AN AI-POWERED APPROACH TO VALUE-BASED HEALTHCARE IN DENMARK

OVERCOMING THE CHALLENGES OF AI IMPLEMENTATIONS IN THE DANISH HEALTHCARE INDUSTRY

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Abstract

Value-based approaches to healthcare focus on improving health care systems by restructuring them around patient-centric outcomes, to achieve greater efficiency in clinical workflows at lower costs. However, there is a lack of research regarding how artificial intelligence can be utilized in value-based approaches. The purpose of this thesis is to study the challenges of implementing AI-tools in the Danish healthcare industry, to create a framework for AI-powered value-based healthcare. An exploratory research approach is used to examine how two important stakeholder groups, namely, clinical staff and technical experts, perceive the challenges of AI to optimize clinical processes. By analyzing the findings from our primary research through the lens of a value-based approach, we construct an implementation matrix to support AI developers and other important stakeholders in identifying the imperative elements of AI projects in healthcare. The findings reveal that accessing quality health data and incentivizing clinical staff to adopt the tools in their workflows are among the biggest barriers limiting AI's capabilities. Furthermore, the practical and ethical implications of working with sensitive health data complicates the development processes. While the findings of this thesis are specific to the Danish healthcare industry, they can presumably be applied in similar projects to drive value-based outcomes in healthcare around the world.

Keywords: value-based healthcare, artificial intelligence, AI-powered healthcare, sensitive data, adoption challenges

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2. Introduction

Digital innovations have been revolutionizing the healthcare industry. With artificial intelligence (AI) becoming increasingly efficient and seeing valuable applications in many industries, the question of how it can lead to a positive impact in the Danish healthcare system becomes prevalent. Healthcare AI offers various opportunities for the healthcare providers to streamline operations, identify and understand patient requirements, increase diagnosis accuracy, and many other applications (HC IT News, 2019). However, while the technology being developed has presented impressive results in test settings, it has yet to make a measurable impact in clinical workflows.

With growing demand for care, many clinicians are struggling to cope with increasing workloads. There is shortage of supply in resources and the demand for frontline workers in healthcare is widening. Most countries in the EU are looking to digitally transform their healthcare systems to close this gap. The ratio of demand vs. availability has posed great pressure on the workers and affected the patients' experience. The fundamental driving force behind digital transformation in healthcare are the emerging technologies like telemedicine, AI-enabled medical devices, and blockchain electronic health records (Reddy, 2021).

The optimization of healthcare is a field that is being continuously researched. Recently, researchers have been aiming their attention at value-based approaches to healthcare (Porter & Teisberg, 2006). This approach seeks to restructure healthcare systems, to center around the goal of providing value for patients. In value-based healthcare (VBHC), value is measured in terms of longitudinal patient-centric outcomes, instead of short-term transactions (Medtronic, n.d.). While value-based healthcare approaches are regarded as a priority in many health systems, few health providers have aligned with the principles of VBHC. Furthermore, there is currently a gap in research regarding how AI can help facilitate value-based healthcare.

With the rapid development of AI, there have been growing concerns about the significant challenges that AI brings to healthcare organizations, thus limiting the integration of these tools into healthcare operations. Furthermore, incorporating AI technology into a highly regulated and complex healthcare system presents a challenge for both the healthcare professionals and AI developers. Hence, it is crucial for both healthcare professionals and AI developers to understand the state of AI technologies and how to integrate AI technologies to improve the efficiency, safety, and access of health services.

Exploring and addressing these challenges in a local setting is important to determine how AI technologies can drive VBHC in a Danish context. The Danish government has already displayed great interest in further digitizing the Danish healthcare sector. However, initiatives like the electronic health record, "Sundhedsplatformen", or IBM's AI-based "Watson Oncology" have been met with great criticism in their ability to provide healthcare value, largely due to their poor implementation efforts (Djursing, 2017; Hult, 2019).

This thesis examines the challenges that AI developers are facing while designing and implementing valuable AI tools in the Danish healthcare industry. The challenges that are identified in this paper are based on the perspectives from both technical experts working with AI, and the clinical staff who will be the end-users of these tools. Aligning these two actors is important in creating a model for AI implementations that utilizes the capabilities of AI, while ensuring adoption among clinical staff. Furthermore, we examine the outside factors such as regulations and need for external collaborators, that need to be addressed due the resource requirements and ethical considerations when working with extremely sensitive data.

The objective of this thesis is to provide a framework for a value-based implementation approach of healthcare AI technologies in Denmark. We hypothesize that incorporating the perception of important stakeholders in what constitutes value-based outcomes, is critical in developing a model for future implementations.

2.1. Research Questions

The core of this thesis is structured around exploring the current landscape of artificial intelligence in the Danish healthcare industry. This is accomplished through extensive research in existing literature alongside a qualitative, interview-based study with the goal of organizing the sentiments of both clinical staff and technical experts. These two groups are also who this thesis aims to position as the main beneficiaries of the results, as we wanted our results to reflect their inputs and ambitions for the future of AI in Danish healthcare.

Due to the inductive approach applied in our research methods, the research question has evolved and changed throughout the span of our work. The data collection revealed key challenges from both the perspective of technical experts and clinical staff, that would be crucial to elucidate, to increase the success rate of healthcare AI. The research question consists of one primary question and two sub questions. The primary question serves to explore what challenges have emerged in previous and current AI implementations in Danish healthcare, while analyzing what can be learned from the challenges these projects encountered:

RQ1: *What are the key challenges of implementing AI tools in the Danish Healthcare Industry and how should they be addressed?*

The second question addresses the important aspect of identifying which stakeholders are imperative to the success of AI in healthcare. Due to the unique nature of the data, one is working with in healthcare, there are many elements and actors that need to be considered to create technologies that are valuable both clinically and commercially, while also being within the constraints of e.g., the GDPR. This question is designed to shed light on everything from incentivizing clinical personnel to apply AI tools in their work, to framing the value of AI in healthcare in a way to incentivize investors:

RQ2: *Who are the important stakeholders in successful AI implementations and how do you incentivize them?*

The third question is designed to analyze the outcomes of existing AI tools alongside our primary data, to propose a model for implementing AI in healthcare. The blueprint for this model will be constructed with value-based healthcare in mind, which is greatly dependent on defining what constitutes "value" in healthcare. The design aspect of this question refers primarily to the "design phase" of AI tools, rather than the technical architecture. Our data collection showed us that the maturity of AI algorithms was rarely the problem in healthcare, but rather properly designing the tools to assist in the workflows that create most value, which leads us to the final question:

RQ3: *How should artificial intelligence technology be designed and implemented to bring value to the systems and workflows in the Danish Healthcare Industry?*

To answer these questions, the thesis will be structured as the following: The theory section will present a review of previous literature within the area of research, to highlight our research approach and how it contributes to existing literature. We then highlight the primary theories and key concepts that support our research and require a more thorough introduction in framing our approach. Afterwards, we present our research methodology and philosophy, as well as data collection methods and how our primary data will be used in the research.

After this, we present the results section which highlights the main findings from our data collection, to answer the descriptive parts of our research questions. This will lead us to the discussion section, where we provide concrete recommendations for solving the challenges we have identified, by comparing our primary research with existing literature. The discussion also contains a section regarding the practical and ethical considerations of implementing AI in healthcare. At the end of the discussion, we reflect on the limitations of the paper and what future research could help expand our model. Finally, we present the conclusion, which summarizes the answers to the research questions and demonstrates what new knowledge has been contributed to the research area.

3. Theory

The following section will present the theories and relevant material that are used throughout this thesis. It is structured in three parts. The first part consists of a review of research, which provides an overview of the most important research that has been conducted within the field of AI transformations in healthcare. These studies provide an overview of the existing knowledge in the field, to help us identify relevant theories and methods that inspire this thesis, as well as establish where our research contributes to the field.

Following the review of the literature, we highlight the most important theories and frameworks that are utilized in the thesis. While defining the theories, the focus will be on highlighting the components that are relevant to analyzing our primary data. For this reason, the theories are not presented in-depth, but restricted to the elements that are relevant to the thesis. Finally, we present important key concepts, that we have chosen to highlight, as they play a significant role in the thesis. The concepts include terms that are relevant within the healthcare industry, such as defining "healthcare value", as well as clarifying the definition of what constitutes "artificial intelligence" in the context of the thesis.

3.1. Previous Research within Healthcare AI

Artificial intelligence in healthcare is still in its early stages, but the move towards digitizing end-to-end hospital processes is accelerating faster than ever before. In this section, we explore what groundwork has been done within the research area of AI in healthcare, to identify some of the challenges that have arisen in studies like this one. Furthermore, we compare some of the approaches that have been taken to address these challenges, to allow us to illustrate where our research contributes to the field. This study of previous literature ultimately led us to have a clear idea of what stakeholders we were interested in interviewing and what questions we should ask them. Naturally, we returned to existing literature continuously while working on the thesis, as new information from our primary data collection narrowed the scope of our research goals.

A study by Lindskow et al. (2020) was posted in the Danish Medical Journey to highlight the vast potential for artificial intelligence to assist doctors when diagnosing and treating patients. The paper summarizes some of the initiatives in funding and development of AI tools that have been implemented in Denmark. The authors highlight that while Denmark has some of the best data on their citizens in the world due to the CPR-system, factors like lack of competent IT specialists and regulations that limit data access make it difficult to establish the organizational readiness in hospitals, which is necessary to complete a digital transformation.

Wu et al. (2021) explore the limitations of evaluating medical AI devices for FDA approvals. As best practices for evaluating the reliability and safety of algorithms have yet to be established, it is difficult to assess the validity of the testing. The authors examine if common shortcomings of AI such as overfitting to training data, vulnerability to data shifts, and bias against underrepresented patient subgroups is properly addressed. Their analysis revealed that the evaluation and testing of almost all the FDA approved medical AI devices had been lackluster. Based on the findings, the authors recommend more comprehensive prospective testing, to ensure that algorithms perform well on a diverse group of people. Furthermore, Wu et al. argues for the importance of post-market surveillance of AI devices.

In a research paper conducted by Fürstenau et al. (2019), a case study is conducted on multi-sided platforms (SMP) in healthcare. The study established two business models, “care coordination” and “care research”, designed to create value for patients and insights into long-term care improvements. It was found that good governance is extremely important, especially when working within the health care sector. Due to the nature of the industry, it was found that it is important to build trust in the health care community and emphasize a focus on medical optimization, rather than business and technical optimization. The study also emphasizes the importance of value-based healthcare (Porter, 2008), by creating value for patients in three steps: 1) efficient and effective coordination of the provision of care and the underlying transactions during the first phase, 2) managing the quality of care and medical outcomes, and 3) direct patient involvement through app-based monitoring and transaction support.

Wessel et al. (2021) compared the traditional idea of a digital transformation with the concept of an IT-enabled organizational transformation. The paper compared two companies, and the different journeys and outcomes they had while increasing the IT presence in their companies. One of the companies, which is a manufacturing company, used technology to redefine their value propositions, which led to roles changing within the organization, e.g., the sales role becoming a more consultancy-based role. This is what is classified as a digital transformation. The other company used the technology to enhance their current value propositions without changing the underlying roles of the employees. This was classified as an IT-enabled organizational transformation. The differences in the roles of the internal stakeholders are important to consider in the context of health care.

A PhD thesis by Blomberg, S (2021) explored the potentials of machine learning models in recognizing out-of-hospital cardiac arrest during emergency calls. A natural language processing (NPL) tool eavesdropped on the Danish emergency number (1-1-2), that transferred the information to an ML model which alerted the medical dispatcher if the model suspected a cardiac arrest. The ML models were able to recognize cardiac arrests in 85 percent of the calls, which surpassed the human dispatchers by a margin greater than 10 percent. Interestingly, there was no statistically significant increase in life-saving potential, largely due to lack of adoption from the human actors. In conclusion, Blomberg highlights the great potential of ML in healthcare, while also emphasizing the importance of education and proper implementations of technology that support medical personnel.

In a collaborative research paper between American universities and hospitals, Drysdale, E. et al. (2020) identified the key "dos and don'ts" for deploying machine learning models in healthcare. As the deployment strategies for ML in healthcare currently lack structure and can be described as ad-hoc for most applications, the authors identified three themes that needed to be realized to implement good AI. These three themes were: 1) Contextualization: the AI and ML tools must be contextualized specifically to match the unique workflows of the healthcare instance they are being implemented in. 2) Life-cycle Planning: The AI and ML tools must have a clear implementation plan throughout all the stages of the healthcare stages, as too many are only focused on the early stages. 3) Stakeholder involvement: Any successful AI project requires the correct stakeholders to be involved to address potential risks. This is especially relevant in healthcare, where clinicians may be more inclined to be careful when trusting technology, due to the nature of their work.

In a study conducted by Frank, M. et al. (2019), the potential disruption of labor following AI implementations is analyzed. With AI rapidly becoming more advanced, the typical labor tasks of workers in certain fields are changing. The authors argue that the alterations will diffuse the whole economy, as it will greatly influence skill requirements, career mobility, as well as societal well-being. The study stresses the importance of being ready for these changes, by prioritizing real-time collection of data to track these changes while they are happening. The study concludes that while the modern labor market will change, its disruptions can be positive if advanced data models are built to predict and understand the future of work.

Chen, M., and Decary, M. (2019), conducted a study to provide guidelines to understand the fundamentals of various AI technologies, and their effective deployment and use in healthcare. Chen & Decary outline how humans and machines have their own strengths and weaknesses, and how their integration can complement each other in providing optimal healthcare solutions. Thereby, AI should be used to enhance human intelligence rather than replacing it. Further, AI features can be embedded in healthcare workflows to optimize and support clinical decisions and improve patient outcomes. Finally, the authors postulate that healthcare leaders need to play a pivotal role in designing a clear AI strategy and infrastructure capabilities with a view on current and future implementation.

In a research paper Gerke et al., 2020, the authors posit that the growth of AI technology in recent years have given rise to several ethical challenges. Gerke et al. states that it is crucial to involve all stakeholders in an AI implementation to ensure that the AI tools are used ethically and legally. The authors examine four primary ethical challenges and five legal challenges and provide the strategies to address them in the early stages of development. The study concludes that the regulatory bodies should sanction effective governing frameworks that need to evolve with the technology. In addition, the national governing bodies should develop a compliance framework for the collection, storage and use of data in the health sector that is consistent with internationally recognized data protection principles.

Our analysis of previous literature within the field of AI in healthcare creates an overview of the most modern research in the field. This overview shows us that there is currently no clear approach to how to structure AI implementations in healthcare. The papers identify a wide variety of challenges that need to be addressed, such as stakeholder involvement, regulations, lack of IT-specialist competencies, etc. However, addressing these challenges are presented primarily through a technical lens, in that the researchers propose methods for improving the technological component itself. We categorize this approach as what we would describe as a traditional *technology-driven implementation approach.*

While this approach has presented results, it lacks some of the effective methods related to value-based outcomes as presented by Fürstenau et al. (2019) in their work with multi-sided platforms in healthcare. Value-based healthcare (Porter, 2008) approaches are focused on optimizing the final medical outcomes for patients, rather than the technology itself. We believe this approach is crucial in healthcare, as the literature reveals that there is often a lack of adoption from clinical staff in new digital appliances, due to low perceived value.

While there is a considerable amount of research within value-based approaches to general digitization efforts in healthcare, there is a gap in value-based approaches to AI implementations. Utilizing AI comes with its own unique set of challenges, like the ethical considerations regarding automating tasks that are traditionally conducted by human actors. Therefore, we wish to bridge the gap in the literature by examining how AI implementations can drive value in healthcare. This approach is primarily concerned with the valuable outcomes from technologies, rather than the technology itself. The approach we choose to implement throughout this thesis can be described as a *value-based AI implementation approach.* This approach is also inspired by the concept of IT-enabled organizational transformation as opposed to traditional digital transformations (Wessel et al., 2021), as we are not seeking to change the roles of clinical staff, but rather support their current workflows.

3.2. Value-based Healthcare

Traditionally, value-based healthcare (VBHC) is a concept that is particularly relevant for the US healthcare system, where a fee-for-service (FFS) structure dictates the price of healthcare services after a patient's interaction with a doctor. With the FFS model, doctors are compensated depending on the number of services they provide, which incentivizes them to provide a greater number of services than what is necessarily optimal for the patient. In a value-based healthcare model, clinical staff are compensated based on the health outcomes of their patients, which is determined by metrics such as effectiveness, timeliness, patient focus, and safety (Porter & Teisberg, 2006).

The Danish healthcare structure is quite different from the American structure, as payments for medical procedures are handled through taxes and patients rarely see any additional costs. However, the strategies for implementing value-based healthcare are also very relevant in Denmark, as reducing costs and improving patient outcomes is equally important in the Danish system. The World Health Organization (WHO) and the Organization for Economic Co-operation and Development (OECD) both estimate that 30% of resources spent in healthcare are wasted on avoidable complications, unnecessary treatments or administrative inefficiencies (Katz, 2020).

Value-based healthcare proposes a vision where everything in the healthcare system is realigned around the fundamental purpose of patient health. In a value-based healthcare system, healthcare providers compete on value, which creates a positive-sum competition where all participants can win (Porter & Teisberg, 2006). While it is more than 15 years since Porter and Teisberg introduced the concept of VBHC, many European countries have yet to align their healthcare processes with VBHC-principles (Kimpen, 2019).

3.3. Value-based Healthcare Implementation Matrix

The European Institute of Innovation and Technology (EIT) is a network founded by the European Union with the goal of offering a wide variety of innovation and entrepreneurship activities in European industries. One of the innovation communities, EIT Health, has created a framework for bringing a more value-based approach to healthcare inspired by Porter & Teisberg's definition of VBHC (2006). The framework is based on more than 240 expert interviews in a close collaboration with medical centers in the EU. The framework is intended to support practitioners, innovators and policy makers who want to drive change towards a high value approach to healthcare by helping them understand what constitutes "value" in the context of healthcare (Katz, 2020).

There is no one-size-fits-all solution to providing value and measuring outcomes, and each organization must fit the framework to fit their specific needs. However, through the research of EIT Health, it was found that providers, i.e., technical experts must overcome similar problems and converge on similar solutions to bring value to their healthcare organization. These patterns were used to create the VBHC Implementation Matrix (**Figure 1**), which defines five key dimensions that need to be addressed in these initiatives. The five dimensions are: 1) *Recording*, referring to measuring processes and outcomes, 2) *Comparing,* referring to benchmarking external and internal teams, 3) *Rewarding*, referring to investing in resources and creating outcome-based incentives, 4) *Improving*, which refers to organizing improvement cycles through collective learning, and 5) *Partnering,* which refers to aligning the internal and external forces and forging collaborations (Katz, 2020).

Each of the five dimensions are made up by building blocks that represent the concrete concepts that need to be addressed in successful implementation of VBHC. The nine building blocks are 1) Condition, 2) Internal forces, 3) Scorecard, 4) Data platform, 5) Benchmarks, 6) Investments, 7) Incentives, 8) Learning community, and 9) External collaborations. Below, we present the Implementation Matrix and the relationships between the dimensions and the building blocks:

Figure 1: VBHC Implementation Matrix (Katz, 2020)

The implementation matrix highlights a roadmap for which elements are important to consider in a value-based approach to healthcare implementations. In this thesis, we take inspiration from this model and modify it to represent a roadmap for AI-powered value-based healthcare. The modifications are based on the qualitative research that is presented later in the thesis, and centers around AI-powered VBHC. We have excluded the 1. *Condition* building block from the modified model, as our primary data focuses on the relationships between technical experts and clinical staff, instead of patients. We also exclude the 8. *Learning Community* building block, as the scope of this thesis exclusively focuses on the design and implementation phase of AI in healthcare. The modified model is presented in **Appendix A**, which includes insights from our qualitative research which will be addressed in the results section of the paper. As the inner dimensions of the model primarily serve to group the dimensions, they do not play an important part in our final model, as our fundamental focus is on the building blocks.

The seven building blocks included in our modified model are: 1) *Internal Forces,* this building block represents the clinical staff, who we describe as the end-users of these tools, as they will be the ones utilizing them in their workflows, 2) *External*

Collaborators, represents the technical experts and other important stakeholders who are developing and governing healthcare AI technologies, 3) *Scorecard*, represents the measuring of value through cost and outcome indicators, 4) *Data Platform,* represents the platforms where healthcare data is stored, which in the context of this thesis is primarily Sundhedsplatformen, 5) *Benchmarks,* which represents the need for transparency in outcomes to measure the performance of AI tools against alternatives, 6) *Investments*, representing the resources and costs of AI-powered healthcare, 7) *Incentives,* which represents the importance of properly incentivizing both end-users and other stakeholders in the creation of AI tools in healthcare.

At the end of the discussion segment, we are presenting the modified version of the matrix with actionable recommendations on how to drive value-based healthcare in Denmark through the power of artificial intelligence.

3.4. CRISP-DM Methodology

Cross Industry Standard Process for development of Data Mining (CRISP-DM) is an open standard process model that describes common approaches used by data mining experts (Chatterjee, 2020). The CRISP-DM methodology serves as a blueprint to gain better and faster results when carrying out data mining projects. It is a one size fits all solution and is applicable in any industry.

Due to the increased digitization efforts in healthcare, structured data mining is essential in achieving conclusive medical decisions. Hence, CRISP-DM serves as a tool that is used to support and assumes a high significance for all parties involved in the healthcare industry (Tiwari et al., 2015). "Some of the shortcomings of this methodology are that it does not perform project management activities" (Chatterjee, 2020). In this thesis, we incorporated four key phases: Data Understanding, Data Preparation, Modelling and Evaluation. The CRISP-DM methodology (**Figure 2**) is used alongside a modified implementation matrix (**Appendix A**) in designing a value-based approach for AI.

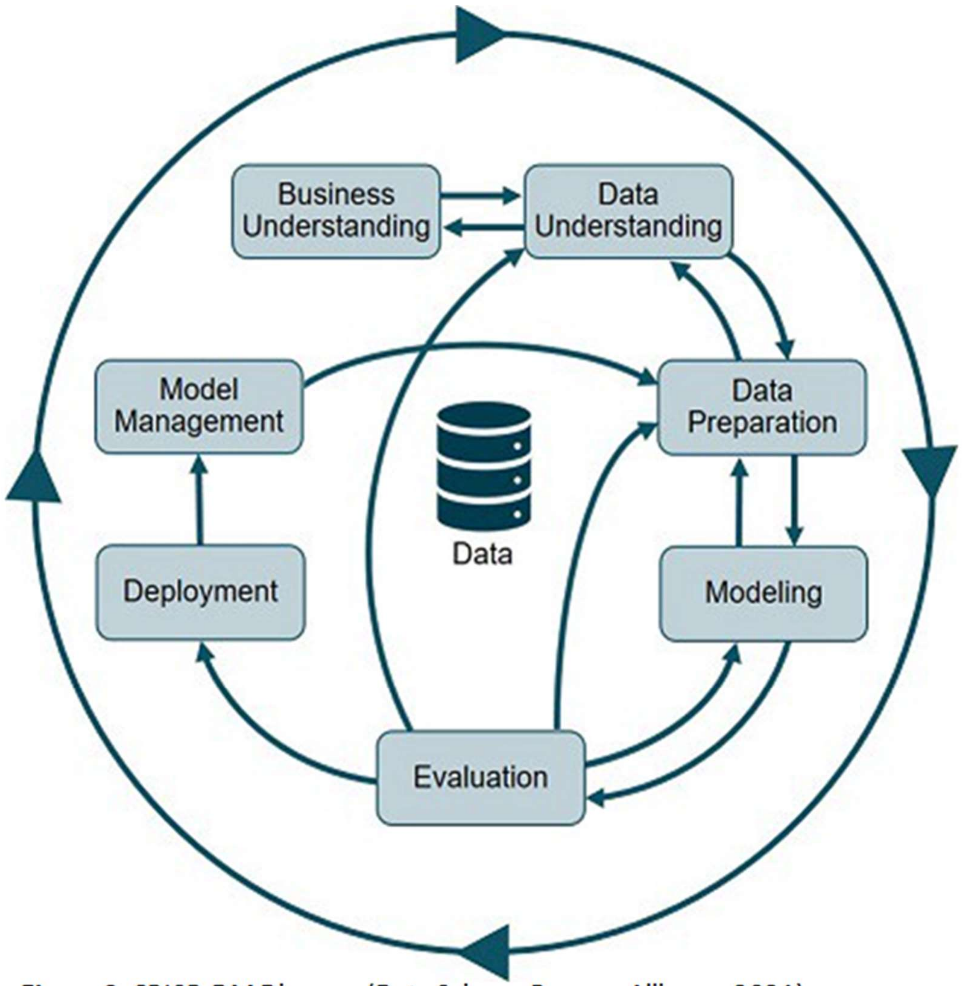


Figure 2: CRISP-DM Diagram (Data Science Process Alliance, 2021)

CRISP-DM consists of six phases that serve as a roadmap for data analytics to generate actionable insights when extracting patterns and identifying relationships from large datasets.

