pushed into Machine Learning

algorithms, which classify, cluster, and analyse the given input (Alloghani et al. 2020; Zhang and Lu 2021). In the case of unstructured data, originating from written or spoken language, Natural-Language-Processing techniques are employed to extract later-usable information and complement structured data.

Finally, this Al-based model leads to a variety of clinical outcomes, such as disease and health-risk prediction, the support of diagnosis, simulation of drug-use, and many more (He et al. 2019). Deducing from our findings the figure below visualises the generalised value chain of an *Al-solution-specialist* embedded in the theoretical model from subchapter 2.3.2 - marking the additions and/ or differences in **bold**:

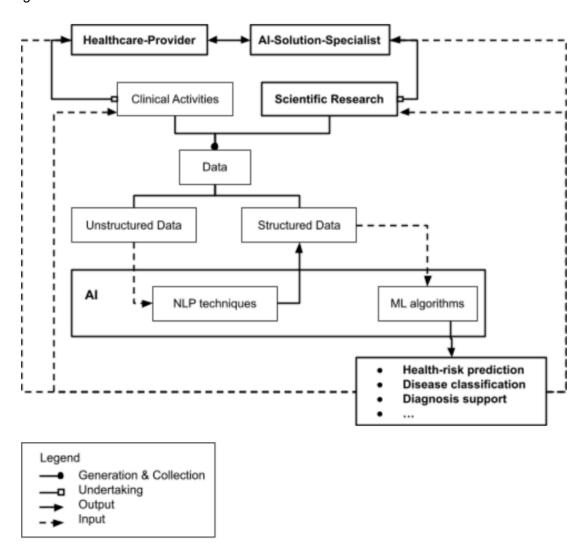


Figure 4: Extended Al-based Value Chain for Healthcare.

Source: Own Illustration.

6. Conclusion

6.1. Did we answer our research questions?

This study has sought to investigate *which* Al-use-types are employed in healthcare firms, *how* these are operationalised into their products, processes and/ or services *and* ultimately *how* these are commercialised through the company's respective BMs. With our research we provide a thorough investigation of relevant literature regarding Artificial Intelligence, business models and business model innovation, as well as their connection to the prevailing healthcare sector. Additionally, through the analysis of seven industry cases, we deliver empirical insights regarding the Al-utility in healthcare businesses and the Al-integration into corresponding firm operating models. Lastly, we establish a healthcare-specific framework for Al-enabled business model modifications, demonstrating Al-related changes for each business model component.

6.2. Theoretical Implications

This thesis highly contributes to the current literature on Al-enabled business model innovation, as it tests, validates, and extends two proposed theoretical frameworks in the given field. In this manner, we want to highlight three main theoretical implications:

First, our findings clearly show that *Al-solution-specialists* integrate a high variety of Al-based technologies into single healthcare offerings. Contrary to previous literature, our study suggests that the different Al use types Assisted, and Augmented Intelligence are used together, directed at improving and/ or altering healthcare operation and delivery processes (Åström et al. 2022; Garbuio and Lin 2019). In this way, we believe that the proposed Al use types should be considered interlinked levels rather than independent classifications.

Second, our empirical data confirms that the implementation of Al-fuelled systems into products, processes and/ or services results in numerous Al-enabled changes in the firm's value operating models (Bouncken et al. 2021; Dmitriev et al. 2014). Furthermore, we tested the theoretical framework of general, **industry-unspecific** Al-related BM modifications as well as supplemented it through **healthcare-specific** findings (see Table 3). In this manner, we could identify common, industry-independent Al-caused changes, such as: the automation and optimization of value chain activities, the improvement of business processes' monitoring and control, the identification of novel and the improvement of existing revenue sources and the decrease of value chain costs (Burström et al. 2019; Kiel et al. 2017). Additionally, we could observe following healthcare-specific, Al-related effects for each business model

component: 1) the creation of novel healthcare insights and medically-relevant learnings, as well as the improvement of clinical output and the reduction of therapeutic error for the *value creation* dimension, 2) the alignment of back-end processes with *healthcare-providers*' and patients' needs as well as the creation of an enhanced understanding of patient's health status for the *value delivery* dimension, *and* 3) the increased cost for Al-related personnel for the *value capture* dimension.

Lastly, strongly linked to Al-utility matters, we provide a more comprehensive perspective on Al-based value chain activities in healthcare businesses. Heavily complying with recent literature, our findings indicate a great shift regarding responsibility and value aspects in the conventional patient-physician-model (Topol 2019). Thus, our proposed "Extended Al-based Value Chain for Healthcare" (see Figure 4) includes both the healthcare-provider and the Al-solution-specialist as data- and/ or input sources - either originating from clinical activities or scientific research. In line with previous research, the offered Al-solution packages deliver different medically related output activities such as: supporting medical professionals in decision-making processes, reducing therapeutic and clinical errors, predicting health risks, etc. (Jiang et al. 2017; Minas and Triantafillou 2020).