The CRISP-DM methodology consists of 1) Business understanding, which is the first phase where business objectives are converted to data mining subtasks, 2) Data understanding, which focuses on identifying the data, collecting the data, exploring the data and assessing the quality of available data, to provide an initial hypothesis of how to use the data for development. 3) Data preparation, which focuses on data sorting, data cleaning and creating a formatted dataset. 4) Modelling, where models are built and assessed through an iterative process. 5) Evaluation, where the results are evaluated against business objectives and developers assess if the model is ready for deployment or should be iterated further. Evaluation begins with pilot testing and reviewing the model using a tight feedback loop, to carefully evaluate the model before deployment and make sure that business objectives are achieved (Tiwar et al., 2015). 6) Deployment, where a deployment- and maintenance plan is created to avoid issues in the operational phase of the model (Tiwar et al., 2015).

3.5. Participatory Design

Traditionally, the most common approach to technology development utilizes a strategy where developers collect data from end-users, to then withdraw from the users' workplace. The technology is then designed and developed off-site, using an imagined setting and hypothetical tasks (Blomberg et al., 1993). In more recent times, the importance of involving end-users has become increasingly apparent. Developers have had to adapt their workflows from simply being a technical solution provider, to becoming advisors working closely with end-users.

"No project which will affect socioeconomic change can possibly succeed if the recipients do not participate (...) It appears that the principal reason why this primary ingredient has been overlooked so often is that many technical advisers have viewed their task as simply one of providing some kind of technical solution" (Niehoff in Blomberg et al., 1993. p. 140).

Blomberg et al. (1993) describes participatory design as focusing on the work of the end-users, which allows developers to gain a better understanding of the relationship between the technological component and the workflows it should support. Participatory design lies within a larger body of studies relating to design processes centered around work. We have chosen to highlight it for this thesis specifically, as it examines the values of human-centered design, which is essential in the healthcare industry (Blomberg et al, 1993; Brown & Wyatt, 2010).

Both our preliminary research and data collection reveals the importance of clinical staff being involved in the design process for them to see the value of the AI tools and wanting to adopt them in their workflows. Throughout this thesis we will highlight some of these findings and propose how participatory design can be implemented in

AI-powered value-based healthcare implementations. The data collection also shows the importance of involving stakeholders other than the immediate end-users, which is somewhat out of the scope of participatory design as presented by Blomberg et al. (1993). These limitations will briefly be addressed in the reflections section.

3.6. Defining Value in Healthcare

In order to analyze how AI tools can bring value to the Danish healthcare industry, it is important to first determine what "value" constitutes. In this thesis, our definition of value is based on existing literature on value-creation in healthcare, as well as primary data from our interviews. We are presenting a single definition of value, based on what both clinical staff and technical experts believe is most valuable in IT transformations in healthcare.

The overarching theme of what establishes a change as valuable, is its patient-centricity. One aspect of this is the medical benefits of the patients, which includes the improvement of quality of life, improvement of state of health, a reduction in the duration of disease, and the prolongation of survival (BfArM, 2020). While these direct measurements are important in determining the value of healthcare, an important aspect we explore in this thesis is integrating the processes between patients and healthcare providers. An example of this is being able to coordinate the treatment processes between several healthcare providers, which results in more accurate treatments of patients while reducing diagnosis lead time. Furthermore, digital health applications can help by facilitating access to care and letting patients contribute important data points to the healthcare provider, which reduces the need for clinical staff to spend time on administrative tasks (ibid).

A valuable aspect of digital health transformations that is notably applicable in AI-based transformations is health literacy. According to several studies, patients generally find it very difficult to correctly evaluate and use health-related information (BfArM, 2020). Increasing health literacy by providing patients with information that is important for their own actions during their treatment is especially relevant today. Clinical practitioners have noted a recent shift where patient autonomy has become increasingly important, as patients want more information and control over their own treatment.

“Value” is generally a vague term, so in this thesis, we are going to be working with value by the following definition: *Value in healthcare is the direct and indirect improvements in patients’ health outcomes derived from optimization of clinical workflows, therapy-related efforts, and adherence to established processes.*

In order to determine if “value” has been achieved, the manufacturer of the technology must be able to prove that the digital health tool is more effective than current outcomes without the use of technology or compared to an existing tool. The comparative study must be centered around the patient's health outcomes, where the new AI tool most represent a significant increase in quality. As the primary data in this thesis is exclusively collected from clinical and staff and technical experts, there will be a predominant focus on the indirect value added from AI in healthcare, from optimizing the workflows of clinical staff, which will ultimately benefit the patients.

3.7. Artificial Intelligence

Artificial Intelligence (AI) has existed for decades, with the earliest research tracking back all the way to the late 1930s, culminating in 1950, when Alan Turing published his book “Computing Machinery and Intelligence”, where the question: *Can machines think?* was asked (Panesar, 2021). AI can generally be understood as the simulation of intelligent behavior in agents, like computers, to act in a manner that would be considered “smart” or “rational”. While we mention that AI is not a new concept, the recent developments in technology and processing power have allowed AI to do things that are far more impressive than that of its inception.

AI has been receiving a lot of hype in the media and tech industry in recent years. This has led to a lot of technology being labelled as artificial intelligence, without necessarily meeting the criteria of what constitutes AI. While there is not a clear definition presented that completely encompasses what AI is (Kaplan, 2016), we argue that establishing a definition of what AI is in healthcare is important in order to distinguish it from other traditional methods. To meet the criteria of being defined as

AI in the context of this thesis, the technology should generally be capable of 1) being programmed to act rationally in a similar fashion to how human actors would, 2) being able to learn, discover, and predict, and 3) being able to communicate their outcomes with humans (Panesar, 2021).

This list is by no means exhaustive of the capabilities of AI but provides an overview of the capabilities of the tools that are explored in this thesis. There are several types of AI, with terms like "machine learning" often being used interchangeably with artificial intelligence. However, they are not the same. Machine learning (ML) is a subcategory of AI that is distinguished by its ability to train itself, rather than simply following instructions to how a task is carried out. Machine learning refers to the study of algorithms that allow computer programs to automatically improve through experience. There exist different types of machine learning models, however going into the technical details are outside the scope of this thesis, as we focus our efforts on the implementation process of these tools. The strength of a machine learning model is often based on the amount of available data and processing power (Sutskever, I. et al, 2014; Jean, S. et al, 2014).

Another part of AI that is especially relevant to this thesis is natural language processing (NLP). NLP is a subfield within artificial intelligence that allows technology to "understand" human language. NLP tools are typically used for understanding the sentiment of text, speech recognition and generating responses and recommendations based on the insights (Chen, 2020).

AI has a wide-reaching potential in healthcare. As an example, AI can be deployed in planning and resource allocation in healthcare services, by matching individuals with a care provider that meets their health care needs. AI is used in designing individual care plans and can be used with the aim of improving patient experience, providing information on demand, and equipping clinicians with information to help them to deliver appropriate treatments. Artificial Intelligence has the potential to restructure the healthcare industry by simplifying the lives of doctors, patients, and hospital administrators by automating tasks that are usually conducted by humans (Takyar, 2021).

Denmark has one of the most digitized public sectors and is one of the leading countries in collecting data (Agency for Digitization, n.d.). The large amount of health information that resides in Denmark improves the potential of utilizing AI, due to its heavy dependency on data. In 2019, Denmark published its first nation-wide strategy for artificial intelligence. The strategy focused on implementing several signature AI projects in the public sector and establishing an investment pool for Danish AI companies (McKinsey & Company & The Innovation Fund Denmark, 2019). Four sectors have been prioritized as strategically important, and healthcare is one of them.

Healthcare has seen a rapid increase in the use of artificial intelligence, with various uses in a wide variety of domains within medicine. Currently, however, the use of AI in clinical practices is limited, as it has been regarded with skepticism. This is generally because early applications of AI have struggled in some settings, alongside with general distrust in automating advanced clinical processes (Chen & Asch, 2017). Still, some recent studies in using AI in healthcare have been successful. As an example, in a recent study a machine learning model using natural language processing outperformed trained dispatchers in both speed and accuracy of early detection of cardiac arrest during emergency calls (Blomberg, 2021).

There are many other types of AI that can perform various tasks within the healthcare industry. Throughout this thesis, we have chosen to use the umbrella term “AI” to describe the full technology stack within artificial intelligence, without detailing the subcategory unless relevant for that specific statement. We have made this choice as the framework we are developing throughout this thesis intends to be applicable to all healthcare AI tools. The challenges we identify in our data collection show no significant differences in challenges when comparing the different subcategories of AI.

3.8. Explainable AI

The recent and relatively rapid success of AI solutions has produced very impressive practical applications such as autonomous driving and face recognition. However, while Google DeepMind’s AlphaZero can defeat even the very best humans in chess, it is unable to define its mechanisms in a way that is understandable by humans

(Goebel et al., 2018). Explainable AI in its simplest form is when the AI produces results that can be understood by humans.

The ability to understand how an AI has come to its conclusions is crucial in sensitive fields such as in the medical domain, which this thesis examines. If an AI is not able to communicate effectively with its users, it produces results that while they may be correct, are neither explainable nor replicable. To achieve the trustworthiness and ethical standards of an AI tool, it must provide insight into the rationale behind its conclusions (Doran et al., 2017).

Previous research has explored the “dark sides” of AI, where biases against underrepresented patient groups led to AI tools that discriminated against these groups (Meske et al, 2020). Similarly, a machine learning model used the presence of a ruler in images to determine if a skin tumor was malignant. It was found that the reason for this was that dermatologists tend to only use a ruler to measure skin lesions when they already believe that they are a cause for concern. If AI tools are not explainable, it is difficult to identify these biases, which in the worst cases can even lead to the “deskilling” of clinical staff, if they begin to rely on these tools (ibid).

The responsibility of evaluating the explainability of AI does not lie solely with the AI developers. Instead, it is argued that all stakeholders that interact with the AI should be somewhat involved in evaluating its explainability. Below, we present a model which provides an overview of potential stakeholders in explainable AI and their exemplary interests:

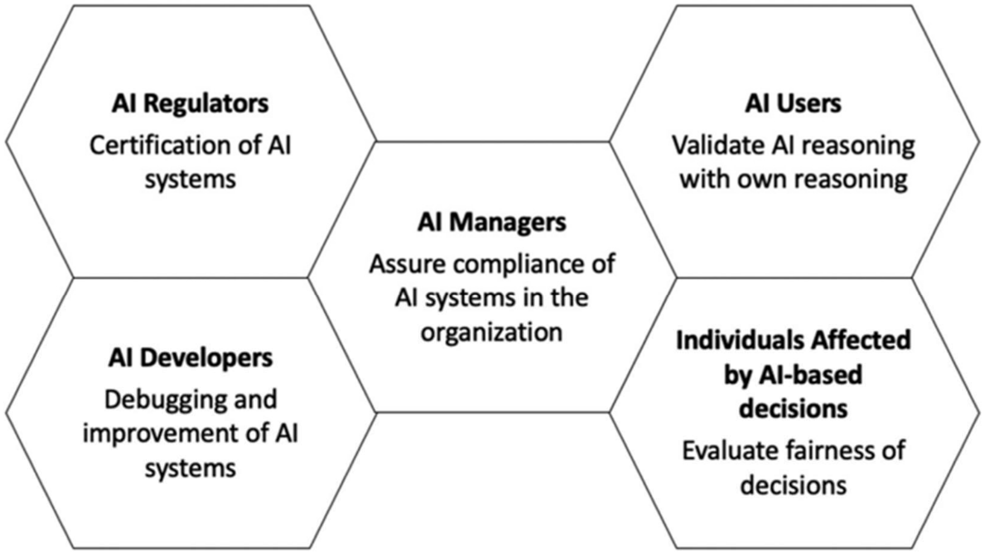


Figure 3: Stakeholder groups of Explainable AI (Meske et al., 2020)

In a medical organization context, *AI Developers* are the people who create the healthcare AI tools, where explainability can help them understand problematic outcomes and areas of improvement. *AI Regulators* represent the Danish government, who need to certify that these systems comply with e.g., GDPR. *AI Managers* can be supervisors from the development team who need to control the algorithm and assure its compliance. *AI Users* are the clinical staff that need to validate that the outcomes make sense, benchmarked against their own conclusions. *Individuals affected by AI-based decisions* are the patients, who may have an interest in explainability to increase trust in the decisions (Meske et al., 2020).

A significant challenge for the future of AI is a contextual adaptation, where the systems help construct models for solving real-world problems. Human expertise is an important part of this in the medical field, where many argue that AI should not replace human intelligence, but rather augment it (Goebel, 2018). Doctors are held accountable for the decisions they make when treating patients. For them to trust and make use of these newly developed tools, they must believe that their decisions are based on ethical grounds to comply with their Hippocratic oath ("Lægeløftet" in Denmark).

4. Research Methodology

A research method is an organized, systematic, data-based, critical, objective oriented scientific investigation into a specific problem, undertaken with the intention of answering a research question (Bryman & Bell, 2007). Selecting an appropriate and robust research methodology is essential to address the research question with a goal of achieving the research objectives. In this thesis, we deploy the "Research Onion" (Saunders et al., 2016), to describe our approach to data collection and research approach.

The objective of this research topic is exploratory in nature. According to Saunders et al. (2016) exploratory studies are useful in developing a robust understanding of the nature of the problem. This type of research is usually conducted to study areas where there is limited theory or insufficient empirical research (Dudovskiy, 2018). As we identified that there is a current lack in research within the field of AI implementations in the Danish healthcare industry, we adopted the exploratory research techniques to answer our research question, by reviewing literature, interviewing experts through semi-structured interviews, and then developing new theories (Saunders et al., 2016). Further, these types of research methods are generally interactive, inexpensive, and open-ended in nature. Robson (2002) explains that an exploratory research methodology can be helpful to "find out what is happening", "seek new insights", "assess phenomena in a new light" and allows for "flexible design" (ibid).

The research process is a systematic process that aims to establish the objective of gathering information for analysis. This process is used in all research and evaluation projects, regardless of the research method (iEduNote, 2021). A research process is a multiple-step process where the steps are interlinked with each other (ibid). If changes are made in one step of the process, the researcher must review all the other steps to ensure that the changes are reflected throughout the process (ibid). The research process for this thesis was as follows:

After identifying the research problem, the next step was reviewing the literature associated. This assisted us in gaining a solid understanding of the topic we investigate. Conducting a thorough literature review helped in facilitating the foundational knowledge about the area that needed to be researched. For this thesis, we reviewed a varied collection of previous literature to understand how AI can bring value to the Danish Healthcare industry. We focused primarily on the literature describing the challenges of deploying AI in healthcare in transforming patient outcomes. As we wanted to educate ourselves about how the previous studies were conducted. This helped us to determine which approach would best fit our research goals. This exercise is what led us to use our *value-based AI implementation approach.*

4.1. Research Onion

We are using the research onion created by Saunders et al. (2016), to organize our research plan which serves as a comprehensive road map for the entire research. The onion is used to specify who will participate in the study and how, when, and where data will be collected. Furthermore, the research onion specifies all the steps that must be carried out to achieve the research objective.

According to Saunders et al. (2016), the research process can be represented as an onion. The research process onion aims to explain the different stages of developing and conducting the research in an organized manner. In other words, the onion layers give a more detailed description of the stages of a research process. It provides an effective progression through which a research methodology can be designed. Its usefulness lies in its adaptability for almost any type of research methodology and can be used in a variety of contexts (Thesis Mind, 2019).

In this thesis, the research onion was deployed to illustrate how different layers and elements are instrumental in conducting and examining the research to come up with a logical conclusion. The research onion consists of six layers. When using the research onion, researchers start at the outer layers of the framework, and work progressively towards the center. Below, we present how we have used the research onion and the different methods that have been used in each layer.

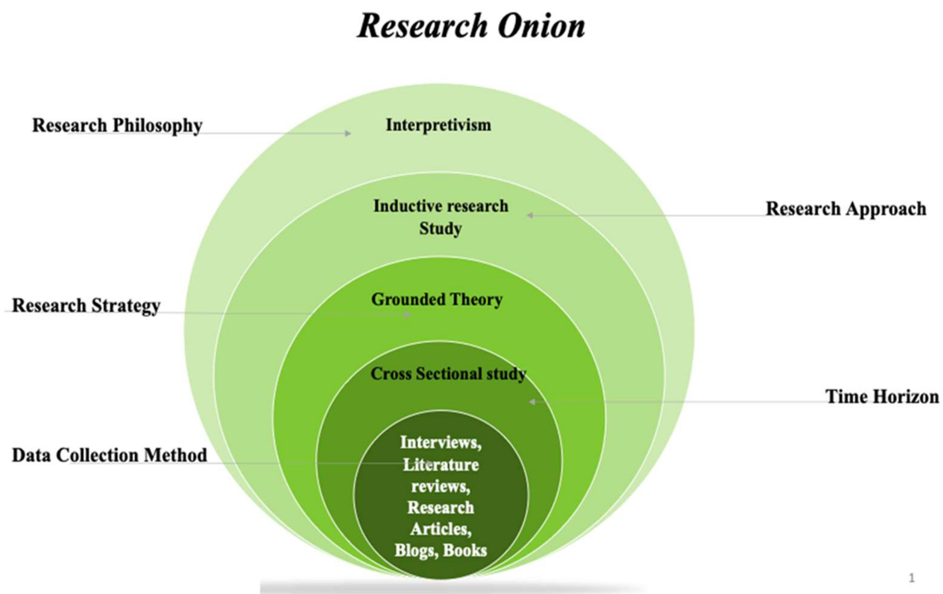


Figure 4: The Research Onion (Saunders et al., 2007)

4.1.1. Research Philosophy

"The research philosophy is a belief or an idea about the collection, interpretation, and analysis of data collected" (Zefeiti & Mohamad, 2015). A research philosophy refers to the development of knowledge in a particular field. There are three main philosophies that are significant in the research process: ontology, epistemology and axiology. In our study, we adopted epistemology as the research philosophy, to reflect on the assumptions and understand whether our direction of study falls under a positivist or interpretivist approach. This influenced our research strategy in relation to the method adopted for our research.

We concluded that the interpretivism view is suitable for the current study as we gathered the textual data using a qualitative research method through semi-structured interviews, to formulate a theory supporting the research work. The interpretivist view offered the flexibility to collect and analyze data simultaneously and iteratively. For instance, we would conduct an interview and code it before proceeding to the next interview. The interpretivist approach also means that we as researchers acknowledge that the findings in this paper are not objective truths, but rather an interpretation of the contextualized environments that are influenced by our qualitative data collection.

4.1.2. Research Approach

The Research approach is the second and the most important layer of Saunders et al.'s research onion (2016). The research approaches are divided into a deductive, inductive and abductive approach (Saunders et al., 2016). The deductive approach centralizes on using the various literature, to develop a hypothesis or hypotheses based on pre-existing theories and ideas that the researcher will test using data (Silverman, 2013). In contrast, the inductive approach involves collecting data and developing a theory based on the results of data analysis (Bryman & Bell, 2007). The inductive approach is characterized as a move from the specific to the general and is used within qualitative research (Bryman & Bell, 2007). In this approach, there is no framework that initially informs the data collection, and the research focus can be established after the data has been collected (Flick, 2015). Hence, we decided to use the inductive research approach. The data was collected by conducting 20 semi-structured interviews with initial inputs being gathered from external sources like research articles, books, podcasts, etc. To streamline our approach to the data collection, we focused on identifying points relevant to the value-based healthcare implementation matrix (**Figure 1**).

4.1.3. Research Strategy and Time Horizons

Research strategy and time horizons are the third and fourth layers of the research onion. Research strategy refers to an overall plan for conducting the research, including data collection, analysis of data and monitoring outcomes. Our research strategy is primarily inspired by grounded theory (Randall et al., 2007). The strategy revolves around "letting the data speak for itself" and grounding the theory in the data. This research strategy works well for this thesis, as our qualitative research approach revolves around identifying commonalities and discrepancies between two interviewee groups. The theories we are using throughout the thesis have largely been selected after the data collection, with the aim of fitting the findings into existing and tested frameworks. While this thesis is not a case study, our research mainly revolves around the Region Zealand in Denmark, which contextualizes our findings to a specific region, which we then generalize to provide recommendations for driving AI-powered healthcare in Denmark.

The time horizons layer defines the time frame for the research, which can either be categorized as cross-sectional or longitudinal. Longitudinal time horizons require that data is collected from multiple points in time to allow researchers to compare data from different time periods (Melnikovas, 2018). In this thesis, our primary data is used to explore the challenges of AI in Danish healthcare at this specific time, therefore, we are working with a cross-sectional time horizon. The qualitative data is collected from semi-structured interviews, which is an interview technique that involves asking open-ended questions to converse with respondents and collect elicit data about a subject. The interviewers mostly have expertise in the subject matter and intend to understand respondent opinions in a well-planned and executed series of questions.

4.1.4. Data Collection Methods

In our research, we are both utilizing primary and secondary data to answer our research questions. The secondary data contains a literature review, research articles, books and blogs. Collecting secondary data helped us organize our initial ideas, develop new concepts, and discover new directions to organize appropriate approaches to the research. The primary data collected were in the form of 20 semi-structured interviews, where we sought to ask questions to close the gaps of the secondary data.

The interview design played a pivotal role in determining how the data was collected for this thesis. The main objective of the data collection was to establish a holistic view of how AI is currently being used in the Danish healthcare system, and which challenges reduce its potential to generate value. Therefore, we chose to interview a varied group of people that interact with AI in Danish healthcare in many ways. This led us in contact with the authors of some of the literature we had initially analyzed, from which we scheduled our first three interviews. The interviewees included: an AI specialist working with the newest AI implementation in Danish healthcare, a Medtronic consultant hired by Rigshospitalet to increase the use of AI in the hospital, and a physician in the burn-unit of Rigshospitalet. These first interviews were designed to narrow our scope further, to get a clearer idea of how we should structure our later interviews and create an interview guide based on an inductive approach.

Following the research philosophy of interpretivism, the interview guide is designed to collect information about our interviewee's observable and measurable facts about the topics we wished to explore (Saunders et al., 2016). To achieve the research objective, we designed an interview guide to facilitate the execution of the interviewing process. It consisted of a list of the high-level topics that we planned on covering in the interviews with high-level questions with an aim to obtain candid answers from the interviewees under each topic.

The objective of the semi-structured interviews was to encourage the interview participants to talk freely and provide their insights on their own terms. Hence, we let our interviewees speak uninterrupted and freely unless they were starting to deviate too away from the research topic. This approach helped us to gain the perspectives of informants, stick to the research philosophy of "letting the data speak for itself", and not influence our interviewees' answers. This also helped us create an interview guide as we gathered more information on the research area. The final interview guide is presented in **Appendix B**.

An overview of the interviews is available below. The interviewees will be referenced throughout the thesis according to their associated names in the "Interviewee" column. The full transcriptions can be found in **Appendix C**.

To create an overview that distinguishes the different opinions regarding AI's role in healthcare, we have separated the interviewees into two groups. The groupings are based on their current job title, where people who work in a similar way with AI have been grouped together. The two groups are: 1) *Clinical Staff,* this group represents physicians, nurses and anyone who interacts directly with patients, and 2) *Technical Experts,* this group consists of the people who work with the development and implementation of artificial intelligence. Below, we present a table with an overview of the interviewees and how they fit into the groupings.

Interview	Interviewer	Interview Length	Interviewee:	Interview Group
#1	Alexander Drejøe & Vidyarani Anvekar	33 minutes	AI Specialist & Physician	Technical Expert
#2	Alexander Drejøe	25 minutes	Physician at Rigshospitalet	Clinical Staff
#3	Alexander Drejøe & Vidyarani Anvekar	46 minutes	Medtronic Consultant	Technical Expert
#4	Alexander Drejøe	25 minutes	Head of Clinically Applied AI at Rigshospitalet	Technical Expert
#5	Vidyrarani Achrekar	25 minutes	Pathologist, Physician at Rigshospitalet	Clinical Staff
#6	Alexander Drejøe	28 minutes	Principal AI Specialist	Technical Expert
#7	Alexander Drejøe	20 minutes	General Practitioner 1	Clinical Staff
#8	Alexander Drejøe	16 minutes	Head of Burn Unit at Rigshospitalet	Clinical Staff
#9	Alexander Drejøe	30 minutes	Professor of Philosophy working with AI	Technical Expert
#10	Alexander Drejøe	24 minutes	Ph.D. in Electronic Health Record	Technical Expert
#11	Alexander Drejøe	47 minutes	Ph.D. in NPL with Corti.ai	Technical Expert
#12	Alexander Drejøe	30 minutes	Doctor/Researcher in AI in Radiology	Technical Expert
#13	Alexander Drejøe	25 minutes	Clinical AI Researcher / Professor	Technical Expert
#14	Vidyarani Achrekar	50 minutes	Data Scientist	Technical Expert
#15	Vidyarani Achrekar	45 minutes	Physician/Researcher at Rigshospitalet	Clinical Staff

#16	Vidyarani Achrekar	40 minutes	Physician/Researcher at Aarhus University	Clinicians/ Technical Expert
#17	Vidyarani Achrekar	65 minutes	Principal Director at Accenture, Denmark	Technical Expert
#18	Vidyarani Achrekar	35 minutes	AI Specialist at Cortrium	Technical Expert
#19	Vidyarani Achrekar	42 minutes	Compliance and Technical Expert	Technical Expert
# 20	Vidyarani Achrekar	19 minutes	General Practitioner 1	Clinical staff

Table 1: Overview of interviews

4.2. Transcribing and Coding

Depending on whether the interview was physical or online, the interviews were either recorded using online software or microphones. The audio tracks were transferred to an online AI-powered application called Sonix (www.sonix.ai) which converted the speech to text with relatively high precision. As the transcriptions were not always perfect, we would manually correct the transcriptions afterwards, to ensure that the transcriptions accurately reflected what was being said in interviews. The sonix.ai app served as a valuable tool in reducing the labor of the subsequent transcription process of manually typing out the transcripts.

After conducting and transcribing the interviews we wanted to extract the relevant data needed for further analysis. According to Saldana's (2016) *Coding Manual for Qualitative Researchers,* coding addresses an important aspect of qualitative research, which is the process of attaching meaningful attributes (codes) to data, that allow researchers to engage in a range of analytical processes, e.g., pattern detection, categorization, and theory building. Coding is a heuristic and an exploratory problem-solving technique. Further, coding is not just labeling, it is organizing the qualitative data to identify different themes and linking it to find the relationships between them (Medelyan, 2021). "It leads you from the data to the idea, and from the idea to all the data pertaining to that idea" *(*Richards & Morse, 2013, p. 154).

Our coding strategy was inspired by a paper by Ciriello et al. (2015). The data was coded in a way to derive common themes across the 20 interviews. As our interview portfolio grew, we continuously discussed what common themes presented themselves such as "data access" and "adoption". Furthermore, as we had identified that we would like to apply our modified version of the Implementation Matrix presented in **Appendix A**, we had structured our interview guide to identify the dimensions we wished to explore and added each of the dimensions as a code of its own.

The categories laid the foundation for the first round of coding with the purpose of clustering the data into the common themes. Afterwards, some categories were removed because of scarce presence in the collected data, as well as others being combined, and new ones being added to better suit the data. In the second round of coding, we re-coded all the interviews with a final codebook to ensure all interviews were coded with the same categories. We used the software NVivo 12 (www.qsrinternational.com, 2021) to code the interviews due to its capabilities in clearly structuring and presenting the different codes in an easily interpretable way. This iterative nature of this approach guaranteed that the themes that were most relevant to our research were clustered, while helping us decide the scope of the project.

At the end of the following results section, we are presenting a diagram showing development of first order concepts to the aggregate dimensions that present our coding categories, inspired by the data structure diagram presented by Gioia et al. (2013).

5. Results

This section will present the primary findings derived from the empirical data collection. The data has been gathered from 20 interviews. The interviewees are all relevant to the research topic as they are either working with healthcare AI or likely to be affected by the changes from it. The results section will provide insights regarding the descriptive parts of our three research questions, namely: *What are the key challenges? What stakeholders are important? What is the value of healthcare AI?*

The first segment of the results will reveal the challenges that were identified by our interviewees. These challenges are important to present early, as they are barriers that need to be addressed when developing healthcare AI. We then present the stakeholders that need to be involved to succeed in these projects, specifically in the Danish healthcare industry. This needs to be considered as it allows us to compare where the stakeholders are aligned and divided, which can help us bridge these gaps. Finally, we present the potential value AI has in healthcare from the point of view of *technical experts* and *clinical staff*. This information is essential to consider when suggesting frameworks for designing healthcare AI, as it allows us to see where AI has its biggest strengths and limits.

Throughout the section, we are continuously referring to direct statements from our interviewees and clarifying the implications they have for successful value-based healthcare. At the end of the section, we present a data structure diagram that illustrates the relations between the concepts identified in our interviews and the aggregate dimensions, which will lead to the discussion section.

5.1. The Challenges of Artificial Intelligence in Healthcare

As a healthcare provider, there is no doubt that keeping up with digital transformation is an overwhelming task. The challenge spans much further than merely selecting the correct technology, as history shows that implementing new IT systems in Danish healthcare is very dependent on principles like correctly onboarding users, as exemplified by the challenges regarding Sundhedsplatformen and Watson Oncology in Rigshospitalet (Drejøe et al., 2019). Furthermore, the healthcare industry brings some unique challenges due to the immense repercussions from mistakes and reliance on sensitive data. The existing literature on the topic shows a varying degree of confidence in AI's role in healthcare. Some believe that AI will completely transform the workflows of doctors, replacing them in certain tasks, reducing errors, assisting in drug and vaccine creation, etc. (Takyar, 2021). While others are quite concerned with delegating any tasks traditionally meant for a physician, to an algorithm developed by a non-clinical programmer, as well as the ethical and societal implications (Panch et al., 2019).

In this segment, we will highlight the main challenges that were identified in our research from the point of view of Clinical Staff and Technical Experts in Denmark. We focus on three main challenges: 1) Data Challenge, 2) Adoption Challenge, and 3) Limitations of AI in Healthcare. These three challenges were selected as they were frequently brought up during the interviews as the biggest concerns when successfully utilizing AI in the Danish healthcare industry. Addressing these challenges is the first step in creating roadmaps for implementations that focus on value-based outcomes.

5.1.1. Data Challenge

In recent years, there has been a massive surge in the use of AI, due to the increased capabilities in collecting data. If there was not such an immense amount of data available, AI algorithms would neither be effective nor necessary (Yanqing et al., 2019). Denmark has one of the most - if not the most - extensive records of healthcare data in the world. The National Patient Register includes healthcare data from examinations and treatment from the last 40 years. Additionally, there is also a register of clinical laboratory information, causes of death, pharmaceutical sales, etc. (HealthcareDenmark, 2021). Essentially, Denmark should have one of the best shots of utilizing AI in healthcare due to their massive amounts of quality data.

As previously mentioned, healthcare data has the constraint of being extremely sensitive. Personal data is protected by the GDPR law that was implemented in the EU in 2016, which reinforces the individuals' rights regarding their personal data. The regulations that are especially pertinent to this study are those regarding: minimal retention of data, the requirement for consent in using data, and the right to be forgotten (GDPR.eu, 2021).

"*That might be number one (challenge). Access is a huge problem. We're working with incredibly sensitive data. And yeah that's the long and short of it. Data access is a massive problem.*" (Medtronic Consultant, 00:16:05)

Furthermore, healthcare data in Denmark is stored in several different electronic health records. The EHR that has been mostly discussed in our interviews, Sundhedsplatformen, is only covering the Capital Region and the Zealand Region. This reduces the data transparency between the systems and creates data in different formats that are difficult to work within an algorithm (Svaneborg, 2018). In order to unlock the potential for AI in Danish healthcare, this data should be made more accessible to create a Data Platform that enables data capture, analytics and access to those who need it.

Fortunately, some of these concerns are beginning to be addressed by the Danish government. The Danish Ministry of Health has recently been bringing attention to the difficulties of accessing healthcare data. The most important aspects of the recent vision for healthcare data includes: a faster and easier way to request access to healthcare data for projects through uniform legal processes, as well as supporting research that analyses healthcare data on a national level to ensure confidential analysis environments (Sundhedsministeriet, 2021). Denmark has the potential to be the front-runner in healthcare AI, if we manage to expose this vast amount of data to the technical experts working with AI:

"*I have an ongoing prediction that within the next 10-15 years someone, somewhere in the world will breed a company the size of Novo Nordisk doing AI healthcare, and Denmark has a damn good shot at it. Either us, China or the States (...) If we leverage the data, we are probably going to make it. If we give China another five years and their data centers are gonna be as big as ours - then, whatever*." (Medtronic Consultant, 00:16:52)

Data quantity is extremely important when developing AI tools, especially if you want to avoid common pitfalls like biases and underrepresented groups. However, healthcare AI is often restricted by limited quantities of data. While the Danish CPR-system does provide the amazing potential for healthcare data, there are still a lot of diseases that are so rare that there is simply not enough data to train a model. A surprising finding in our research was that AI is currently not a limiting factor in providing valuable assistance to clinical staff, but rather the lack of data.

"*I mean the AI technology is there. It's also in many respects, pretty mature. So it's rare that you find a group with a good data set and then they say we just cannot build the A.I. it's just impossible. I don't think I've ever heard that. So the technology in itself is not a problem.*" (Clinical AI Researcher / Professor, 00:06:09)

AI algorithms require large quantities of data to be accurate. Best practices, which can not be disregarded in the high-stakes environment of healthcare, need to be followed. This includes having a training dataset, a validation dataset and an independent dataset to make sure that the AI functions in the intended settings and not only from the initial training data (Clinical AI Researcher / Professor, 21:54). Different hospitals in Denmark have vastly different patient cases and serve different demographics within the Danish population. Lack of data is one of the main reasons why some patient groups may be discriminated against when an AI algorithm is being used - this will be further explored in the Discussion segment of the paper.

"*Unless you have a really sizable dataset, I would say you should probably go for something simpler than artificial intelligence (...) when they don't work, it's difficult to debug them and figure out where the problem is. Most of the time you just add more data and hope it goes a little bit better.* "(Clinical AI Researcher / Professor, 00:23:37)

The data quantity challenge brings attention to a very important aspect of implementing AI in healthcare: If you want to create value-based outcomes from the AI tools that are applicable in a general setting in Danish healthcare, it is imperative to focus on those applications where the appropriate data is available. However, this does not mean that all hope is lost in using AI for more rare diseases. Processes like transfer learning may be able to help solve these data challenges by providing alternative methods of training AI algorithms. This will be further explored in the segment regarding designing valuable AI.

While the dependency on data quantity is crucial, data is only worth accessing if it is of high quality. While it is undeniably true that Denmark has some of the best and most extensive electronic health records, our research showed an overwhelming concern of how unstructured our current health data is. Looking past the fragmented system, the nature of healthcare data makes it challenging to work with AI algorithms, as the quality of the output is directly correlated to the data that enters the system.

"*I think the quality of the data is very important as well. When you make these models, it's like in all other parts of life, you know, trash in, trash out.*" (Doctor/Researcher in AI in Radiology, 00:16:46).

Healthcare data is oftentimes messy. Healthcare organizations in Denmark are not designed to create an infrastructure to support the data needed to optimally train the algorithms. Sundhedsplatformen has been criticized heavily by physicians due to its new requirements of having clinical staff enter information in real-time throughout their workday. This task was previously delegated to medical secretaries to a greater degree (Svaneborg, 2018). These new workflows, combined with the busy day of a physician, result in healthcare data being input in an unstructured, plain-text format (Physician, 15:11). Additionally, not all healthcare data is collected by clinical staff, there is a vast amount of data being collected directly from the patients. In one of the more successful AI experiments in Danish healthcare, a Natural Language Processing AI tool developed by Corti (www.corti.ai), was used during emergency calls to assist dispatchers in detecting cardiac arrest.

"*They thought they could use some off-the-shelf speech to text system. They could not, because when you call 1-1-2, the phone quality is quite poor, it's heavily compressed. People are talking in distress either very fast or snubbing the words. Sometimes the phone is on speakerphone and they're shouting at it. So all the normal systems could not be used, and Corti developed a new speech to text system.* " (Ph.D. in NPL with Corti.ai, 00:04:41)

This presents a challenge in developing a data platform that can support the variations of all kinds of healthcare data, and that is built around the complexities of it. Traditionally, data is a representation of the truth, but in healthcare, data is trying to represent the truth. This makes the data unique from other industries, where there is a much more predictable causality between data and events:

"*I have a lot of friends, for example working in Finance where the data quality is quite different (...) it has the nice attribute that data is the reality. If the banks say that money was moved, money was actually moved (...). In healthcare, data is trying to represent the truth. Even if the system says that this patient has diabetes, the patient might not have diabetes, and no matter how much the system says it, the patient ain't gonna get diabetes from it.*" (Medtronic Consultant, 00:13:54)

The data challenges are among the biggest barriers to the development of valuable healthcare AI. The main data challenges that were identified in our research are: 1) Data Access, which represents the lack of data availability and the political and ethical factors that limit technical experts' ability to work with the data, 2) Data Quantity, which is AI's reliance on large amounts of data, which is especially challenging with rare diseases and minority patient groups, 3) Data Quality, which refers to the complexity of healthcare data and its unstructured nature. Addressing these three main challenges is important to create a robust data platform to support value-based AI initiatives in the Danish healthcare industry.

5.1.2. Adoption Challenge

No matter how accurate or beneficial an AI tool is in a test setting, it will not lead to clinical impact if its intended users are not adopting it. In value-based healthcare, it is essential to mobilize the internal forces, by having clinicians working closely with administrative leaders and developers to ensure the outcomes of the tools provide value to the doctors and patients (Katz, 2020). In the previous segment, it was illustrated how the suboptimal adoption of Sundhedsplatformen has led to data being stored in an unstructured manner that is difficult to work with. This highlights the importance of aligning with clinicians when developing these AI tools.

Currently, healthcare AI is still in its very early stages and adoption in terms of utilizing AI tools is quite limited. The general attitude towards AI in healthcare from clinical is different from person to person:

"*I think that you know, they fall in several categories. You know, you have the believers, which is like all for it (...) then you have some who are very sceptical and don't want to use it ever (...) And then you have the large group which is in between which I would be part of myself. Actually, I'm not in the believer category, even though I do this for a living, I would say I am in the gray zone where I want to see how it works before I can take a stand on if I'm going to use it or not.*" (Doctor / Researcher in AI in Radiology, 00:25:19)

A general concession held among the clinical staff we interviewed was that they would need to see the value provided by the AI before they would use it. Their definition of value was dependent on how well the AI was benchmarked against traditional methods, both in terms of accuracy and speed (Head of Burn Unit at Rigshospitalet, Physician, and Doctor / Researcher in AI in Radiology). The adoption rate is also dependent on the different departments at the hospitals. At Rigshospitalet, AI tools are already being used in the Radiology department. However, the AI processes are working behind the scenes, so while radiologists know they are there, they are not sure how they work and what their value is (Doctor / Researcher in AI in Radiology, 09:35).

"*Doctors do have access to them, so there are about 18 doctors who if they were to click a link on their desktop, would have access to the first one of these tools. We know for a fact they are not clicking the link, which might be a good thing as there's a lot of testing to be done, and they're in a test phase so they shouldn't do too much decision making on it*" (Medtronic Consultant, 00:11:00)

At this moment, AI tools are generally not being used at all by clinical staff in their work. The current technology is still in a testing phase and is struggling to perform well enough to be prescribed to clinical staff at Rigshospitalet. Interestingly, in other projects outside Rigshospitalet, like the Corti project, lack of adoption has been the detrimental barrier in creating valuable outcomes. Corti is a Danish AI company that developed an AI-based Natural Language Processing (NPL) tool that listened in on calls to the Danish emergency number 1-1-2 and alerted the dispatchers in real-time, if it suspected that there is a cardiac arrest, so they could inform the bystander to begin resuscitation. The NPL tool managed to outperform the dispatchers in recognizing cardiac arrest, as it detected around 85% of cardiac arrests up from 75%. However, while the researchers could see that their AI tool worked, it did not increase the clinical outcomes of the calls:

"*It didn't make any change to the patients because when the dispatchers received the alert if they did not feel themselves, it was a cardiac arrest. They discarded the advice from the bottom.* "(Ph.D. in NPL with Corti.ai, 00:09:39)

There were several factors that led to this lack of adoption, that should be addressed to be learned from in future AI implementations. First, dispatchers were overly confident in their own ability to detect cardiac arrests. When questioned about their accuracy, the more conservative dispatchers believed they identified around 98% of cardiac arrests. When they were informed that it was closer to 75%, it did not change their estimates, as they assumed that the skewed results must have been from other dispatchers' mistakes (Ph.D. in NPL with Corti.ai, 15:44). Second, the AI algorithm detected more false positives than dispatchers did. This is a very important detail, as it can lead to "boy who cried wolf" situations, where clinical staff simply stop using the tool after a series of false positives. Third, the dispatchers may not have been onboarded on how to properly use the tool:

"*It might be the problem that we had not explained thoroughly that this machine is not perfect and it's not an ultimate decision. (...) It's an opportunity for the call taker to reconsider (...) So, whenever you have something AI-based which suggests a solution to a clinician, the AI should explain why it reached this advice and the clinician should know AI-based programs are not infallible*." (Ph.D. in NPL with Corti.ai, 00:31:35)

A general challenge with AI that is especially prevalent in healthcare, is the problems with black-boxed processes. The recommendations an AI tool produces is oftentimes based on a tremendous amount of data points, that is difficult, if not impossible for a human to comprehend. Therefore, explainable AI is very important in providing higher transparency in how the outcomes have been reached, as well as informing the users that AI-based programs, just like humans, are not infallible. Overcoming the barrier of mobilizing internal forces and involving them in the development process of AI is something that is already being addressed by AI developers. The technical experts we interviewed, had all attempted to involve clinicians in their work with developing AI. Some of them are even working from Rigshospitalet with the sole task of developing AI tools that could be implemented in the workflows at the hospital.

"*We have at this point more than weekly meetings with the doctors, we are sharing this basically as a research project (...) Once it's backed by peer-reviewed papers, they have a lot of confidence in it. The doctors are used to working with statistics and probabilities, so we find them to be actually surprisingly comfortable with it*" (Medtronic Consultant, 00:09:35)

This close collaboration is one way of facilitating adoption of the tools that are currently being tested and developed. The history of AI projects in Denmark has shown that even the most expensive and glamorous AI tools, like Watson Oncology, did not provide any meaningful clinical impact. AI developers must keep this aspect of AI's history in healthcare in mind, and involve the clinical staff to reduce their legitimate skepticisms:

"*Putting trust in a method is very difficult. So once you implement something, you would really have to argue that this has been trained correctly and it's validated correctly. Building a project so that MDs that are going to utilize it actually trusts that it's correct.*" (Head of Clinically Applied AI at Rigshospitalet, 00:10:43)

Incentivizing internal forces is a crucial step to bring forth the value of AI applications. Developers are realizing this and shifting some of their focus from the technical capabilities of the AI tools to involving clinicians. To incentivize adoption, clinical staff should be involved in 1) requirement specification to ensure that the AI tools have interfaces that doctors can navigate, 2) measuring value to develop tools that assist doctors in their current workflows, and 3) performance benchmarking to measure how well the tools perform and in which workflows clinicians are interested in having AI support them. Furthermore, developers should strive to create explainable AI, or at least be very thorough when onboarding the clinical staff.

"*You need to explain exactly why you reached the decision because what we have seen with AI over the last four or five years is that plenty of examples show that AI has* *matured so much that we can establish it works. It works in a retrospective study, (but) when you test it in a clinical setting, there's no difference. And that's because the clinicians do not adhere to the advice, they ignore it. They have not been onboarded properly. The next efforts should involve clinicians instead of evolving AI." (*Ph.D. in NPL with Corti.ai, 00:37:30)

5.1.3. Applicability Limitations of AI in Healthcare

The primary issue that is being treated in this thesis is how to address the challenges of AI in healthcare, to design products and develop roadmaps that bring value to Danish healthcare. An important aspect of developing value-based healthcare is prioritizing the development of tools that will lead to actual impact, while not spending energy where these tools will not create value (Katz, 2020).

This segment will examine some of the considerations from both Technical Experts and Clinical Staff in which they believe AI will have its limitations in value-creation. The findings of this segment display what factors are affecting the potential of AI, which can help developers in evaluating which challenges need to be addressed, while also highlighting the areas of Danish healthcare where the limits of AI prevent it from value-creation. The ethical considerations of delegating tasks to AI are a limitation that was frequently mentioned during the interviews, however, this will be addressed in a separate segment in the Discussion section of this thesis.

The first limitation of AI in healthcare is the question of properly fitting the AI models with data that is representative of the patient groups it works with. This is a general limitation of AI, but is especially ubiquitous in healthcare, where data is sometimes difficult to correlate with diagnoses:

"*Sometimes, being a physician is dependent on what you call "medical art" (lægekunst). The art happens when logic and theory stops, and when you say "well, I don't know what exactly is wrong, but there is something here that is not okay." I am not sure the machine can become skilled enough to do this"* (Head of Burn Unit at Rigshospitalet, 00:05:53)

Several of our interviewees who work directly with patients had stories where the patients did not show any symptoms that could immediately be correlated with a diagnosis, but where their instincts made them escalate the patients either way (Physician, General Practitioner, Head of Burn Unit at Rigshospitalet). This "gut-feeling" is something that is impossible to recreate in an AI algorithm, as they function purely on the logical calculations based on data input. This limitation is also an extension of the concern regarding explainable AI, as physicians are concerned with their ability to work alongside the AI if they are not able to interpret and evaluate the answers provided by the tools.

"If you don't agree (with AI-based results) and you're not too sure about why the algorithm gave you the answer that you got (...) I cannot look into why did the machine make this decision and why do I agree or do I not agree with this? So that's going to give a huge risk for automation biases and confirmation biases." (Physician/Researcher at Aarhus University, (00:09:52).

Artificial intelligence in its current form is not able to replace clinical staff in any clinical processes (Clinical AI Researcher / Professor, 23:37). Our research showed a general agreement that the strength of AI in healthcare is how it can support clinicians in optimizing their workflows. However, it is still important to consider the biases that can be intensified by AI tools. A limitation of the Corti experiment, which was examined earlier, was that the dispatchers only used the AI tool when it confirmed their existing beliefs. This is not only a concern in terms of the value AI can create, but something that could lead to increased misdiagnoses if the AI tools confirm a clinicians' mistake, by creating a loop of misinformation (Physician/Researcher at Aarhus University, 07:30). In healthcare, data shifts are happening constantly, as seen for example with the COVID-19 pandemic, where a new disease appears, so that the data a model has been trained on instantly becomes outdated.

"*You know because when you overfit a model, you have a model which seems to perform very well in the tests that you're doing. But when you take it out of that setting (...) the model might be overfitted to a population which is not representative of where it has to be used*." (Doctor/Researcher of AI in Radiology, 00:20:04)

These limitations are important to consider when deciding which clinical workflows could benefit from AI. Diagnosis and treatment require very advanced workflows, experience, and quality data and are designed to be completed by human actors. The positive aspect is that while these tasks are very difficult to solve with AI, there are many aspects of a clinician's workflows that are not related to these efforts.