6.3. Practical Implications

Besides Al's numerous benefits on healthcare operation and delivery processes (Leone et al. 2021), solely its implementation into value operating models results in higher business gains (Åström et al. 2022; Lee et al. 2019). Due to scarce knowledge on Al and its related effects on the business model, questions regarding its successful operationalisation and commercialisation in the prevailing healthcare sector arise (Buch and Maruthappu 2018; He et al. 2019). Accordingly, this study contributes with following practical implications:

First, our established framework for healthcare-specific Al-enabled BM changes, strongly supports both present and future *Al-solution-specialists* to either develop or maintain their strategic fit - preserving and improving their competitive advantages (Kotarba 2018; Verhoef et al. 2021). In this context, we unveil Al's impact on current healthcare business activities and medically related practices, guiding practitioners in creating, delivering, and capturing value from Al-based product- and/ or service-portfolios. In this manner, we equip managers with distinct knowledge about *how* each business model component shall be (re-)shaped when integrating Al into healthcare offerings (Berman 2012; Bouwman et al. 2018).

Second, we provide healthcare practitioners with relevant insights into a comprehensive Albased firm operating model. On the one side, through the creation of a generalised process, future *Al-solution-specialists* can be guided in the implementation of Al-fuelled systems into their value chain mechanisms. On the other side, through the focus on automatization and optimisation activities, present Al-healthcare firms can increase efficiency and reduce costs in each presented step. Further, we help *healthcare-providers* in creating a better understanding for *how* Al can be integrated in the value creation logic and ultimately into products, processes and/ or services.

However, Al-applications targeting different medical tasks might transform certain value chain activities, calling for a great need of continuous iteration. Additionally, managers are invited to regularly improve and refine current business models or single components, as research on Al is ongoing and its progress might alter the prevailing healthcare landscape. With this said, our proposed frameworks serve as blueprints for *Al-solution-specialists* to create novel business operations and processes, which ultimately present market traction and allow to be scaled (D'ippolito et al. 2019; Rachinger et al. 2018).

6.4. Limitations and Future Research

Being a highly emerging research field, the topic of Al-enabled business model innovation lacks strong theoretical foundation (Åström et al. 2022) and is therefore in great need for further scholarly attention. Hence, this study faces several limitations but simultaneously offers several possibilities for future research.

First, this thesis is narrowed in its scope, as it applies a qualitative research methodology through a multiple-case study approach, comprising seven cases from the healthcare sector. Therefore, transferability of the proposed frameworks to other industries should be handled with great care. Further, only one representative per firm was interviewed undermining the healthcare-provider's and the patient's perspective. Thus, we propose future research to adopt an ecosystem-perspective taking all relevant healthcare stakeholders into consideration. Although our findings can apply to present and future *Al-solution-specialists* not mentioned in our sample - we advise to reasonably reflect against their national and organisational background. Additionally, we suggest future academics to extend the sample and therefore enhance generalizability-matters through quantitative research. Lastly, as business models continuously get adjusted and modified, future studies shall pursue a longitudinal research design, where changes and Al-related effects in each BM component can be observed over a longer period.

Despite the above-mentioned limitations, this thesis contributes to an improved understanding of how AI is used and integrated into healthcare firms and their corresponding AI-solution packages, as well as how *AI-solution-specialists* can create, deliver, and capture value through AI-based technologies. With our study we hope to inspire future academics to deepen and strengthen theoretical and practical knowledge in the respective field of interest.

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Appendix

Interview guidelines

Interviewer:

- Welcome interviewee and thank for opportunity
- Introduce oneself
- Describe the thesis topic, purpose of the interview and structure of the interview
 - o Personal and company information
 - Al-technology in offerings
 - Value specific questions
- Ask for time they have
- Ask permission for recording and explain why needed (easier interaction and being able to look back) → If yes: start recording, If no: taking notes;

Stage	Question(s)
Personal information about interviewee	We know that your position at the company is x. Can you briefly explain your main area of focus in the company (tasks, function, responsibility)? (Education background)
Company information	When was the company founded? How many employees do you have?
Offerings	What products/ services are Al-enabled in your company? (integrated Al or entirely Al-based)
Clarification	What is your definition/ understanding of AI?
Value Proposition	Can you describe the value or benefit for your customers that arises from the integration of Al into your products/ services?
Value Creation	Resources → What competencies and resources are most important to create the mentioned value? Activities → What are the core activities/ steps in creating value for the customer (or ask for prediction)? Are you B2B?
Value Delivery	Delivery Channels → Which distribution channels are necessary for delivering the value (marketing, sales and distribution)? Are any steps/ main activities of how you deliver the value influenced using Al-tech?
Value Capture	Costs → What are the main categories of costs arising from your Al-based products/ services Revenue → How do you generate revenue? What is the revenue composed of (parts and streams)?
Ending the interview	Is there anything important to you that we haven't talked about, and you want to add? Would you be open to us reaching out to you for any follow-up questions? Using your and company name in our findings. Thank them for their time and effort.