"I definitely think it (AI) has a huge place, but I think at least there should be more focus on the less sexier areas (...) if you have a physician who wants an x-ray, they send a request for the radiological department and then the radiologist, he reads those requests and says, oh, this should be a CT with contrast or contrast enhanced CT because it is something with a tumour (...) at that stage, you know, an AI could probably alleviate a huge part of the work and it would not have such a big impact, as it would when you like, make the diagnosis. "(Doctor/Researcher in AI in Radiology, 00:22:11)

The limitations of AI in healthcare occur when there is a focus on delegating the very abstract physician-related work. Artificial Intelligence lacks the common sense and general intelligence possessed by clinical staff, however, its strength lies in processing large quantities of data and giving history-based predictions very quickly. Independent researcher and strategist Benedict Evans uses the metaphor of AI providing you with an infinite army of interns that can look at structured data and make a logical assessment (Evans, 2018).

"*So you might want to ask, what does a hospital do with infinite interns? You might not want to do heart surgery, you might wanna do something else, hence the data-cleaning where it might make more sense*" (Medtronic Consultant, 00:13:09)

These tasks may not be what has traditionally been considered "healthcare AI" since they are not directly correlated with patient outcomes. However, both clinical staff and technical experts overwhelmingly saw the biggest value of healthcare AI in delegating some of the time-consuming tasks, that are not related to abstract physician work, to AI tools to allow physicians to spend more time with patients. Delivering value-based healthcare is dependent on continuously measuring processes, outcomes and costs (Katz, 2020). Artificial Intelligence has the capabilities of measuring these indicators to create scorecards that can be used to track changes to detect variations in improvement cycles, while applying case-mix variables like age, gender, comorbidities, etc. These case-mix adjustments are essential in limiting adverse selection, i.e., to prevent providers from avoiding treating complex cases to skew their results (ibid).

In conclusion, the limitations in healthcare are a combination of all the challenges that have been presented in previous segments. Value-creation relies on addressing the challenges by applying AI in the areas where clinical staff believe it can have a meaningful impact while avoiding those where it is limited by its lack of human consciousness.

"*In healthcare and life science, the situation where we have unsupervised AI and machine learning is probably some years ahead of us. (...) I'm sure that's going to happen at some point, but it's not just within the next year, right? Something we've discussed for 10 years, but I don't see it happening right now*."(Principal Director at Accenture, 00:35:18)

The following segment will present insights from our data collection on which stakeholders are important in successful AI implementations in Danish healthcare.

5.2. Important Stakeholders

The importance of involving the correct stakeholders in the development of AI is crucial. Medtronic, the world's largest MedTech company, has created a framework for value-based healthcare that is centered around developing a joint business model with their stakeholders. They accomplish this by using a shared accountability program, where providers are sharing the costs and benefits of the projects (HBR, 2016 and Katz, 2020). We have separated our interviewees into two main groups: Technical Expert and Clinical Staff. The primary scope of this thesis is aligning these two groups in value-creation. This segment will break down these roles further, as well as highlight what internal forces and external collaborators our interviewees identified were important, to succeed in AI-powered value-based healthcare.

A central stakeholder that needs to be involved from the beginning to enable AI transformations are the data controllers. These represent the agencies or public authorities that determine the purposes of the healthcare data and the means of processing it. An example of such an entity is the Center for IT & Medicotechnology (CIMT). In the Corti NPL-project we examined earlier, a collaboration with the capital region was necessary as they possessed the emergency-call data, however, the Corti team met a lot of resistance from the data controller CIMT:

When we tried to develop the technical solutions, we met a lot of resistance from the IT department, CIMT. (...) When we needed to do our prospective studies where we needed to tap into our phone systems in a live setting. Then we were met by "No, you cannot be allowed to change the infrastructure of the phone system because you are just doing research". We are handling critical infrastructure." (Ph.D. in NPL with Corti.ai, 00:10:46)

Corti managed to overcome this data issue by using some "alternative" methods of accessing the data they needed (Ph.D. in NPL with Corti.ai, 11:22), but the pushback from the capital region limited the data they could access to develop their AI model. This indicates the importance of having the data controller, in this case the Danish government, on board when developing these tools. The GDPR dictates that when a data controller provides access to a data processor (Healthcare AI developers), the data controller is still responsible for the data to follow GDPR guidelines, i.e. sensitive data regulations (GDPR.eu., 2021). This creates a dilemma in aligning these two essential stakeholders, as the party that is responsible for the data is not the one that will naturally benefit from the project outcomes. This presents a challenge of how these projects should be framed, to incentivize the Danish government to support the development of the systems.

Medtronic's approach to shared accountability programs, where data processor and controller work together have been successful in facilitating this cooperation. Medtronic works closely with Rigshospitalet to create value from within. Their consultancy team is working from offices at Rigshospitalet, where they have direct access to Rigshospitalets technology and employees, allowing them to access data early (Medtronic Consultant, 24:50). Furthermore, the project is co-funded between Rigshospitalet and Medtronic with an even 50/50 split.

"*I think some of the key things to AI healthcare partnerships is to have the closeness we have had, the co-funding, the sitting together and the intimacy we have with Rigshospitalet, has been really key. Exactly how you achieve that, how we got to a point where they trust us this much, I don't know. I haven't tried it before. There's someone on Medtronic doing something incredible.*" (Medtronic Consultant, 00:24:12)

Reaching a point where an AI developer has managed to create such a close partnership with the internal forces of a hospital is exceedingly rare but represents an ideal structure of co-creation of VBHC that developers should strive for.

"Only a few of us have a group such as ours that actually develops from inside, rather than working with external collaborators (...) So the funding from us is more like Novo Nordisk, Lundbeck (...) (So normally it is) the larger funders that actually support the salary." (Head of Clinically Applied AI at Rigshospitalet, 00:02:33)

The common strategy of developing healthcare AI tools off-site from hospitals presents several challenges in aligning stakeholders. First, it is more difficult to work closely with clinicians. Second, the process of accessing data to develop and test these tools will be slower, as well as more difficult, since the data processor will not be able to provide the same level of transparency of their processes to the data controller.

"*I can totally see if we came from a research lab in Minnesota, saying we have had 30 PhDs working on this in a black-box site and here is a great model. The papers coming along with that would have to be really great for the doctors to like it.*" (Medtronic Consultant, 00:10:15)

The technical experts we interviewed all strived for closer collaboration with external collaborators. This means that the challenge is not that developers do not want to work closely with hospitals but being able to frame the outcomes in such a way that they incentivize the data controllers to work with the developers. Aligning data controllers and data processors is essential, but it is important to keep in mind that in the end the data belongs to the data subjects, the patients. This gives a lot of power to the patients, as they have the right to be forgotten, i.e., have their data deleted.

"*When we're talking about COVID and vaccines and all that, (patients) tend to believe more in what they search on the web, than what their clinical expert tells them. I suppose this could mean that in general, they would perhaps trust the systems more than they would trust doctors".* (Head of Burn Unit at Rigshospitalet, 00:13:11)

The trend towards more patient autonomy may be an advantage in AI-powered healthcare, as increased automation and transparency is valuable for the patients. Patients/citizens influence the decisions of the government through their votes and are the ones that are ultimately affected by changes in the healthcare system, making them important stakeholders. The current government is working on initiatives to make healthcare data more accessible to researchers (Sundhedsministeriet, 2021), but a change in public opinion may influence the governments' goal and disturb these initiatives.

5.3. Value of AI in Healthcare

In this thesis, we define healthcare value as *the direct and indirect improvements in patients' health outcomes derived from optimization of clinical workflows, therapy-related efforts, and adherence to established processes.* There's no denying that AI technology has the potential to transform the way healthcare services are delivered (Pritchard, 2021). As AI technologies are advancing, the impact is becoming increasingly integrated into healthcare, where it is driving efficiency and helping in realizing the vision of value-based healthcare in various ways. An area that is particularly acknowledged in the literature, is AI's ability to improve the experience of healthcare practitioners, by enabling them to spend more time in direct patient care (Spatharou et al., 2021).

Despite the growing use of AI in healthcare and its potential to transform patients' outcomes, there is evidence that the integration of AI-based tools is still in the formative stage in Denmark (Ministry of Finance & Ministry of Industry, Business and Financial Affairs, 2019). Integration of AI tools is only possible when all the stakeholders in the healthcare system, like hospitals, municipal health services, clinical staff, and other public and private participants cooperate and invest efforts in utilizing the tools. Hence, it is important that Denmark accelerates its efforts to integrate AI by creating a conducive environment where these stakeholders collaborate effectively to realize the benefits of AI in all areas of healthcare, from diagnostics to treatment.

In this section, we will discuss the potentials of AI as a technology for transforming healthcare to create value. The primary data gathered from interviews and data analysis will be acting as a lens to assess the potential value of AI in Danish healthcare, by dividing it into essential dimensions that should be addressed to create value-based healthcare. This section is structured after our modified implementation matrix (**Appendix A**), to allow us to categorize how each building block is applied, following our *value-based AI implementation approach*.

5.3.1. Internal Forces

The Danish healthcare organization's objective in mobilizing the internal forces was to ensure a smooth engagement of the clinical staff in decision-making processes during AI product development, to drive high-value care and accountability on patient outcomes.

"We are a start-up company at the Computer Science University. But the fact that we are located inside the hospital means that all the way from the hypothesis to the actual implementation is while collaborating with the clinical staff so that we don't implement something that is not really wanted by the medical staff". (Ph.D. in Electronic Health Record, 00:03:26)

The involvement of the internal forces is crucial in creating valuable healthcare tools. Clinical staff possess knowledge on clinical procedures and patients that is important to include in these tools. Some of the AI developers with whom we spoke, mentioned that one of the biggest barriers in creating valuable AI was the "annoyingly high baselines" of clinical staff. If AI tools are to "compete" with the standards of clinical staff, their insights must be included through development.

The data collection revealed that clinical staff are motivated to help in the development of AI tools, if they see its value (Medtronic Consultant, 00:09:35). The clinical staff we interviewed also expressed that they would be more skeptical about tools that have been developed outside of the hospitals. This indicates that a black-boxed approach to the development of healthcare tools likely will result in reduced adoption, leading to less value.

5.3.2. Scorecard

Generally, healthcare units are complex entities whose effectiveness depends on many diverse factors (Cattinelli et al., 2013). Scorecards can help communicate short and long-term goals, set performance indicators, evaluate hospital responses to physician needs, and track process improvement efforts (Hemamalini, 2014). Scorecards can also be used to track the patients' perspective on their hospital interaction, normally referred to as the "patient promoter score". Scorecards can assist Danish hospitals in achieving their value-based healthcare goals by supporting high-quality treatment, more efficient healthcare systems, faster workflows, and better continuity of patient care in clinical pathways (Ministry of Health & Danish Regions, 2018). The data processing capabilities of AI technologies can support the development of a balanced scorecard and provide data points to monitor performance.

"The Danish health care system is actually just running hospitals better and more efficiently. If you know when things are going to happen a little bit beforehand, you can plan better and that can result in sort of better staffing, lower costs". (AI Specialist & Physician, 20:56)

While the Danish healthcare system is generally considered efficient, AI can improve effective allocation of resources, reduce the cost of care and enhance communication between patients and healthcare providers, by incorporating a minimal set of processes. Hence, the successful implementation of AI technology can be influential in the areas where the need is greatest and where immediate gains can be achieved within a few years.

"U.S. hospitals are predicting exactly how many staff they need on every shift. By doing that and having a very tight view of what sort of resources they need. So you can basically try to optimize for quality of care". (AI specialist & Physician, 00:18:44).

AI can assist in triaging patients according to their individual risks and therefore facilitates efficient allocation of resources, which in turn improves patient outcomes.

"Let's say I'm pregnant, and I want to see which is the nearest hospital available, then based on AI, it will guide you like which hospital needs to be registered for you? It should be at that time when you are mature, and you are about to deliver that time, that hospital facility should be available, it should not overstaffed or understaffed, So, all this constraint, a human being cannot understand, but AI can understand to optimize and help in efficient utilization of the health care resources (Data Scientist, 00:19:00)

AI has enormous potential in providing real-time and purposeful information that can enhance the quality of care and patient experience, by reducing the workload of the clinical staff. Deployment of AI in administrative tasks can improve the internal performance metrics, by increasing operational efficiency and optimizing operational costs.

"AI could help us improve quality and ensure that we have taken the right decision, then you can see the health care system would be better because we would admit fewer patients, so it would free resources from the hospitals and from specialists. And that would be very, very positive because that is the big problem right now everywhere in the industrialized world" (General Practitioner 1, 00:07:21)

Allocating more administrative tasks to AI can maximize the efficiency of clinical workflows. By measuring patients' individual requirements, AI can help optimize workflows and precision in treatments. This would allow clinical staff to spend their time more effectively and concentrate their efforts on more abstract physician-related work.

5.3.3. Data Platform

Collecting data across different systems through a healthcare data platform is important for healthcare providers to continuously position patients at the center of healthcare initiatives. Collecting high-quality healthcare datasets in a data platform is essential for the effective development and deployment of AI systems.

"To make AI robust enough, you need lots of data. You have to make sure that your algorithm is capable enough. When I say capable, it's very layman's term. In technical terms, we call it the capacity of your network. You have to improve the algorithms by fine-tuning the hyperparameters and dropping technical stuff". (Data Scientist, 00:46:10)

Data platforms are essential for AI developers to create valuable AI tools, but as healthcare data comes in many forms - journals, images, prescriptions, the data platform must be able to handle the varied structure of the data. While Danish healthcare data is of high quality, it is often fragmented across multiple systems, which makes it difficult to create a holistic overview of a patient's health record. AI can enhance electronic health records by continuously collecting patient data using data standards defined as AI tool deployment.

"*Right now we do have a system that is actually gathering a lot of information, but it is not really doing it structured, so there's tons of information just lying around about every patient - one long word document. (...) You can't really extract the most relevant, or say, right information*" (Physician at Rigshospitalet, 00:15:11)

A structured data platform does not only benefit AI developers. Clinical staff in Region Zealand interact with the electronic health record "Sundhedsplatformen" for several hours every day. Its cumbersome infrastructure significantly reduces the number of patients that clinicians have time to interact with in a day (Head of Burn Unit at Rigshospitalet, 00:05:53). Creating a structurally sound data platform that allows both AI developers and clinical staff to collect information relevant to their specific workflows, would be a huge driving factor in patient-centered value.

5.3.4. Benchmarking

Healthcare organizations are constantly under pressure to benchmark their performance against others to demonstrate their value, which requires data transparency (Katz, 2020). The success of AI can be assessed at every stage from development to implementation of AI tools. It begins with pilot testing, scaled implementation, and validation. Such performance metrics should reflect the values, priorities, and vision of the health organization (Chen & Decary, 2019). There are many aspects of assessing AI technologies like quality, efficiency, improved patient experiences, improved staff satisfaction, reduced costs, increased revenue, etc. (Chen & Decary, 2019).

Benchmarking empowers organizations to develop plans to make necessary improvements and foster best practices to increase the overall performance of the healthcare organization. Benchmarking should offer a comparison between the outcomes of traditional clinical workflows, with those enhanced by artificial intelligence. AI providers should use benchmarking to make comparisons in key performance areas, enabling leaders to either reaffirm current practices or identify potential areas for change (Use Good Benchmarking Data to Your Advantage, 2018).

Healthcare AI systems must be built to be humble, just like humans. Where AI knows when it is not sure about the right answer, it needs to transfer the critical decision-making process back to people (DataRobot, 2021). AI developers can implement this concept of "humble AI" in benchmarking to ensure the trustworthiness, ethicality, and reliability of the tools

"Make sure the model is humble like it's not too confident in its own views. Make sure that you have a good validation scheme, so you are doing lots of cross-validation or you have what we call hold-out sets of data from the different places. You tend to want to apply it and you test them all before you use it. And then it's not just periodic testing before you put it into production, it's actually, the more often you can test it in the real world, the better.". (AI Specialist & Physician: 00:44:00)

The goal of open benchmarks is not about blaming underperformers but focusing on lessons that can be learned from high performers (Katz, 2020). Comparison and benchmarking of the AI models helps in establishing a shared data platform to facilitate knowledge exchange and improve the competency of the AI models.

"Running two separate projects with two sets of researchers that don't talk to each other, and they both train different models, ideally different styles of models. One can be a deep learning model, and one could be a gradient boosting model, and they train them on their own data with different features. And then maybe you ensemble the results, or at least you test what it would be like to basically have a voting scheme. The two models vote on the right decision as equal partners". (AI Specialist & Physician: 00:44:21)

This statement illustrates the benefit of training and testing two separate models, to benchmark their outcomes towards each other. Outcome-based benchmarks should be conducted internally, between projects, and across multiple providers. In all cases, aligning all participants on a common, risk-adjusted scorecard is a prerequisite to prevent the adverse selection of patients and ensure statistically comparable results (Katz, 2020).

Before deploying a model in a real-life setting, developers should conduct a risk assessment to help in identifying some areas of risk and come up with a necessary action plan to mitigate those identified risks. It is usually necessary to train many candidate models to select the best-performing one (Lapach, 2021).

"You can identify some areas which are risk areas where the focus should be more on that. Then you come up with mitigating actions" (Compliance and Technical Expert, 00:29:00)

Conducting an ongoing risk assessment is a way of benchmarking the AI model and assessing the model performance. The main objective of risk assessment for the machine learning models is to attain high accuracy in the model.

"If you don't follow the processes and if you don't focus on the risk assessments, if you don't focus on ensuring that you have sufficiently tested and validated, there is

always a risk that the results that you get from machine learning could have a severe impact". (Compliance and Technical Expert, 00:30:00)

Ensuring enough testing and validation has been completed before deploying the AI models, increases their efficiency and accuracy and reduces the potential of AI tools not bringing value to healthcare workflows.

5.3.5. Investments

Implementing AI in healthcare is not cheap. These projects require investments both in terms of allocating capital to sponsor these projects, as well as investing in teams for change management (Katz, 2020). There is currently a lack of IT-specialists in Denmark that are competent in running AI projects in healthcare (Lindskow et al., 2020). This means that it may be necessary to employ developers from outside of Denmark to support the development of these tools. However, as our data collection revealed that clinical staff generally much prefer that AI tools are developed on-site (Medtronic Consultant, 00:09:35), it may become challenging to utilize these resources.

Hospitals and universities should increase their investments in training their clinical staff and future physicians in using AI applications. As there is currently a large gap between the general technical competencies among clinical staff, investing in these initiatives is crucial in succeeding in generating value from the tools

"*It would be ideal to have all the med students take a course where they could be taught more about AI and how these tools can be handy and how you can use or how you can leverage this tool. (...) Also, some kind of constant training for the doctors should be helpful*" (Pathologist, Physician at Rigshospitalet: 00:14:38)

Currently, most of the funding comes from external collaborators rather than internally. There is a lack of budget in funding these initiatives, which results in most AI technologies being developed outside of the hospitals.

"*Funding comes from outside, and I think that's something that you might be interested in striking down on. A lot of hospitals have a strategy towards implementing*

AI, but there is no money on any of the budgets to support this. So all of the departments have to get people like us or my group to apply for external funding in order to do some type of research project" (Head of Clinically Applied AI at Rigshospitalet, 00:01:09).

While we find that hospitals do consider artificial intelligence as an important part of optimizing their workflows, the lack of internal funding necessitates those developers seek capital from external sources. While this is not necessarily a negative thing, it may increase the difficulties of aligning the AI tools with patient value, rather than commercial goals.

5.3.6. Incentives

Incentivizing key stakeholders is a crucial element of developing and deploying AI in healthcare. It is important to create incentives for clinical staff to use the tools to boost adoption. Optimizing clinical workflows through AI can be used to meet the growing healthcare demands to let the healthcare providers enhance their productivity in clinical practice which can lead to higher job satisfaction. Thereby, relieving healthcare providers of time-intensive, manual tasks, reducing burnout, and helping focus valuable human time on those tasks of the highest value (Lubarsky, 2021). This section includes the interview insights into the potential benefits of AI applications in healthcare.

"So let's move that workload somewhere else. We get something that can do the data entry for us, right? That's a different kind of efficiency. It's not about saving money, it's just about being wiser about what you spend your money on, right?" (Principal Director at Accenture, 00:42:43)

AI has proven to be extremely competent and can play a pivotal role in medical diagnosis to reduce the pressure on physicians when working through humongous amounts of patients' information (Long, 2020). Further, AI solutions can incentivize physicians in easing their administrative burden for e.g., translating clinical notes, streamlining appointments, tracking patient notes, and following up on care recommendations. This allows doctors to spend more time with patients, which increases their productivity and improves the quality of patient care (Geller, 2020).

"The autogenerated AI reports for general practitioners can enable them to look at all the fine details in the ECG. They are very happy to get more, you could say, crude analysis where they will not have to do much other than look at the report and then decide if they agree with the proposed diagnosis in the report or not." (AI specialist at Cortrium, 00:04:01)

Further, AI can be helpful in early detection, also helping in treatment decision making and reducing doctors' direct engagement in potentially repetitive tasks (Artificial Intelligence in Health, n.d.).

"Yeah, I think maybe early warning signs could be amplified by AI, where you can take this with a more seriousness and make the good, better diagnosis" (Physician/Researcher at Rigshospitalet, 00:36:36)

AI has demonstrated remarkable progress in image-recognition tasks. AI works remarkably brilliantly in recognizing complex patterns in imaging data and providing quantitative, rather than qualitative, assessments of radiographic characteristics (Long, 2019). Thus, AI exceeds human performance in complex tasks and avoids unnecessary repeat examinations. AI can read the laboratory values that are used to signal alarms for an acutely decompensating patient (Giordano et al., 2021).

"It's extremely difficult to basically use A.I. in a lot of cases when it comes to human health. I would say that imaging tasks like looking at x-rays or looking at MRIs or other things are an exception because you can look at one picture and then a computer can analyze it in a really concrete way. I would say that signals like analyzing an ECG and monitoring the heart are other things that AI can do better than humans," (AI specialist & Physician 00:20:56)

AI can incentivize and accelerate the radiologists to achieve accurate image interpretation and analysis, thus providing a deeper insight into the medical condition for better care.

“Radiology also is a sort of bottleneck because we need people working in this area. We need the hands that are always a need of radiologists in this situation. If AI just gets into the action, it will be a huge help”. (Physician/Researcher at Rigshospitalet, 00:06:00)

AI can significantly influence the routine radiology activities that need to be carried out every single day which are time- and labor intensive. AI can optimize these repetitive clinical processes with high levels of accuracy, thus equipping physicians with sufficient time and energy to focus on essential and higher value-adding tasks.

One should focus on where there is a need for manpower. I mean, skilled labor, I mean, professionals, where they're lacking. Suppose, for example, in chronic diseases, when the patients, once diagnosed, are on the follow up throughout their life. It's quite a burden on the health system” (Physician/Researcher at Rigshospitalet, 00:03:27)

AI has the capability to measure the number of patients who need treatment follow-up and can also efficiently execute the follow-ups at prescribed intervals.

”The autogenerated AI reports for general practitioners can enable them to look at all the fine details in the ECG. They are very happy to get more, you could say, crude analysis where they will not have to do much other than look at the report and then decide if they agree with the proposed diagnosis in the report or not”. (AI Specialist at Cortrium, 00:04:01)

AI can be deployed to identify patterns within patient data to determine their probability of getting a specific disease or illness. Such proactive insights can offer enormous value to the healthcare sector by providing early warning and thus reducing the likelihood of potential mistakes.

In addition to showcasing the tangible benefits of AI, the AI developers should aim to provide psychological incentives by displaying transparency in healthcare AI. This can be achieved by explaining the logic from which an AI tool has come to a conclusion, and with what confidence it is making a recommendation. Adding explainability to the AI tools helps in building trust and provides assurance to the diverse stakeholders in embracing AI technologies in healthcare.

5.3.7. External Collaborations

The high pace of digital innovations is challenging traditional business models and reshaping the competitive landscape of many industries, including the healthcare industry (Kambli, 2020). Healthcare organizations are proactively managing the change by engaging in external collaborations. This collaboration helps healthcare organizations gain agility and cost-effective value as well as an opportunity to digitally transform themselves to enhance the wellbeing of the society (Kambli, 2020). Danish health care organizations are partnering with AI-focused start-ups, multinational companies, and educational institutions to ensure patients have access to the best possible treatment, especially when the resources are limited (Ministry of Finance & Ministry of Industry, Business and Financial Affairs, 2019).

The hospitals in Region Zealand collaborating with Cortrium have made significant moves towards advancing medical care and supporting Danish engineering with their decision to adopt new electrocardiogram (ECG) equipment (www.cortrium.com). The initiatives by the Danish government to collaborate with partners across the industry positively facilitate the use of AI in Danish healthcare.

"Cortrium has produced a hardware device holder (...) *the device can live stream the signal to a mobile device such as an iPhone or whatever, and a phone or tablet, and you can have a live preview of the ECG signal"* (AI Specialist at Cortrium: 00:02:00)

Artificial intelligence vendors like Cortrium are partnering with the Danish hospitals to identify practical challenges of AI in healthcare. Cortrium's AI technology can be used as a potential solution, offering valuable analysis and insights of cardiac and non-cardiac health and disease, to transform the prevention and diagnosis of cardiovascular diseases. This type of collaboration acts as a catalyst in designing technologies that can tackle real-world healthcare problems and is crucial to effective AI adoption.

"We first approved our hardware product, we ran a study with a hospital with around 200 patients, which is a necessity most often if you produce new medical devices to do such a study, so you can do a clinical evaluation, which is part of the requirements for the CE approval to bring the product to market." (AI Specialist at Cortrium, 00:09:40)

The health system needs to work closely with private companies behind these technologies to understand and capitalize on its potential to enhance the benefits of patients and clinical staff.

"I think DTU is really pushing out a lot of great spin-outs and a lot of brilliant people, students with a lot of knowledge in AI. And as you can see, we're in many fields."(AI Specialist at Cortrium: 00:14:08)

In Denmark, universities like the Danish Technical University (DTU) collaborate closely with hospitals, AI companies, and governing bodies to expose students to valuable clinical experience, to provide them with competencies within the field of research. Their main aim is to create the best possible framework for interdisciplinary collaborations across basic research and hospital treatments with the inclusion of regional experiences with patient contact (Ministry of Foreign Affairs of Denmark, 2016).

"So in a typical industry collaboration with a research lab, it only works because the highly paid, highly experienced researchers are actually not very expensive for that project." (AI specialist & Physician, 00:06:00)

It can be expensive to collaborate with a research lab, as they have highly paid and highly experienced researchers. Having said that, the cost for collaborating with the research lab could be less expensive/cost-effective compared to hiring more expensive individual AI developers. Researchers in the lab can collectively bring its strong AI computational knowledge and expertise, and together with the information provided by clinicians, it can drive significant improvements in AI systems. This interplay with human experts in the healthcare discipline can improve the credibility and trustworthiness of AI systems.

The efficiencies achieved from deployment of an effectively designed AI would outweigh the cost incurred at the design and development phase (Principal Director at Accenture, 00:43:00). Hence, the Danish government should support and invest in collaborative projects involving researchers and healthcare providers for building a conducive AI ecosystem. For example, the Chinese government has developed a range of policies showing its commitment to the use of AI in healthcare, setting the goal of becoming a global innovation center by 2030 and laying out recommendations for the use of AI to improve population health. In recent years, the government has also invested not only in academic collaborations, but also directly in innovative startups (EIT Health and McKinsey & Company, 2020)

5.3.8. Choosing the Right Branch of AI

Based on the primary data and literature, we have identified multiple opportunities in Danish healthcare for optimizing operational processes and supporting clinical decision-making using AI. As we are using the umbrella term "AI" to describe the technologies, this section focuses on highlighting which branches of the "AI technology stack" can provide value in healthcare, and how they differ.

While it is not directly related to patient health outcomes, back-office functions like billing and invoicing take up a large number of resources in any healthcare organization. Machine learning can be used alongside natural language processing (NLP) to process medical codes and billing codes to automatically extract information from medical journals, to assist in proper coding and billing (Bharadwaj, 2019).

"AI's benefit to back-office functions, things like handling invoices and HR-processes is huge. People should definitely do that, also at hospitals, which obviously also have a lot of invoice handling and HR things." (Medtronic Consultant, 00:16:42)

The subset of machine learning referred to as deep learning is already being utilized in the radiology department of Rigshospitalet. Deep learning algorithms work well in image diagnostics to extract useful information and output insights about potential diseases, which can assist radiologists in their diagnosis or free up their time for other clinical work.

"Radiology being very image-heavy is huge with AI. I've heard a rumour that you aren't allowed to call AI projects innovation at Rigshospitalet if you are within radiology - it's not innovative anymore, now it's implementation. In general AI is really really good at images, text, video, audio, and to some degree signals, and less

good at classical tabular data like age, diabetes and these things." (IT-Consultant at Rigshospitalet 00:18:41)

Machine learning has the potential to improve the capabilities, efficiency, and accuracy of radiologists by quickly analyzing the images and comparing them to data registries (Mohan, 2018).

"And we say that when you have a stroke. Time is brain, so you need to treat the patient as quickly as possible. At the same time, you want to treat the patient based on as much information as possible because you want to give the patient the optimal treatment. So you have the time constraint and you have an information constraint. And that bottleneck is really well suited for AI." (Clinical AI Researcher / Professor: 00:01:41)

Supervised machine learning algorithms can quickly run through electronic health records (EHR) and patient's data from a particular patient's journal, and provide cognitive insights for diagnosing a stroke and facilitate personalized treatment plans (Clinical AI Researcher / Professor, 00:01:41). Machine Learning algorithms are helpful in areas where the diagnostic information a doctor examines is already digitized (Schmitt, n.d.), thus making the clinical diagnosis faster and easily accessible for the clinicians. Further, ML algorithms can be deployed in making correct tumor identification, suggesting correct treatment decisions, reducing unnecessary surgeries, and helping oncologists improve patients' cancer treatment plans (ibid).

"There's a need for any computerized decision support system where the people answering the phone can be aided in triaging the patients to the right place and within that area." (Ph.D. in NPL with Corti.ai, 00:26:59)

The AI subfield of natural language processing can understand the text and spoken words to extract meaningful information that can be processed by other technologies. NLP can assist in real-time second opinions, note-taking, quality assurance, task prioritization, etc. (AI for Patient Consultations, n.d.). NLP was used alongside a machine learning model to assist emergency dispatchers in detecting cardiac arrests, and even showed a higher detection rate than the human dispatchers (Ph.D. in NPL with Corti.ai, 00:06:54).

5.4. Summary of Results

In this section, we will summarize the findings from our interviews that answer the descriptive element of our three research questions. The challenges presented in the results are not an exhaustive list of what needs to be addressed to succeed in AI implementations in Danish healthcare. They present areas from our primary data where both clinical staff and technical experts see barriers that limit AI's capabilities in creating value-based healthcare. While the segment is separated into three categories, the challenges related to data quality, quantity and access are perpetual throughout most of the interviews, as this is naturally the driving factor for AI algorithms that produce meaningful outcomes. The results also showed that while AI in healthcare is still in its very early stages in terms of adoption, the technology itself is quite mature. This means that increasing the value obtained from AI does not rely on creating stronger AI algorithms but enables these algorithms to be effective.

Through our data collection, we identified that this can be accomplished by mobilizing the internal forces, i.e., clinical staff to ensure that the AI is designed to support the workflows of the end-users. Furthermore, the onboarding process and explainability of the AI is crucial in increasing adoption of these tools and incentivizing clinical staff to work with technical experts. A strong data platform that contains the medical data in a structured and accessible way is also central in developing these tools, so their outputs are accurate and unbiased. Finally, the limitations of AI should be clearly addressed from the beginning, as in its current form, it is unable to complete more abstract clinical tasks. Identifying limitations allow technical experts to focus on the fields of healthcare, where AI will have a positive impact in establishing value-based healthcare.

The results revealed that clinical staff and technical experts agreed that AI's biggest strength in healthcare currently lies in workflow optimization. The more abstract physician-related work is still outside the scope of its value. This encompasses why data is so important, as these more "administrative" healthcare-related tasks rely on a sufficient quantity of quality data. The challenges of adoption are centralized around a form of participatory design (Blomberg & Kensing, 1998), where physicians and other clinical staff are involved in defining the processes where AI can help them, while being involved throughout the design process. These steps will also help identify the areas where AI's uses are currently limited, to allow developers to focus on those areas that lead to impact in value.

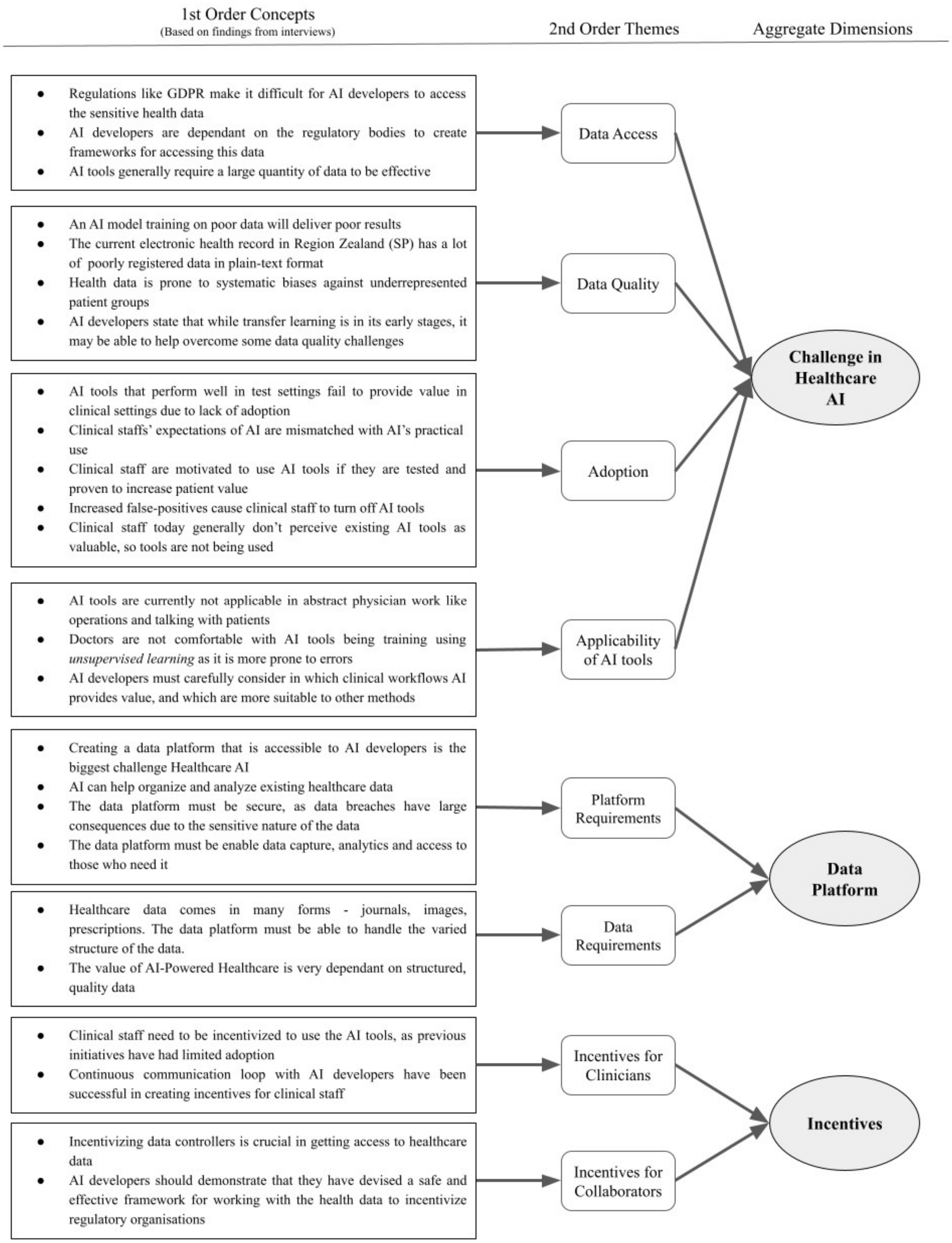
The results also highlighted which stakeholders are crucial to involve in AI-powered value-based health care. In the current Danish healthcare landscape, the stakeholder that represents the biggest barrier is the data controller, i.e., the Danish government. Furthermore, clinical staff and patients also represent important stakeholders as they are ultimately the end-users that the AI tools aim at benefitting. These stakeholders need to be aligned with the technical experts, i.e., developers to create collaborative projects with shared responsibility.

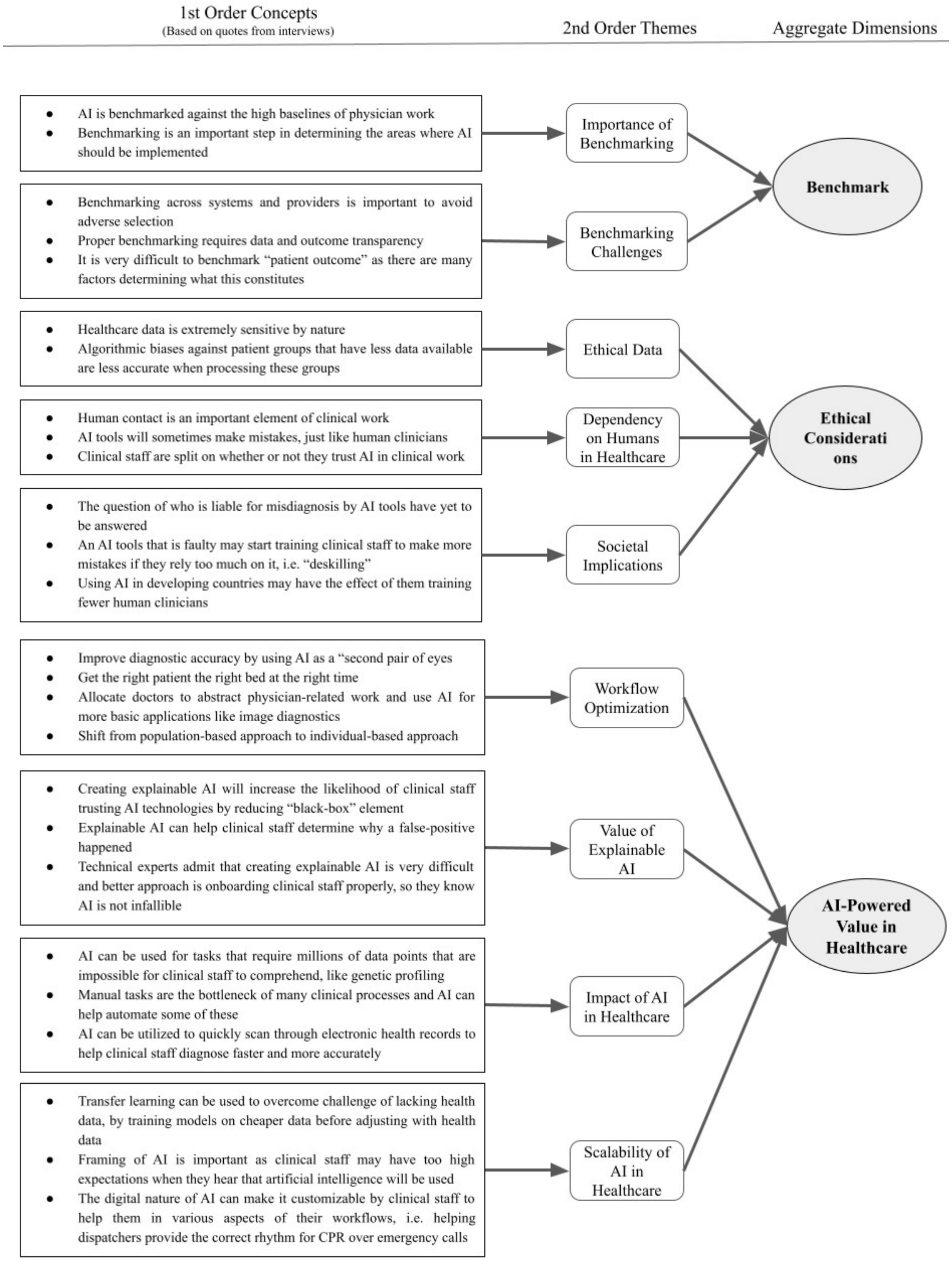
After addressing the potential challenges of AI and who the important stakeholders are, the next segment examines the potentials of AI as a technology for transforming healthcare to create value. The primary data gathered from interviews and data analysis, helped us assess the potential value of AI in Danish healthcare by dividing it into essential dimensions that should be addressed to create value-based healthcare. By this, it is evident that AI has begun to affect some aspects of the Danish healthcare system, like clinical decision support in oncology, pathology, cardiology and dermatology. However, the development and deployment of AI technology is costly and equally challenging, which limits its effects in these areas. This revealed the significance of developing a clear strategy on how to integrate AI tools into existing workflows, and how a strong collaboration with various IT experts to launch pilot projects with the private sector, researcher and public authorities is essential in achieving the potential value of artificial intelligence.

In addition, setting up of benchmarking standards, as well as monitoring healthcare services delivered through proper risk assessments can help the healthcare services identify unjustified anomalies, to develop action plans to mitigate them. Evaluation of the consequences of false positives and false negatives before and after releasing the product, including monitoring and prevention protocols is critical in the adoption of the AI tools.

Furthermore, the critical clinical processes that can lead to serious implications on the patient outcomes e.g., making medical diagnosis and treatment decisions, should be incorporated in such a way that the doctors are the ones who make the final decision, by leveraging insights generated by AI tools as references. Implementing any artificial intelligence technology requires a huge resource investment, hence, our data collection indicated that healthcare organizations should start small by investing in projects in private sectors to realize returns on the invested capital and resources.

Below, we present a data structure diagram inspired by Gioia et al. (2013) that illustrates how the 1st order concepts derived from our interviews relate to the aggregate dimensions that have been discussed in the results section. In the following discussion segment, we will analyze results and provide concrete recommendations on how to address the challenges and incentivize stakeholders, to enable the creation of AI-powered value-based healthcare AI. The data structure's goal is to have all aggregate dimensions be mutually exclusive, while collectively exhaustive (Minto & McKinsey, 1968), to break down the dimensions into logical buckets for analysis.


1st Order Concepts
(Based on findings from interviews)
2nd Order Themes
Aggregate Dimensions
Regulations like GDPR make it difficult for AI developers to access the sensitive health data
AI developers are dependant on the regulatory bodies to create frameworks for accessing this data
AI tools generally require a large quantity of data to be effective
Data Access
An AI model training on poor data will deliver poor results
The current electronic health record in Region Zealand (SP) has a lot of poorly registered data in plain-text format
Health data is prone to systematic biases against underrepresented patient groups
AI developers state that while transfer learning is in its early stages, it may be able to help overcome some data quality challenges
Data Quality
AI tools that perform well in test settings fail to provide value in clinical settings due to lack of adoption
Clinical staffs' expectations of AI are mismatched with AI's practical use
Clinical staff are motivated to use AI tools if they are tested and proven to increase patient value
Increased false-positives cause clinical staff to turn off AI tools
Clinical staff today generally don't perceive existing AI tools as valuable, so tools are not being used
Adoption
AI tools are currently not applicable in abstract physician work like operations and talking with patients
Doctors are not comfortable with AI tools being training using *unsupervised learning* as it is more prone to errors
AI developers must carefully consider in which clinical workflows AI provides value, and which are more suitable to other methods
Applicability of AI tools
Challenge in Healthcare AI
Creating a data platform that is accessible to AI developers is the biggest challenge Healthcare AI
AI can help organize and analyze existing healthcare data
The data platform must be secure, as data breaches have large consequences due to the sensitive nature of the data
The data platform must be enable data capture, analytics and access to those who need it
Platform Requirements
Healthcare data comes in many forms - journals, images, prescriptions. The data platform must be able to handle the varied structure of the data.
The value of AI-Powered Healthcare is very dependant on structured, quality data
Data Requirements
Data Platform
Clinical staff need to be incentivized to use the AI tools, as previous initiatives have had limited adoption
Continuous communication loop with AI developers have been successful in creating incentives for clinical staff
Incentives for Clinicians
Incentivizing data controllers is crucial in getting access to healthcare data
AI developers should demonstrate that they have devised a safe and effective framework for working with the health data to incentivize regulatory organisations
Incentives for Collaborators
Incentives


1st Order Concepts
(Based on quotes from interviews)
2nd Order Themes
Aggregate Dimensions
AI is benchmarked against the high baselines of physician work
Benchmarking is an important step in determining the areas where AI should be implemented
Importance of Benchmarking
Benchmarking across systems and providers is important to avoid adverse selection
Proper benchmarking requires data and outcome transparency
It is very difficult to benchmark "patient outcome" as there are many factors determining what this constitutes
Benchmarking Challenges
Benchmark
Healthcare data is extremely sensitive by nature
Algorithmic biases against patient groups that have less data available are less accurate when processing these groups
Ethical Data
Human contact is an important element of clinical work
AI tools will sometimes make mistakes, just like human clinicians
Clinical staff are split on whether or not they trust AI in clinical work
Dependency on Humans in Healthcare
Ethical Considerati ons
The question of who is liable for misdiagnosis by AI tools have yet to be answered
An AI tools that is faulty may start training clinical staff to make more mistakes if they rely too much on it, i.e. "deskilling"
Using AI in developing countries may have the effect of them training fewer human clinicians
Societal Implications
Improve diagnostic accuracy by using AI as a "second pair of eyes
Get the right patient the right bed at the right time
Allocate doctors to abstract physician-related work and use AI for more basic applications like image diagnostics
Shift from population-based approach to individual-based approach
Workflow Optimization
Creating explainable AI will increase the likelihood of clinical staff trusting AI technologies by reducing "black-box" element
Explainable AI can help clinical staff determine why a false-positive happened
Technical experts admit that creating explainable AI is very difficult and better approach is onboarding clinical staff properly, so they know AI is not infallible
Value of Explainable AI
AI-Powered Value in Healthcare
AI can be used for tasks that require millions of data points that are impossible for clinical staff to comprehend, like genetic profiling
Manual tasks are the bottleneck of many clinical processes and AI can help automate some of these
AI can be utilized to quickly scan through electronic health records to help clinical staff diagnose faster and more accurately
Impact of AI in Healthcare
Transfer learning can be used to overcome challenge of lacking health data, by training models on cheaper data before adjusting with health data
Framing of AI is important as clinical staff may have too high expectations when they hear that artificial intelligence will be used
The digital nature of AI can make it customizable by clinical staff to help them in various aspects of their workflows, i.e. helping dispatchers provide the correct rhythm for CPR over emergency calls
Scalability of AI in Healthcare

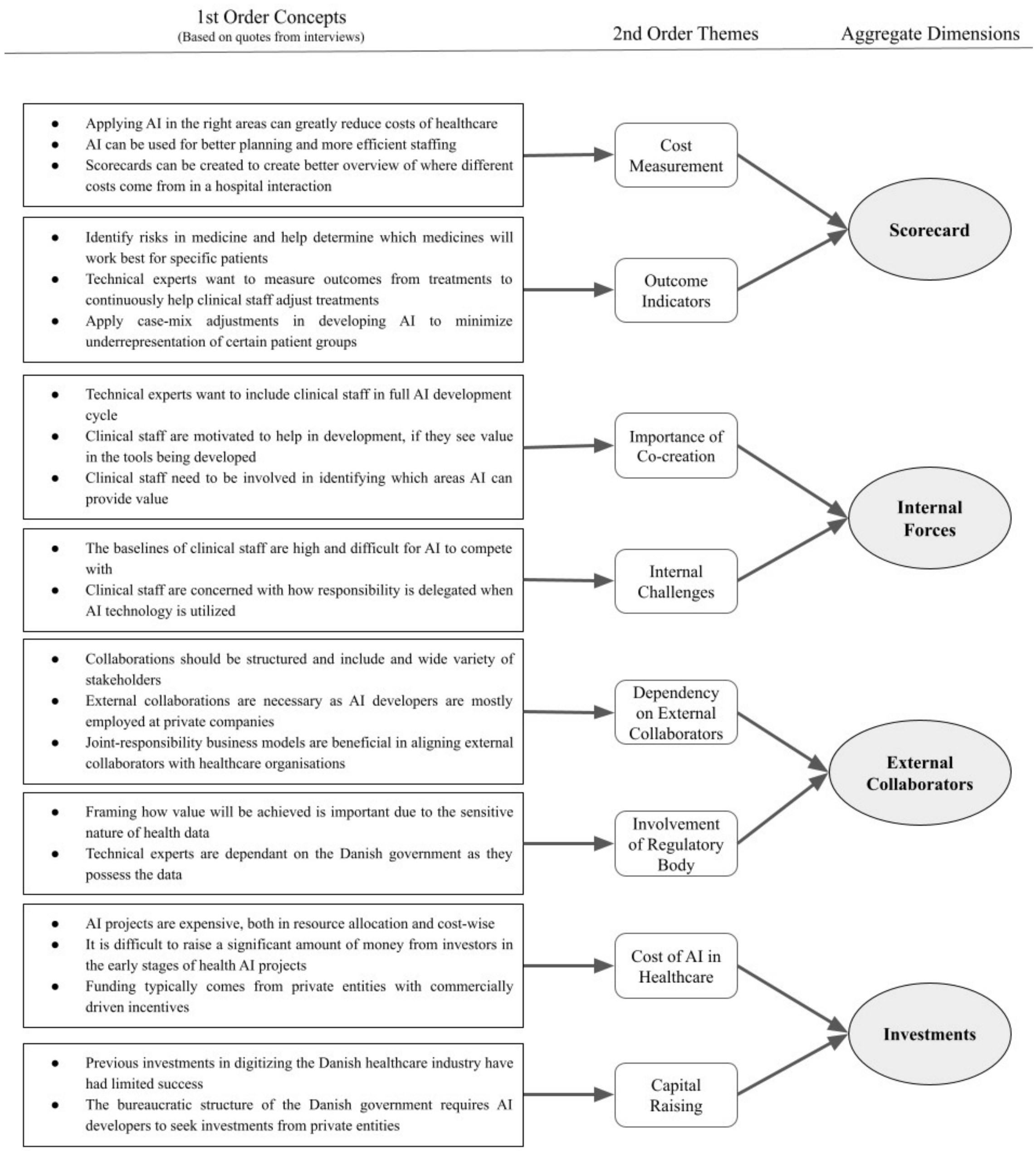


Figure 4: Data Structure showing relationship between interview findings and aggregate dimensions

6. Discussion

This section will build on the results section, by working with our data through a more analytical approach and applying relevant theories, to present recommendations on how the challenges can be overcome to produce value. To support the theories, we are also highlighting specific statements from our interviewees that support the recommendations' value in a Danish context. The discussion section will provide insights regarding the analytical and prescriptive aspects of our research questions, namely: *How should the data challenges be addressed? How should important stakeholders be incentivized? How should healthcare AI be designed to provide value?*

Before presenting our comprehensive answers to these questions, we are summarizing the main findings from the discussion. The first part of the discussion body will address the challenges presented in the results section and provide insights into what initiatives are currently being instituted by the Danish government to increase data access. We argue how these initiatives should be deployed to support AI-powered value-based healthcare, and how technical experts should manage these changes. We then present recommendations for how to deal with the challenge of data quality in healthcare. Afterwards, we discuss how adoption from clinical staff can be encouraged by using participatory design. We then address the applicability limitations of AI in healthcare and clarify which type of processes AI can support, and which are outside its scope. After the main challenges have been addressed, we discuss how to incentivize the different stakeholders and their importance to the success of the technologies.

Addressing these points will lead us to make recommendations on how to engage in AI projects to drive value in new projects. These recommendations are centered on the dimensions that we identified in our primary research and are heavily based on the value-based healthcare implementation matrix (Katz, 2020) together with elements of the CRISP-DM methodology (Gaultier, 2021). At the end of this section, we are presenting a modified implementation matrix that visualizes the recommendations for driving AI-powered value-based healthcare. We are then presenting the practical implications of these initiatives, and how existing policies may complicate the AI initiatives.

Finally, we address the ethical considerations that exist specifically in the area of healthcare, and the restraints they impose on AI in the industry. Before presenting our conclusion, we reflect on which areas are yet to be addressed and the limitations of our paper.

6.1. Discussion Summary

This section summarizes the essential interpretations and recommendations based on the key research findings. Furthermore, it considers the ethical and practical implications for these initiatives to provide value. Driving value-based usage of AI in the Danish healthcare system is faced with multiple challenges. The most pressing challenges that were identified in our research are related to data. The data challenge can be broken into three categories: limited access to data, lack of data standardization, and data quality. Furthermore, adoption from end-users, i.e., clinical staff presented a huge challenge due to the end users' lack of trust in the AI technologies or lack of onboarding. Finally, the limited applicability of AI in healthcare is addressed, as certain workflows in clinical processes can not currently be solved with artificial intelligence.

The limitation of data access is the main hindrance in realizing the true value of AI in healthcare. The Danish government is taking several initiatives to create a robust data platform that establishes a single point of contact, which will contain both health information and guidelines for how to access it for research purposes. The platform should have sufficient calculation- and storage capabilities to support advanced data analytics across big data in several formats, to support the varied structure of health data (Sundhedsministeriet, 2021).

It is essential that the data in the platform should be pseudonymized to prevent individual level profiling and enhance data security and transparency. We recommend that the government carefully considers the scalability of this platform, to support the rapid development of AI. Furthermore, the government should collaborate with AI developers in their efforts to create the guidelines for utilizing the data, as our research revealed a lack of standardization in applying for access to health data. The Danish government is taking initiatives to provide data in the form of data packages, which could contain subsets of data within different medical fields, which would allow developers to create tools based on real-life examples.

Data quality is another important element that impacts the performance and accuracy of AI predictions in clinical decision making. Higher quality of data can be achieved by clearly specifying the requirements of what data is needed for building AI tools for healthcare. AI developers must collaborate with clinical staff to attain their knowledge regarding how data should be weighted. In lieu of higher data quality, AI developers can achieve higher performance of the machine learning algorithms by applying transfer learning to new AI models from the pre-trained models, thereby enhancing the ML algorithms rather than training with only a small amount of data.

To address the challenge of poor adoption of AI tools in healthcare, AI developers must instill trust in end-users towards their systems, by formulating how these tools provide value. Clinical adoption can be encouraged by developing the AI tools by giving the end-users an important role in the design process through participatory design, thus increasing transparency and trust (Kushniruk & Nøhr, 2016). Also, AI developers must consider their post-implementation strategy and prioritize extensive onboarding, to ensure that clinical staff are trained in how to use these tools.

AI technology often faces applicability challenges, especially in healthcare which requires domain-specific knowledge or circumstances which are outside the AI models training set. This can be addressed by deploying supervised learning ML algorithms that consider inputs from clinical staff in their predictions, to make them less error-prone and more explainable. Expectation management is also an important part of solving this limitation of applicability, as AI developers should only focus on those areas within AI where these tools are able to create valuable outcomes.

A key enabler for successful AI development is the identification of key stakeholders and incentivizing their participation. The stakeholders and their expectations should be managed through active collaboration with AI developers. Developers should strive to create outcome-based contracts with sponsors and healthcare organizations, allowing the negotiating parties to set realistic joint targets and implement appropriate incentives and penalties. We propose that AI developers facilitate these joint-responsibility programs by adapting the Health Outcome Platform (HOP) developed by EY, to create outcome-based contracts.

The research findings indicate that the application of AI in Denmark in clinical practices is still in a nascent stage. We recommend utilizing a modified implementation matrix for AI-powered value-based healthcare (**Figure 5**) to guide future implementations. The building blocks of this model addresses the most important aspects identified in our analysis of our primary data and existing literature.

Through the matrix, we recommend which steps should be taken in these AI projects to drive value. The steps can be summarized as the following: Mobilizing *internal forces* through proper stakeholder identification and assigning a mix of resources and competencies, where clinicians and administrative leaders work in tandem to develop AI tools. Creating a *data platform* that contains structured, quality data with clear guidelines for requesting access. The implementation efforts should be measured by iteratively evaluating and validating the tools using *scorecards*. AI developers must continuously *benchmark* their tools against traditional approaches and other technology. Successful transformations of healthcare using AI can only be achieved through adequate *investments* and strong *external collaborations*. Finally, different *incentives* must be provided to stakeholders, to ensure their participation in development.

There is currently a lack of funding from the Danish government in AI healthcare initiatives (EIT Health, 2020). The Danish Government should prioritize AI-based projects in healthcare equally with other projects, with clear justification for securing adequate budget allocation in time. Alternatively, AI developers can attempt to secure funding from venture capital investors, however, this approach may not align perfectly with the value-based approach if investors are only in it for the money. Danish healthcare organizations should engage in strong collaborations with AI companies and educational institutions to take advantage of the current hype of AI for healthcare-related services. This can increase the general competency level of Denmark in terms of healthcare AI.

AI technology is producing an unconventional set of ethical and practical challenges that can present a barrier in patient autonomy, trust, safety, and privacy. To increase the trust of patients, clinical staff, and healthcare providers, the AI tools must align with European data regulations, to minimize the chance of data breaches. Further, developers should attempt to reduce biases against certain patient groups by establishing regular technical and medical reviews, as well as striving for explainable AI.

6.2. Addressing the Challenges

6.2.1. Accelerate Data Access

The challenge of data access is two-fold: The first aspect is the challenge of getting lawful access to the data while following the GDPR, the second aspect is getting access to healthcare providers like hospitals to get access to real-time relevant data. The first of these challenges is by far the most complicated of the two, as well as being somewhat out of the hands of AI developers and clinical staff. Healthcare data is some of the most sensitive information that exists about individuals. It is vital to the ethical principle of privacy and patient autonomy and is strictly regulated in Denmark through EU's GDPR (Reddy et al., 2019).

To realize the potential of AI in healthcare, the fundamental issues of healthcare data must be addressed: who owns the data, who is responsible for it, and who can use it (Panch et al., 2019)? According to the GDPR, it is the individual patients who own their own personal data, and they are the ones who have the right to decide what it is used for. The data controller is the healthcare institution, which in Denmark is the government. The data controller also has the responsibility of handling this data according to regulations (GDPR.eu, 2021).

The future of AI-Powered Value-based AI is dependent on the social understanding of healthcare as a public good, the tolerance of partnerships with private AI developers, and the public's trust in both governments and the private sector in treating their healthcare with care (Panch et al., 2019). To succeed in bringing AI applications to healthcare, there need to be specific contracting instruments to align developers and other stakeholders to ensure that data sharing involves the necessary protection, where outcomes are specifically directed at benefitting the patients. These considerations are essential when designing the data platform that should contain the healthcare data. Currently, the data is stored in various electronic health records, which in Region Zealand is "Sundhedsplatformen". The interviews with AI developers in the previous section revealed that the biggest challenge in creating valuable healthcare AI, is the inconvenient processes related to accessing healthcare data.

In a recent publication from the Danish government, these data challenges are acknowledged. A collaboration between the Danish Health Ministry, the Danish Health Data Authority, the Danish regions and other important stakeholders seek to address these challenges to enable a strategic roadmap for the future of healthcare data. The vision of the new initiatives correctly identifies some of the challenges that were exposed in the results section. These include: complicated administrative processes when applying for access to healthcare data, too many different avenues and processes for applications, lack of guidance, varying interpretations of rules across jurisdictions, and lack of analysis capabilities (Sundhedsministeriet, 2021). To solve these challenges, the initiative will seek to focus on four objectives:

1) *Quick and easy applications and approvals.* A single point of contact for information and guidance will be created with the intention of accumulating all healthcare data controllers in one place. The new data platform will enable different jurisdictions to follow a streamlined and consistent path for applications for data (ibid). Succeeding in this objective will be a huge catalyst for the potential of AI. To further support the development of healthcare AI, we suggest that this data platform should also include standards related to how AI models should be designed, to conform to the requirements of GDPR and medical ethical standards (Reddy et al., 2019).

2) *Safe and flexible access to data on a national analytics platform.* This vision constitutes creating a platform where users can combine health data with other relevant data points in secure environments. The platform should have sufficient calculation- and storage capabilities to support advanced data analytics across big data in several formats (Sundhedsministeriet, 2021). This initiative will greatly benefit AI, as it means that newer AI models can benefit from a larger quantity of data in the development and training of algorithms.

"*We are working with the public sector. We won the tender in the region, Zealand and just doing the data processing agreements - it's incredibly challenging because it takes such a long time because the lawyers will usually always have additional things and new questions. So yes, it is challenging to start up any collaboration with the public sector. And right now, there's quite a big debate about how it's countering innovation, that there's so much overhead in terms of GDPR and legal requirements*." (AI Specialist at Cortrium, 00:10:52)

It was not uncommon for the AI developers from our interviews to spend more than half of the total project time working with lawyers doing data processing agreements with the government, instead of working on developing the AI tools (Ph.D. in Electronic Health Record, 00:08:34). A national analytics platform that facilitates quick and secure access to a large quantity of data would be an incredible driver in healthcare AI development in Denmark, as it would solve the issue developers are facing.

3) *Better and collective data service.* The Danish government has the goal of providing data support to its users, such as data packages and analysis on demand. These services are constituted to support specific initiatives like artificial intelligence tools, clinical decision making and access to patient data (Sundhedsministeriet, 2021). This service can support AI developers in solving the complex problems that may be out of their expertise, such as enabling informed consent for dating sharing and protecting confidentiality (Panch et al., 2019). Creating a data infrastructure that will enable AI developers to focus on development decreases the likelihood of potential data breaches, which can lead to increased incentives in developing AI tools in the Danish healthcare industry.

4) *High data security and transparency.* Proportionality and data ethics need to be a condition governed by the platform, to ensure that users are only able to access the data that is required for their specific goals. The data in the platform will be pseudo anonymized so that it cannot be pulled on an individual level (Sundhedsministeriet, 2021). To enable valuable AI development, it is important for the governing bodies to consider what constitutes that a second party should be able to access the health data. While we argue that data should be made more easily accessible for developers, it is still important to carefully select who should get the access, and monitor their use afterwards (Panch et al., 2019).

"*I think times are changing, and I would think that as AI technologies are reaching the clinical market and clinical workflows, physicians will realize that robustness only comes from more data and I think that's going to sort of soften up this process because the stakeholders now have aligned interest*" (Clinical AI Researcher / Professor, 00:06:09)

Our results revealed that the biggest challenge in healthcare AI is data access. The above-mentioned initiatives have the potential to position Denmark as a front-runner in healthcare AI. As previously mentioned, Denmark is in the unique position of having healthcare data from several decades, which presents amazing technical and commercial potential for Danish AI developers. The potential of AI in healthcare is well established, but if these initiatives fall flat, the potential of AI-powered value-based AI will not be reached in Denmark. Without creating a structured data platform that follows the vision of these new initiatives, AI developers must significantly downgrade the enthusiasm regarding AI in clinical practices. Opportunities for healthcare AI in Denmark without data will remain just that - opportunities (Panch et al., 2019).

6.2.2. Increase Data Quality

While data access to large quantities of healthcare data is crucial, the data should also be of high quality to ensure that the AI models perform well in their designated environments. Denmark has one of the oldest nationwide hospital registries through The National Patient Registry (CPR in Danish), however, the reports are typically fragmented with a very limited overview (Schmidt et al., 2015). The fragmentation of the data is a result of how health data is being collected. Health data completeness depends on hospital patterns and diagnostic accuracy, and since there is no single reference source, it is difficult to estimate the completeness of the data relative to the general population. Conditions such as hip fractures that will almost always lead to hospitalization are registered consistently in the system, while lifestyle risk factors like smoking, obesity, and alcohol consumption which are most often treated by general practitioners, are not completely registered (ibid).

Furthermore, the data entry process is an issue that is well documented by clinical staff when talking about health data registries. The implementation of various digital health registries in Denmark have been lackluster in onboarding clinicians of how to input data. Implementation efforts have often been localized to different hospitals, with lacking management and coordination in terms of who is responsible for training and streamlining processes (Egholm et al., 2019). This has resulted in a large discrepancy between how clinicians are using the system and inputting data.

The lack of training and busy workflows of clinicians has led to them using workarounds to move quickly through the system such as writing all patient notes in a plain-text formatted report, with no categorization of the structure of the data (ibid). This flawed data entry process creates data that is very difficult for AI algorithms to process, which presents a challenge that needs to be addressed: these systems should be designed to incentivize clinical staff to input data in a way AI can work with. As there is already a massive amount of data in these platforms, initiatives to harmonize the existing data is also important.

Existing literature points out the potential of utilizing AI tools like machine learning and natural language processing that can be utilized in harmonizing health data (Kumar et al., 2021). While the technical details of this are somewhat out of the scope of this thesis, AI developers should pursue creating tools to harmonize health data, as it would be of incredible value to existing data platforms.

Another challenge that is related to data quality is the variability of healthcare data in other areas than those from which the data has been collected. The diseases and comorbidities in Denmark may be very different from those in other countries. Similarly, there are likely significant discrepancies between the different regions in Denmark, which is an important consideration when deciding where AI models are applicable.

"*If there are systematic biases on gender, on age, on certain comorbidities like diabetes where the model performs unreasonably poorly, we'll usually as part of development, slice out a strong population and say "this model cannot be used on everyone, it can only be used on people within this age-range". We would probably not split on gender, that wouldn't be too fortunate, but we might be able to say if the patient has diabetes, the model is inaccurate, we don't recommend using it, use classical human judgement"* (Medtronic Consultant, 00:30:01)

This challenge should be addressed by AI developers to work with clinicians to carefully select which patient groups their AI models are representative of. While this may present an ethical consideration related to exclusion of certain demographics, it is a necessary step in accurately fitting models to provide value (Siwicki, 2019). An alternative way of solving this challenge is by utilizing *transfer learning* (TL). Transfer learning is the discipline of using the information from a pre-trained system to train new AI models provided by new data. This let's AI developers calibrate existing models, which is much quicker and simpler than starting from scratch (Mehrotra et al., 2020).

"*Using transfer learning, you can train it (AI model) on cheap data first, learn all kinds of basic things, and then we do what we call fine-tuning on the specialised expensive data. I think that has huge potential in healthcare, because fundamentally, healthcare is super expensive, and has been a huge constraint historically.*" (Medtronic Consultant, 00:21:11)

Transfer learning has immense potential in healthcare AI due to the limited data that exists on rare diseases. An application of TL in healthcare could be training an AI model to detect a common cancer like lung cancer, and then calibrating it with data from a rarer type like thyroid cancer, to create a new model that has practically been trained on more data than it is available regarding that specific disease. Transfer learning is a relatively new field in AI development, which presents some framing challenges if this technology is to be used in healthcare.

"*That is something holding it back a little bit, because people in healthcare dont really like it when they don't understand how things are working. It's not a complete showstopper, but it is uncomfortable that the model was training on cats and dogs, and now it works in humans and what's the protocol in that? And is that okay? We're working on that.*" (Medtronic Consultant, 21:55).

To build trust in these technologies, it is advisable for AI developers to justify to clinicians why these recommendations have been made. This returns to the complex task of creating explainable AI. Alternatively, AI developers should remain as transparent as possible by providing an audit trail that leads to the output of the AI. Insights from clinical notes that are used in the AI algorithms need to be traceable to the exact part of a document it references (Siwicki, 2019). This would enable clinical staff to more easily validate the findings and build confidence in the AI tools.

6.2.3. Encourage Adoption from Clinical Staff

Our results section revealed that even though artificial intelligence tools have reached a point where they are able to benchmark well against clinical staff in a test environment, they still rarely provide any differences in clinical setting (Ph.D. in NPL with Corti.ai, 00:37:30). There are several reasons for why AI developers see limited adoption from their tools. Denmark has a history of problematic digitization initiatives in healthcare, e.g., Watson Oncology and Sundhedsplatformen, both of which have received a tremendous amount of critique from clinical staff (Djursing, 2017 & Mazor, 2019). However, the most distinguished point from our interviews that limited adoption was lack of trust in systems due to low perceived value. Artificial intelligence has been hyped by the media for some time, which may have created problems in terms of clinicians' expectations towards AI's value.

"*I'm not sure that you're really managing expectations. And if you're a radiologist, you're probably getting the impression that we are trying to compete with that person's* *ability in ultimately the job. And I usually say, you know, that's not the case*." (Clinical AI Researcher / Professor, 00:07:34)

AI, in its current state, is not applicable in abstract physician related work, and is not about to replace clinical staff. The strength of AI is in supporting existing workflows with the goal of reducing administrative tasks that let physicians spend more time with patients. AI developers should focus on this aspect of value, as our research showed that this is where the clinical staff wants to see change. This framing of how the technology can assist clinicians should be part of the early stages of healthcare AI development. Our research showed that AI developers that spent a lot of time with clinicians in framing the value of their product, were generally met with enthusiastic medical staff regarding their products. No one knows the urgency of improving the workflows of clinical processes better than clinicians.

"*They embraced the idea of using AI. They thought it was fascinating and they were very positive towards this because they do as health professionals know that if they miss a cardiac arrest, the patient will die. And remain dead, so they know it's urgent*" (Ph.D. in NPL with Corti.ai, 00:17:58)

Becoming a licensed physician in Denmark is a long process and requires extensive education. While this provides a challenge of high baselines that AI must compete with, it also has the advantage of the clinical staff generally being comfortable with more complicated systems, and trusted research.

"*The plan is to develop quite a lot of research on top of this, and the doctors are super onboard with that. Once it's backed by peer-reviewed papers, they have a lot of confidence in it. The doctors are used to working with statistics and probabilities, so we find them to be actually surprisingly comfortable with it.*" (Medtronic Consultant, 00:10:02)

While the framing of AI is important in increasing adoption, the primary focus of attention should still be developing and calibrating these tools in a way that provides clinical value. Like humans, AI is not infallible and will sometimes make mistakes. However, due to the severe impact of making mistakes in healthcare, AI tools are often calibrated with a "better safe than sorry" mindset.

"*We had some more false positives than the human dispatchers had, but we had a 10 percent better recognition rate. And we accepted the false positives, as the consequence of not recognizing a cardiac arrest is so much more severe than the consequence of thinking something is a cardiac arrest when it is not.* "(Ph.D. in NPL with Corti.ai, 00:06:54)

While it is difficult to argue against this approach in healthcare, it presents severe challenges in adoption. Clinical staff generally have busy workflows, and if a tool they're supposed to utilize continuously produces false positives, they will be inclined to switch it off and go back to their normal workflows (Doctor/Researcher in AI in Radiology, Ph.D. in NPL with Corti.ai). To address this challenge, it is recommended that AI developers prioritize extensive onboarding processes to ensure that clinical staff are certain in how to use these tools. In the case of detecting cardiac arrest, the tool should not be used as a binary indicator to overrule the dispatchers' suspicion. Instead, it should be considered an opportunity for the dispatcher to reconsider their initial interpretation and restate the questions that could identify cardiac arrest (Ph.D. in NPL with Corti.ai, 00:31:35). An increased focus on onboarding could be the approach that bridges the gap between AI tools' performance in testing to its performance in randomized trials.

Designing and evaluating valuable healthcare IT is greatly dependent on interpreting the knowledge from which clinical staff decide to act. In order to apply this knowledge, it is important to give the end-users (clinical staff) an important role in the design process (Kushniruk & Nøhr, 2016). Involving end-users in the design phase is not a new concept, and there are several strategies for accomplishing this. Our research has shown that while clinical staff are interested in the capabilities of AI-powered value-based healthcare, they want to spend their time with patients. For this reason, we propose AI developers use a user-centered design approach throughout their projects. The approach involves classic usability testing, where clinicians should be observed while being asked to carry out tasks in a prototype environment. This allows developers to continuously identify problems and design opportunities, to refine the systems according to end-user requirements (ibid).

This approach has been proven effective in creating a substantial reduction in user problems from one iteration to the next. Literature regarding IT implementations in healthcare have shown that lack of user input has been the single biggest contributing factor in the failure of IT systems to be adopted by end-users (Kushniruk & Nøhr, 2016). The benefits of increased user involvement through design (particularly from participatory design) have included: 1) improved system quality as a result of better and more accurate user requirements gathering, 2) greater likelihood of inclusion of features users want, while avoiding addition during the design of costly features users do not perceive as valuable, 3) higher levels of user acceptance, 4) improved understanding of the final system by end-users leading to lessened training needs and fewer usage issues, and 5) a higher level of participation in decision making by users in the organization to which they belong (ibid). The complex nature and inexplicability of AI makes this approach crucial in driving AI-powered value-based healthcare.

6.2.4. Manage Limitations

In the results section of the thesis, we elaborated on some of the limitations that AI is currently facing in value-creation in healthcare. While our research showed that AI's progress is not necessarily limited by the advancement of the technology itself, the complex nature of the healthcare industry presents limitations that need to be managed properly, to implement AI in areas of healthcare that lead to impact. Areas in healthcare that require domain-specific knowledge or circumstances that are outside the AI models training set, must be clearly managed, as AI tools may be less applicable (Chen & Decary, 2019).

This creates an essential task for AI developers in identifying wherein the clinical workflows there is a problem that can be alleviated with AI. In line with the previous section, this should be done alongside clinical staff. There are currently very few applications in healthcare where AI can stand on its own. These processes are not what is traditionally considered healthcare workflows, but rather tasks like invoicing and data cleaning that are not directly correlated with patient value (Medtronic Consultant, 17:10). Where AI shines in its clinical applications is when it is working as a powerful tool and partners with clinical staff. The key in this human-machine partnership is to strike a balance between valuable care and the levels of automation AI offers.

The limitations of healthcare AI are important to address when building AI models. *Unsupervised learning* refers to a method of training AI algorithms, where the model discovers the structure of data itself and makes predictions based on input alone. Unsupervised learning in healthcare is effective at e.g., predicting disease risks using genetic biomarkers (Chen & Decary, 2019). However, due to the lack of human teaching, unsupervised learning is more prone to errors, as it may include trivial features from the data to make predictions. On the other hand, *supervised learning* uses data as input, as well as labelled outcomes determined by human actors. In this approach, the AI algorithm correlates the input with the labelled outcomes for making predictions (ibid).

In the supervised learning approach, the algorithm needs to know the conclusions it should come up with from a given training set, which will let it train itself to eventually be able to make predictions on data it has not seen before. Supervised learning is the most applied strategy in healthcare currently, as it is less black-boxed, less error-prone, and more explainable than unsupervised learning. Therefore, it is recommended that AI developers choose the supervised learning approach when training their models, which also has the benefit of including clinical staff early in the design process.

While these algorithms have been shown to be very effective in testing environments, our research revealed that this is not proof of their value in clinical processes. As mentioned previously, effective AI is reliant on massive amounts of data to identify patterns to a sufficient degree and may not always be the answer.

"*It sounds like I'm shooting myself in the foot, but you know, unless you have a really sizable dataset, I would say you should probably go for something simpler than artificial intelligence, at least in the sense of a deep neural network, because they are sort of brittle and they are so full of parameters. And when they don't work, it's difficult to debug them"* (Clinical AI Researcher / Professor, 00:23:37).

AI tools provide amazing potential, but there are other methods, like logistic regression, that may be able to solve some of the tasks where AI is being pushed. It is important to be honest about the limitations of AI in where it doesn't work, as well as where it is not necessary. Previous technologies have come and gone in the Danish healthcare industry, and few of them have lived up to the hype, which could present problems if it results in wrong applications and lack of testing (Physician/Researcher at Aarhus University, 00:25:30).

6.3. Incentivizing Stakeholders

Throughout this thesis, we have highlighted the importance of promoting collaboration in AI projects in healthcare. The previous section specifically discussed how to encourage the clinical staff, who will be the end-users of most of the technologies. This section highlights the importance of incentivizing other stakeholders, in order to create valuable partnerships to increase the success rate of AI-powered digitization efforts in Danish healthcare.

The Medtronic case that was highlighted in the results section showed the benefits in working with AI developers as a valued partner, instead of a siloed supplier. There is very little overlap between the competencies of an AI developer and a clinician, therefore, there needs to be a clear channel for communication throughout the development of the technologies. Medtronic's approach to incentivizing stakeholders like hospital administration, is by their shared accountability business model. In the case of Rigshospitalet, Medtronic and the Danish hospital are co-sponsoring the project, with Rigshospitalet providing offices and half of the salary of the Medtronic consultants. While the intellectual property of the AI tools belongs 100% to Medtronic, the incentive for Rigshospitalet is that they will receive free licenses of any products that are developed (Medtronic Consultant). Furthermore, as the AI tools are being trained within the walls of Rigshospitalet using their data, the likelihood of them being valuable to them increases.

The healthcare industry is very dependent on continuous research, with funding being provided from both the government and funds (RegionH, 2021). AI developers should strive to contribute to healthcare research through their projects, to ensure that some value is being provided, even if their specific AI tools cannot be used.

"*If I were to recommend something to anyone, I would say go to the hospital, propose the partnership and then ask for one of the more recent slices of research data (...) Sit with that data with some doctors (...) Start to get some ideas and get prototypes rolling early. That has worked tremendously well. (...) I think that path is helpful. And it's a little bit unique in healthcare because you can leverage the research side of things*." (Medtronic Consultant, 00:26:10).

AI developers must demonstrate how their products and services help healthcare providers deliver improved patient outcomes. They must be transparent in their dependency on the healthcare data that the providers possess, as well as accepting a level of accountability for the outcomes.

"*You also can, from a regulatory point of view, demonstrate that you have devised a safe and effective equipment that has a place in the clinical workflow. First of all, we want to make intelligent products and products that we can sell, but also from a regulatory and the expectation management point of view."* (Clinical AI Researcher / Professor, 00:15:37)

On the regulatory side of things, there is currently a disconnect between who is benefitting from the technologies (clinical staff practically and AI developers financially), and who takes the blame for e.g., data breaches (data controllers). This discrepancy discourages important stakeholders and should be addressed (Medtronic Consultant, 15:58). To facilitate value-based negotiations, Ernst & Young (EY) has created a platform for managing outcome-based contracts with payers. The Health Outcome Platform (HOP) includes a catalogue of outcomes, health effects, cost of care, etc. to allow the negotiating parties to set realistic joint targets and implement appropriate incentives and penalties (Katz, 2020). To incentivize active collaboration from stakeholders, we recommend that AI developers use a framework like HOP that is adapted to the Danish context. Outcome-based contracts with clear guidelines on e.g., data sharing that is compliant with GDPR can help unite developers and regulatory bodies in co-creating value-based healthcare through artificial intelligence.

While this thesis is based around the Danish healthcare system, it should be noted that due to hospitals in Denmark being subsidized by the government and the strict regulations of GDPR, AI developers may have an easier time co-creating value in e.g., the American healthcare system. Many hospitals in the US are private with more lenient data privacy regulations, meaning that there is a greater financial incentive for American hospitals that can be leveraged to enter collaborations with developers.

6.4. A Value-based Design Approach to Healthcare AI

The analysis of our primary data and existing literature review clearly indicates that the application and adoption of AI in Denmark in the clinical practice is still in a nascent stage. This offers multiple opportunities to enhance AI's maturity in building a value-based healthcare system. It must be noted that a mature AI system should not replace the important elements of the human interaction in medicine, but rather focus on improving the efficiency and effectiveness of that interaction (Bajwa et al., 2021). In this section, we present an approach to implement AI-powered value-based healthcare tools primarily using our *modified implementation matrix* (**Figure 5**). Additionally, we have incorporated aspects of the *CRISP-DM methodology* (**Figure 2)** in the data understanding process and model evaluation.

The first step in AI implementations involve a human-centered approach, which begins with mobilizing the *internal forces.* This includes stakeholder identification, mapping and assigning the correct mix of resources and competencies. This is done to create a multidisciplinary team involving computer scientists, operational and research leaders, clinical stakeholders and relevant subject experts (Bajwa et al., 2021). Following the steps prescribed in CRISP-DM methodology for business understanding, the team should conduct a series of process mapping workshops to assess in which areas AI can create value and how the tools should function.

"We work a lot with physicians. We do include them. So as you develop medical software, you have before you actually start working on a product, you have to have a user requirement specification to actually have to go to the end-users and say, we're going to build this thing and we would like you to specify with some requirements

what are the elements of the requirements for a successful product?" (Clinical AI Researcher / Professor, 00:15:37)

The team should quantify the current IT infrastructure, existing organizational inefficiencies using the bottom-up approach to identify the gaps in the existing operating model to define the problem, goals, success metrics and intermediate milestones (Bajwa et al., 2021).

"It's a four-step process, the first step is you start interviewing all the business users to identify the problem statements. And then once you have the problem statement, you start generating ideas. Once you have the ideas, then, you choose the best idea that fits well with all the discussions and interviews that we have. And translate that into a proof of concept. So, this process will actually help you to make sure that this whole designing process is going smoothly." (Compliance and Technical Expert, 00:25:19)

After defining key problems, it becomes vital to incorporate *scorecards* that can help measure and communicate short and long-term goals, set performance indicators, define cost-efficiency indicators, evaluate hospital responses to physician needs and track process improvement efforts (Hemamalini, 2014). Different scorecards should be created for different stakeholder groups, to ensure that each stakeholders' role can be measured and iteratively enhanced.

The next step is to design a comprehensive solution to improve health outcomes using AI. This should be done by first identifying which problems are appropriate for AI to address, and whether there is access and availability of applicable datasets. This is followed by building a healthy and sustainable *data platform* which is a key source for any AI tool. Many AI implementation initiatives fail due to the "garbage in, garbage out" principle, so it is critical for Danish hospitals to build a foundation of high-quality and standardized data that can be scaled and adjusted over time (Intellishore, 2019).

A healthy and sustainable data platform can be achieved by following the data protocols that have been addressed in the discussion section related to **6.2.1.**. Once the data platform has been built, the next step is to identify and select useful data sources in collaboration with physicians that align with the project goals. This is an important phase under the *CRISP-DM methodology* which includes selecting an initial dataset, verifying the data quality and selecting the final dataset for the analysis. This is followed by a data cleaning process, where the desired dataset is cleaned and transformed for data modelling. A statistical analysis of the datasets that includes the participation of physicians is necessary, as it is important to understand which data needs cleaning and the problems that are present in the datasets (Villamil, 2011). The results are evaluated, and if required, further data reprocessing is performed.

The availability of structured data paves way for the data mining process, where the data mining tools and techniques are used to identify the main characteristics of the data and discover interesting patterns. These patterns are then used for identifying significant connections and correlations between medical treatment and patient outcomes across patient populations (Wehrstein, 2020). Further, a relevant data modeling technique is applied to the datasets and the created model is assessed against the specific requirements.

"As I said, to make A.I. robust enough, you need lots of data. You have to make sure that your algorithm is capable enough. When I say capable, it's very layman's term. In technical terms, we call it the capacity of your network, right? You have to improve the algorithms by fine-tuning the hyperparameters and dropping technical stuff". (Data Scientist, 00:46:10)

The performance of the AI tool should be assessed at every stage from development to implementation. It begins with a pilot testing of experiments while developing the AI tools, using tight feedback loops from stakeholders, like clinicians and medical experts, to facilitate rapid experiential learning to allow for incremental changes (Bajwa et al., 2021). The feedback loop can further be strengthened through partnerships among other hospitals in Denmark during the pilot testing stage. Such partnerships can help in attaining new insights and trying out new ideas for adding value to the patient outcomes. Experimentation and feedback will help to elucidate the purpose and intended uses of the AI system and identify the potential risks and ethical implications that the AI tools present to the end-users (Bajwa et al., 2021).

"I'm worried that something that works really well in a research environment is going to work really badly in a clinical environment. So for correct implementation, I think even before the software is going to be implemented, the users should be educated in how to be critical about software tools and the results of precision of a software tool or clinical tool." (Physician/Researcher at Aarhus University 00:23:30)

Benchmarking is a critical and continuous process, where the evaluation is based on three dimensions: statistical validity, clinical utility and economic utility (Bajwa et al., 2021). Validation addresses the modeling accuracy of a computational simulation by comparing the computational results with experimental data (Bajwa et al., 2021).

"It's really important to monitor your models when they're sort of in production and when you're using them. We find that for the most dynamic cases, sometimes we end up retraining models on a weekly basis, which most people don't expect." (Physician & AI Specialist, 00:41:24)

Statistical validation are important measures that should be incorporated to evaluate and analyze a model's performance post-training. Model results are iteratively compared against initial validation and tested for satisfactory performance. Such performance indicators assess the AI tool on metrics of accuracy, reliability, and robustness (Bajwa et al., 2021).

The clinical utility requires evaluation of its impact on patient outcomes, also referred to as useability assessments. In this process, the AI tools are evaluated in a real-time environment to make assessment of whether a technology affects treatment outcomes and demonstrate the clinical effectiveness, risks and perceived value in clinical decision making. Further, it is important to also include ethical and social implications of AI in the evaluation stage, to determine if the tools discriminate against certain patient groups, and potentially remove these groups from the AI algorithm (Medtronic Consultant, 00:30:31). Lastly, economic utility includes a cost- benefit analysis of the AI tool, to determine if the tools provide sufficient value in their applications.

After an AI system has been deployed clinically, the AI developers must continually monitor and maintain it, by continuously benchmarking it against traditional processes, to ensure that potential data skews do not disrupt its applicability. This helps the developers in evaluating the outcomes of medical devices that have been placed on the market, and to identify the need for adjustments (World Health Organization, 2021).

"It's a new requirement of the (AI Developers), to conduct post-market surveillance requirements and it is mostly about the safety of AI devices. I believe we're implementing that and of course, we survey the market and we have support where we record every issue with the device is documented . So we get a lot of feedback from the market, in terms of the device performance, we are, of course, trying to continuously improve." (AI Specialist at Cortrium, 00:18:45)

In addition, AI developers should use data benchmarking to measure the data quality and address any gaps that are identified. This is particularly important when new data sets or categories are introduced in AI modelling. AI developers must consult clinical staff in this type of benchmarking, as their knowledge regarding moves in public health is crucial in understanding how data changes may affect the algorithms.

The Danish health organizations should also conduct benchmarking activities, specifically strategic and internal benchmarking. Strategic benchmarking is used to compare the performance of AI tools with other healthcare organizations across different demographics. This approach will help in identifying the strengths and weaknesses of AI tools implemented by other healthcare organizations, to help iteratively improve all these tools.

"You could run two separate projects with two sets of researchers that don't talk to each other, and they both train different models, ideally different styles of models. One can be a deep learning model, and one could be a gradient boosting model, and they train them on their own data with different features. And then maybe you ensemble the results, or at least you test what it would be like to basically have a voting scheme? The two models vote on the right decision as equal partners." (AI specialist and Physician, 00:37:57)

Internal benchmarking is key to understanding the effectiveness of AI tools in meeting the internally defined outcomes, especially by comparing the effectiveness of processes before AI was implemented. Danish hospitals should conduct internal benchmarking by establishing a multidisciplinary team to discuss possible drivers of observed variations in AI outcomes and evaluate the cause for differences. These differences could be caused by data collection biases, patient mix or treatment choices, and clinical staff should be involved in identifying these health-related problems.

"Risk assessment is kind of a critical part in the process. Make sure we have a kind of sufficiently tested and validated system. As long as you don't do the risk assessment, you won't be able to identify the areas of risk which you might have overlooked." (Compliance and Technical Expert, 00:21:33)

The clinical staff, who are the end-users, should set benchmarks to compare the progress they have made with AI against their progress without using the AI, as this helps to determine the value realized from AI deployment.

Securing adequate *investments* is one of the key factors to transform and shape the future of AI in healthcare, as AI implementations require substantial time and development efforts. Consequently, it is important for the Danish government to arrange adequate funding for the planned AI projects linked to healthcare. It should be clearly communicated to the public and private sectors which AI projects are planned for execution, how much funding is available, and how to participate in the projects.

The government must also explore different options for sourcing funds, either internally through state budget allocations, or externally through alternative methods. While internal funding through state budget allocation is normally cheaper (Funding an Innovative Future with AI in Healthcare, n.d.), the allocation process could take longer, as the state budget involves taxpayers' money, which requires multiple levels of approval. The size of allocation will also depend on the funding required for other public welfare priorities, e.g., related to infrastructure, public education, sustainability etc. The Danish Government should prioritize AI-based projects in healthcare equally with other projects, with clear justification for securing adequate budget allocation in time.

The Danish government can also explore external sources for funding the AI projects in healthcare. One of the possible solutions would be private investments in the form of Venture Capital (VC) financing. VC is a type of financing that private investors provide to startup companies or projects that are believed to have long term growth potential. VC financing generally comes from well-off investors, investment banks, financial institutions and any other corporate houses, with a clear expectation of generating a return on investments (Funding an Innovative Future with AI in Healthcare, n.d.).

Increasing private investments in the form of VC funding for AI in healthcare can potentially help in scaling the technology. While VC funding for innovative AI solutions in healthcare has risen steadily in recent years, Europe remains behind other regions such as the US and Asia (ibid). One of the challenges in securing VC funding in healthcare is demonstrating the value of such solutions and its potential to generate an acceptable return on investment. The Danish government should therefore collaborate with AI developers to demonstrate the value of AI through use cases of AI deployed in healthcare across the globe. While we recommend that the government prioritizes collaborations like the one between Rigshospitalet and Medtronic through creating co-funded joint-responsibility programs, VC funding may be able to assist in bridging the current funding gap.

"A compelling private technology that was developed using VC funding then applies to multiple industries, which happens to be easily used in the Danish context." (AI Specialist & Physician 00:17:13)

Investments in AI for healthcare is not limited to the development of AI tools. Investments are also needed in creating an ecosystem of innovation wherein the benefits of AI can best be realized. Hence, the *external collaborators* must ensure that there is adequate investment, not only in infrastructure to support the digitization of the healthcare system, but also in education and training to enable clinical staff to use AI in their practice. Medical professionals need to be adequately trained in AI technology, to improve the quality of care, while outlining the shortfalls such as transparency and liability, to promote a seamless integration of AI with current IT systems. Furthermore, the government should strive to build and maintain a balanced regulatory environment, based on existing applicable regulations, that enables and stimulates future technological innovation.

Incentives are the form of rewards that can be used to motivate and encourage stakeholders to use AI to improve their workflows. To accelerate AI adoption across the Danish healthcare system, clinical staff should be given incentives to substitute some clinical tasks with artificial intelligence. These incentives should be centered around patient value, as our research showed that clinical staffs' motivation to utilize new tools are dependent on the patient value they can generate. A successful AI deployment can help in mitigating the problems causes by a shortage of doctors and frontline workers, by handling a large capacity of tasks that are well suited for automation, to aid in the proper allocation of resources (Kelly et al., 2019).

"*We also like trying to discover an efficient way of doing this preliminary work, like collecting this database, which I'm talking about. It's actually quite tedious work because you have to have experts looking at images which are already, you know, described in the clinic by a radiologist. But you need to do it perfectly, and you need to do it again. And it is obviously time consuming and we don't have that many radiologists and it is very expensive.*" (Doctor/Researcher in AI in Radiology, 00:03:40)

Clinical staff can also be incentivized to adopt AI as it can streamline their processes by embedding them seamlessly into the clinical workflows, to support clinical decision-making at the point of care.

Machine learning algorithms when applied in the administrative process, can incentivize the physicians by easing their administrative burden. ML can be used to streamline appointments, thereby improving the quality of care and productivity of the doctor by allowing them to spend more time with patients (Medtronic Consultant, 00:17:22; Physician/Researcher at Aarhus University, 00:04:30).

Health organizations' collaboration with AI developers is key in building their AI capabilities and incentivizing the adoption of AI technology in healthcare. Danish healthcare organizations should make use of partnering approaches like hiring external talent, building capabilities in-house, licensing capabilities from technology firms, and partnering with other educational institutions (Chen & Decary, 2019).

Developing strong partnerships with several *external collaborators* like AI companies can be of mutual benefit. Such collaborations can improve the effectiveness, access, and affordability of AI-related healthcare services. In order to ensure partnering, AI developers should increase the exchange of information and the degree of interaction between healthcare providers to develop AI tools that meet clinicians' needs. In this way, the AI developers can instill trust in their products and services. Further, the AI developers should provide perpetual support to the IT departments of the healthcare organization, to ensure that AI technology is integrated effectively and seamlessly. AI developers can collaborate and increase their engagement with healthcare providers by delivering adequate education and training about the AI tool, which increases the likelihood of clinical adoption.

"And we made this collaboration with Corti, where Corti said we wish to provide all the technical support and solutions and legwork in making the AI tool and then Copenhagen emergency medical services said we will do the research and documentation and deliver all the data needed for the models." (Ph.D. in NPL with Corti.ai, 00:04:41)

Other healthcare organizations in Denmark should take inspiration from existing AI projects, and initiate collaboration with startups to initiate the deployment of AI tools based on clinical needs and requirements. For example, Radiobotics has in collaboration with clinical staff developed an AI-based diagnostics tool for the quick and effective analysis of X-ray images (EIT Health, 2020; Ph.D. in Electronic Health Record, 00:18:47).

AI companies should be transparent with healthcare organisations about the data sources that have been used in developing the AI tool, and how the patients' data is being handled. Complying with these regulatory requirements and building trust can increase the AI adoption rate and bridge the gap between government and developers that was identified in our research.

"We get all the data from the patients and that's how we can collect the data because as part of our quality control, we have to have people looking at it with all the GDPR

requirements and everything, all of the formalities and also encryption, et cetera, et cetera, in place." (AI Specialist at Cortrium, 00:09:40)

Further, the AI companies should demonstrate the logic behind the AI solutions that are being used and how the AI tools come up with logical conclusions. This is an important step towards incorporating explainable AI, which can instill trust and confidence in clinical staff when implementing the recommendations of an AI algorithm during clinical decision-making.

"And that is something holding it back a little bit, because people in healthcare dont really like it when they don't understand how things are working. It's not a complete showstopper, but it is uncomfortable that the model was training on cats and dogs, and now it works in humans and what's the protocol in that? And is that okay?" (Medtronic Consultant, 00:21:11)

Below we present a version of the implementation matrix (Katz, 2020), that has been modified to center around AI-powered value-based healthcare (**Figure 5)**. This model provides an overview of some of the most important insights from our research and can be used by AI developers in future healthcare implementations in Denmark.

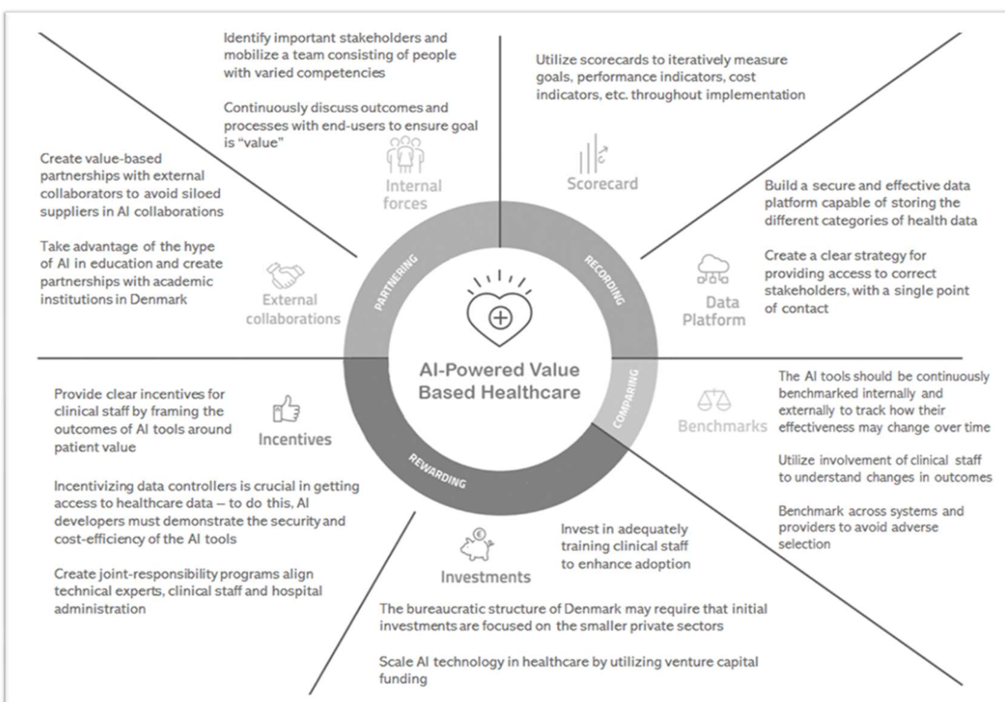


Figure 5: AI-Powered Value Based Healthcare Implementation Matrix

The Matrix represents the most important recommendations in creating a *value-based AI implementation approach*. Where existing literature focuses on either the technological component of artificial intelligence or the value-based approach to digital transformation, this model attempts to combine these two areas by providing insights into how AI can be used in value-based healthcare. The model only contains the most important recommendations from our data collection and is not exhaustive of the challenges that should be addressed. However, it can function as a starting point for AI developers, to help them create a framework for AI deployments in the Danish healthcare system.

While we present an order to address the building blocks of the implementation matrix (**Figure 5)** moving clockwise from "Internal Forces", there is no set methodological order in how to use the matrix. All seven building blocks are crucial in succeeding in AI-powered value-based healthcare. While the building blocks are separate, there are causal relationships between each of them. *Benchmarking* is dependent on the availability of *internal forces*, *investments* typically come from *external collaborators*, and having a structured *data platform* is of course instrumental in being able to create any AI algorithms. Therefore, the building blocks of this model are not mutually exclusive, but co-dependent.

The model is limited by the fact that the data collection for this thesis only took place in Denmark. This results in some of these recommendations being less applicable in other countries, where government regulations and payment structures for hospital services are different. Additionally, our Matrix stands out significantly from other literature related to value-based healthcare, due to our predominant focus on the two groups: clinical staff and technical experts. Value-based healthcare is all about patient outcomes, however, due to the currently very limited application of AI in Danish healthcare, it is basically impossible to measure patient outcomes related to AI. We suggest that using the implementation matrix to create AI implementations that support clinical staff and improve their workflows will inevitably lead to increased patient value. However, we do acknowledge that this approach is not traditional in value-based healthcare.

6.5. Practical Implications

This section examines some of the policy implications that need to be considered within the Danish policy framework, to promote faster adoption of AI in Denmark.

The existing regulatory landscape in Denmark restricts sharing of healthcare data without the valid consent of the data subjects, which introduces significant challenges in accessing patients' data for developing healthcare AI tools. Further, the strict EU legal requirements that are relevant for data access and ownership, the General Data Protection Regulation (GDPR), do not facilitate easy data sharing and access. Most of the AI applications are dependent on enormous volumes of data to learn and make intelligent decisions, hence, the existing challenges with data access, especially in Europe, slows the development and adoption of AI.

"*It is challenging to start up any collaboration with the public sector. And right now, there's quite a big debate about how it's countering innovation, that there's so much overhead in terms of GDPR and legal requirements. And I can testify that that's true and really annoying, that it is not simple at all, and it takes a long time.*" (AI Specialist at Cortrium: 00:10:52)

To accelerate the research and development of AI in healthcare, the Danish regulatory authorities should evolve and support the provision of data through coherent incentive mechanisms and sustainable business models, while acknowledging the sensitivity of data.

The regulatory authorities should provide clear mandates on how healthcare data can be accessed and used for AI development. The mandate should also adequately address the questions on whether the mandate is applicable to Danish start-ups, small and medium-sized enterprises, and/or large multinational companies, whether it is acceptable to pay for data, and how the compliance with the mandate is monitored (ConnectedHealthInitiative, n.d.).

In addition to addressing data access challenges, the Danish authorities should also encourage the participation of private and nonprofit sectors in the development of AI, mainly to build diverse expertise and knowledge base. This could be done by providing incentives in the form of taxation benefits, subsidies on investment in AI in research and development, training sponsorships etc (ConnectedHealthInitiative, n.d.)

Another important element in the AI lifecycle is the AI performance management. Danish authorities should consider defining minimum requirements to ensure that the AI tools are performing at acceptable standards and providing anticipated benefits. The regulatory bodies like the EU Medical Device Authorities (EMDA) provide guidelines for AI developers in measuring and assessing how good the performance of AI devices needs to be, in addition to post-market surveillance requirements. This could be an inspiration for Denmark to develop a minimum performance standard for AI.

"*It's mainly that's the regulatory requirement to provide performance results, but there is no requirement on how good the performance needs to be.*"(AI Specialist at Cortrium: 00:18:11)

The regulatory framework should address liability concerns related to who is liable when AI tools make mistakes despite being used as per the standard operating instructions. In the current healthcare set up, there are no clear guidelines for assigning responsibility and accountability for AI performance issues.

As we are recommending that AI in its current state should only support clinical staff, rather than replace them, it is hard to argue that the responsibility changes from its current set up, where clinical staff are held responsible for patient outcomes. The governing body should also create structured and simple incident reporting procedures, to report an adverse event caused by anomalies in an AI tool used in clinical decisions.

The government should encourage the creation of an operating model that encourages positive collaboration and dialogue between clinical staff, AI developers, and other healthcare stakeholders with the objective to have all perspectives reflected in AI solutions.

The authorities should also work towards addressing the general public perception of AI taking over humans and their decision-making (ConnectedHealthInitiative, n.d.).

They should categorically highlight, through effective communication channels, that the purpose of AI is to equip and support humans in their decision making, rather than replacing them.

Another practical implication in the Danish healthcare system is the scattered choice of suppliers in different regions. This thesis collects data primarily from Region Zealand, where the company "Epic" has been chosen to develop the electronic health record "Sundhedsplatformen". However, this EHR is not used in other regions of Denmark, with "Systematic" having been chosen as the provider of an EHR for Region North, the Central Region and the Region of Southern Denmark (Healthcare Denmark, 2021).

This means that all of Jutland is using an entirely different EHR system than Region Zealand, which presents communication challenges between these EHRs. The Danish government should strive towards more effectively aligning the whole country on which systems are being used, rather than focusing on individual regions. As Systematic now occupies three out of five regions in Denmark, it is perhaps time to reconsider the use of "Sundhedsplatformen" in Region Zealand.

Transparency is key to building trust among clinicians and patients for faster adoption of AI. This is only possible if there is adequate access to datasets and algorithms used by AI developers from which outcomes are derived. The authorities should make transparency a key requirement in the AI deployment cycle and introduce regular audits of AI datasets used for clinical decisions. This step will not only mitigate demographic bias but also encourages inclusion and diversity.

Finally, the regulatory authorities should introduce programs that support training and education of medical students in AI technology, especially in their early years of medical education. To increase awareness as well as highlight the importance of AI in medical education (Imran. N et al.,2020). These programs should emphasize on teaching students the value of these tools, to ensure that they understand why these tools should be applied.

6.6. Ethical Considerations

As the foundation of AI is based on the collection and analysis of a large amount of data, including sensitive data, it is crucial that clinical staff and patients have confidence in the health system to store their health data securely. The regulations of the GDPR enforces that any individual's right to data privacy must be respected and data should be accessed only when it is required for diagnosis and treatment (GDPR.eu, 2021).

Healthcare AI comes with its own unconventional ethical challenges that must be identified and mitigated, especially considering AI's capability to interfere with patients' safety and privacy (Rigby, 2019). This section will outline some of the primary ethical challenges of AI discovered in our research, namely, 1) Safety and transparency, 2) Data privacy, 3) Reduced human contact, 4) Lack of trust, 5) Algorithmic fairness and biases, and 6) Over-reliance on AI.

6.6.1. Safety and Transparency

Patients' safety is one of the key ethical concerns of using AI tools in healthcare, especially if the systems interact directly with the physical world (Stahl, 2021). For example, if an AI tool fails to notice a malignant tumor on a radiological scan, or a hospital bed is allocated to the wrong patient. These are cases where an AI algorithm makes wrong calculations leading to "unsafe" recommendations and thus risking and compromising patients' health. This creates concerns regarding the reliability and transparency of calculations made by AI.

"Who is going to take the responsibility, suppose a patient is having high blood pressure or he's having high blood sugar. He feeds that data into that AI software, whatever it is, and then the AI software says, OK, you're fine to the patent, actually, the patient is not fine." (Pathologist, Physician at Rigshospitalet 00:10:49)

Any AI tool that can make health-related diagnoses and recommendations should be developed in close collaboration with the specialized clinical staff, using the parameters provided by them based on their experience and expertise in their field. For example, urologists should be involved in all stages of the development of an AI tool used for kidney-related clinical decisions. This will not only reduce the incorrect inputs of data into an AI tool, but also improve the accuracy of recommendations made by AI as these will be based on the parameters provided by the experts. Further, an AI tool should be considered only as a decision-supporting tool rather than a decision-making tool. In other words, health specialists should review and validate the AI output before giving any diagnosis or treatment recommendations. So, in effect, health specialists should be the gatekeepers for clinical decision-making protocols.

"The issue becomes that there is always a human actor on the other end that creates the algorithms that the system is run by. If you consider that the algorithm makes a small mistake which is potentially increased exponentially, it can have affect a lot of patients" (Head of Burn Unit at Rigshospitalet, 00:05:53)

Finally, according to Denmark's six principles for artificial intelligence (Ministry of Business and Financial Affairs, 2019), it should be possible to place the responsibility of mistakes from AI on a human being. This includes clinical staff, developers, users, authorities, etc. However, there are no clear guidelines for when the different actors should be held responsible, which must be addressed.

6.6.2. Data Privacy

It is crucial that patients have confidence in the Danish healthcare system to store their health data and information securely. Sensitive data should only be accessible when it is required for diagnosis and treatment and must consider the patient's intention of sharing their private health data. However, the adoption of AI into the Danish healthcare system has magnified AI's ability to use personal information in ways that can intrude on privacy, by raising the analysis of personal information to new levels of power and speed (Kerry, 2020).

"We have to protect it very carefully because there's just so much data on each of us that we can use for statistical purposes, but we can't link anything up that's person-specific" (AI Specialist & Physician, 00:23:24)

To overcome the data privacy challenges arising from AI, the development and use of AI technology must be within the relevant legislative framework. Hence it is important for Denmark to put the legal framework of EU's General Data Protection Regulation 2016/679 (GDPR) to prevent wrongful use of healthcare data. Further, Denmark should come up with a strategy that not only aims to maintain and reinforce the security of personal health data, but also ensures a safe and secure exchange of relevant data across health sectors.

Information Commissioner Elizabeth Denham correctly points out that "the price of innovation does not need to be the erosion of fundamental privacy rights". This clearly highlights that the use of advanced technology must comply with fundamental human privacy rights (Gerke et al, 2020).

"A process with the participants who are going to join these clinical trials where they have procedures to get consent from those participants. But this data is kind of the responsibility of those organizations, who are kind of processing that data and storing that data for any medical use." (Compliance and Technical Expert, 00:14:00)

The provisions of GDPR that are especially relevant to AI-based healthcare, where personal data is collected, is the controllers' responsibility to provide data subjects with *information* about "the existence of automated decision-making, including profiling, referred to in Article 22(1) and (4) and, at least in those cases, where meaningful information about the logic involved, as well as the significance and the predicted consequences of processing on behalf for the data subject" [Arts. 13(2)(f), 14(2)(g) of the GDPR] (Gerke et al, 2020).

According to Sundhedsjournalen (The Danish Health Journal), in order to increase greater interaction between the patient and healthcare system, it becomes a requisite to get patients involved as active partners in the process. Patients must be provided with a complete digital overview of their registered personal health data. Further, Denmark aims for patients to be able to see their complete patient pathway from diagnosis to treatment journey (ibid). This means that it is very important to consider patients when designing these tools.

6.6.3. Reduced Human Contact

While some patients consider face-to-face interactions with the health system crucial for their treatment, there are others who are very self-reliant and have the resources to handle more digital interaction with the health system. Recent research indicates that a large portion of patients are reluctant to use healthcare provided by medical artificial intelligence, even when it outperforms human doctors. Patients believe that their medical needs are unique and cannot be adequately addressed by algorithms (Longoni et al, 2019).

"I mean, people are not happy with that transition because they want a human doctor involved in anything that has to do with medicine." (AI Specialist and Physician, 00:30:00)

Healthcare providers can address the patients' reluctance to AI by increasing the perceived personalization of the overall care. The Danish healthcare system should strategize the use of AI tools to create a unique profile for every patient, including their lifestyle, family history, genetic profiles and details about their environment, and provide personalized advice based on their unique profile.

6.6.4. Lack of Trust

Clinical staff and patients are concerned over the 'black box' nature of the AI systems, due to the threat of algorithmic bias (Hatherley, 2020). The advancement of medical AI has displaced the roles of human clinicians, but the lack of visibility on AI's data modelling and deduction process could lead to the displacement of patients' trust in AI systems, especially when these systems are entrusted to make critical diagnostic decisions.

"It's really an ethical problem. Well, is the patient comfortable and is the doctor comfortable with trusting an AI in the decision-making process? And doctors are deeply split on how AI should be trusted." (AI Specialist and Physician, 00:26:27)

The Danish society is based on trust and is generally positive towards digital and new technological developments. However, the rapid development may make some feel insecure about the future due to the uncertain behavior of knowledge-based systems such as AI. Therefore, it is very important to create a healthy relationship in human-AI collaboration through extensive involvement of Danish health specialists in the development of AI tools. and educating patients regarding where AI is applied. Also, the Danish government should attempt to make the entire society feel secure and confident, by assuring those digital advancements, including the use of AI, will be centered on Danish shared values of freedom, liberty, security and equality (Ministry of Finance & Ministry of Industry, Business and Financial Affairs, 2019).

6.6.5. Algorithmic Fairness and Biases

Algorithmic bias occurs when the AI algorithms make repeatable errors that are less favorable to certain individuals and create unfair outcomes, such as privileging one arbitrary group over others (Lee et al., 2019). Data-driven algorithms are widely used to make or assist decisions in sensitive domains like healthcare. These biases can emerge from unrepresentative or incomplete training datasets, or the reliance on flawed information that reflects historical inequalities (Lee et al., 2019). If unaddressed, these biased algorithms can lead to decisions that can have a collective, disparate impact on certain groups of people, even without the developers' intention to discriminate.

"AI tools, even though they claim to be prospectively tested, and the type of development are very sustainable and can very easily have a huge burden of selection bias so that the data is selected for a certain situation and tested in the same type of situation. But then when it's implemented, it's used in a different situation so that you can get a high precision because you're testing and selecting the data with a low degree of diversity." (Physician/Researcher at Aarhus University, 00:14:32)

In an ideal world, AI should be free of selection biases, which means that AI should not cater to a particular dataset, but rather a broader set of diverse data points and attributes. This will reduce the risk of selection biases so that the data sample reflects the realities of the environment in which a model will run. For example, when using natural language processing to help emergency dispatchers detect cardiac arrest, people with rarer accents were discriminated against, as the NPL tool had a harder time understanding what they were saying.

"Non-native Danes were partially discriminated against by machine, but that was because the language models did not fully understand what was being said. And so we could see we had problems discriminating against some groups in society. But that was not a problem which had been created, it was a problem which was a result of a too small training dataset." (Ph.D. in NPL with Corti.ai, 00:45:03)

AI models and its outcomes should be subjected to rigorous testing and validation to eliminate errors arising from any kinds of anomalies in algorithms and the data selection. Some biases may be impossible to erase, which may necessitate the AI developers to acknowledge that some AI tools only work on specific patient groups (Medtronic Consultant, 00:30:01).

"If they're not properly tested it can have dire consequences for their patients and also actually for the future of this technology when it gets implemented too fast with no or low degree of testing of patient safety after a certain tool, then we can have a huge problem, something like a public fear of AI" (Physician/Researcher at Aarhus University, 00:20:28)

Algorithms used in machine learning systems and artificial intelligence (AI) are only as good as the data used for their development. High-quality data is essential for high-quality algorithms, as the data quality drives the outcomes produced by the ML algorithms (European Union Agency for Fundamental rights, 2019). Some of the key factors that contribute to low-quality data are algorithms trained with small datasets or the omission of data without knowing the implications of the outcome. Hence, it is vital for the users of AI-related technology to know where the data comes from and the potential shortcomings of the data. "AI systems based on incomplete or biased data can lead to inaccurate outcomes that infringe on peoples' fundamental rights, including discrimination" (European Union Agency for Fundamental rights, 2019).

"The quality of data will have a direct impact on the product quality and to the patients' safety, right? So let's imagine, if the labelling is going through the software that will generate the label that will go on the medicine bottle. If that information on

those labels is incorrect, then this will impact the patient." (Compliance and Technical Expert, 00:08:00)

The operators and other stakeholders must be diligent in proactively addressing these factors that contribute to bias (Lee et al., 2019). Addressing algorithmic biases early can potentially avert harmful impacts to users and liabilities against the clinical staff and developers (ibid).

It is an absolute requirement for Danish healthcare sectors to institute some form of scrutiny to assess the quality of the training data, to ensure the data represents diverse population groups, based on co-morbidities, race, gender, etc. Further, there should be an effective process to perform risk and impact assessments on the training data and then validate the data algorithms and their outcomes against these assessments (European Union Agency for Fundamental rights, 2019).

6.6.6 Over-reliance on AI

Humans have made great advancements in technology, which have simplified human life in a significant way. However, the technology boom also has created a sense of complacency and laziness among humans mainly due to overreliance on technology. An obvious example is the auto-spell check functionality in a word processing application. This functionality has reduced the need for humans to use their memory or learning capabilities for spelling but instead, they rely more on these applications to provide suggestions for the correct spelling. Similar is the case for AI where humans may begin to overly rely on AI and allow it to make decisions on their behalf. In the long term, this will certainly be a threat to AI in healthcare, as clinical staff may start accepting AI recommendations without critical analysis by humans.

"*It's basically that we start trusting the A.I. from its suggestions and we learn from it and we allow these loops to just continue without breaking the loop at some point.*" (Principal Director at Accenture, Denmark, 00:40:30)

Over-reliance on AI presents a threat in a clinical setting like diagnostic decision making, where over-reliance can be dangerous. In order to mitigate this, physicians should strike a correct balance between the reliance on AI advice and their own knowledge, professional experience and cognitive skills in the decision-making process. It is an accepted principle that trust is good, but controls are better (Gerke et al, 2020).

"Initially, we were talking, should it be some sort of speedometer showing what are the odds of a cardiac arrest call? But we thought it might not really be a good idea because cardiac arrest is very rare. It's less than one percent of the calls (...) So we feared that the dispatchers would be focused on the cardiac arrest speedometer on all the calls and may miss other important bits because ninety-nine per cent of the calls, which are not cardiac arrest, should not be focused on cardiac arrest. So we reported this and went for the very binary alert." (PhD in NPL with Corti.ai, 00:15:44)

AI can provide valuable leading indicators regarding diagnostics and thus helping physicians to take proactive actions on treatment. But these indicators could focus on identifying only a specific health ailment, which is a risk. Too much focus on a particular leading indicator will overshadow the other important indicators relating to other health issues. So, in effect, AI should not just solve one problem and create other multiple problems, but rather should be used judiciously and in a holistic way, with adequate human oversight.

"If we have built based on data as sort of a loop which promotes an unintended behaviour, then that unintended behaviour becomes stronger and stronger unless we find a way of breaking that loop. And I think that is where we have these ethical things and risks and so forth because at some point you will start making decisions based on what was supposed to be suggestions from what we take as the final truth." (Principal Director at Accenture, Denmark 00:57:26)

Over-reliance and lack of critical review of AI outcomes will lead to a behavior where these outcomes are accepted as the final truth and not just suggestions supporting the final decisions. In a worst-case scenario, these biases may be accepted as truths by the clinical staff, which creates a loop of "deskilling" of clinical staff (Meske et al, 2020).

6.7. Reflections

In this section, we reflect on some of the decisions we made during our research and in the development of the thesis, as well as some study limitations that should be addressed. Furthermore, we highlight some of the areas that were outside the scope of this paper but would be interesting to explore further in future research. We acknowledge that the conclusions in this thesis do not represent an end-to-end roadmap for AI-powered value-based healthcare, as we primarily directed our focus on the relationship between clinical staff and technical experts.

The primary data, i.e., our 20 semi-structured interviews lacked representation from some important stakeholders. Initially, we wanted a third interviewee group that would be referred to as the *governing body*. However, it proved to be very difficult to arrange these interviews, as people from this category were concerned with how their statements might be represented in the thesis. Therefore, our data from this group was collected from existing literature and statements from publicly available government websites. Additionally, as value-based healthcare is centered around patient outcomes, the thesis would have benefitted from more data directly from patients in how they perceived the value of AI technologies in healthcare.

Our approach to facilitating value-based healthcare was creating processes that principally benefited clinical staff and AI developers, with the expectation of these improvements translating to improved patient outcomes. While patients are the ultimate consumers of medical AI, little is known about their receptivity to the technology (Longoni et al., 2019). Further research in this area could provide valuable insights on the “real” end-users - patients.

In this thesis, we put a lot of emphasis on the importance of stakeholder involvement through methods such as participatory design. In a modern approach to participatory design, *all* important stakeholders should be included in the design process (Bjögvinsson et al., 2012). This means that the participatory design approach as presented by Blomberg et al. (1993) is too restrictive in the context of healthcare, as it only focuses on involving end-users. Involving the more abstract stakeholders, like the Danish government, will likely be a difficult task in the context of the bureaucratic structure of the government, especially considering the previous complications in digitizing the Danish healthcare sector.

One of the greater limitations of this thesis is the lack of successful AI projects to draw inspiration from. As of today, the AI projects that have been launched in Denmark have either not been able to perform on the level required for healthcare or failed to show value in clinical processes due to lack of adoption. This means that most recommendations that are proposed throughout this paper are not based on previously successful strategies, but rather on a collection of previous barriers and how to address them. There are hospitals, e.g., in the United States that have seen benefits from employing AI in healthcare, however, as the American system is vastly different from Danish, those learnings may not be applicable in Denmark and are therefore outside the scope of this thesis.

Finally, artificial intelligence and the general practice of delegating human tasks to machines may have societal implications that could limit its adoption. While outside the scope of this paper, it would be interesting to explore how AI in healthcare may generate value on a societal level in Denmark, and which forces may impact its potential. Furthermore, as this thesis is specifically concerned with healthcare AI in the Danish context, we do not analyze how AI could impact societies that are very different from Denmark. In a third-world setting, it may be interesting to examine how AI can help developing countries, or how it could potentially harm development by e.g., limiting the training of physicians if AI tools are available in their stead (Professor of Philosophy working with AI, 00:22:47).

7. Conclusion

In this thesis, the subject of implementing artificial intelligence tools to support value-based healthcare in Denmark has been treated. Denmark has had a history of problematic digitization efforts, with electronic health records like "Sundhedsplatformen" and AI tools like "IBM Watson" having received large amounts of criticism from their supposed end-users. The challenges have ultimately led to a lack of value-creation from these efforts, which this thesis aims to address. This thesis seeks to identify the challenges that are present in two specific groups, which are referred to as technical experts, i.e., AI developers, and clinical staff, i.e., the end-users. The research questions were designed to explore these relationships between the two interview groups and other important elements that should be addressed to succeed in AI-powered value-based healthcare implementations in Denmark going forward. The primary research question that was posed is:

What are the key challenges of implementing AI tools in the Danish Healthcare Industry and how should they be addressed?

Additionally, two supporting research questions were posed, which were designed to explore the importance of stakeholder involvement and provide recommendations for how implementations of AI in healthcare should be designed.

Who are the important stakeholders in successful AI implementations and how do you incentivize them?

and

How should artificial intelligence technology be designed and implemented to bring value to the systems and workflows in the Danish Healthcare Industry?

The results section answered the descriptive parts of the research questions, by comparing previous literature with our primary data collection. This comparative analysis provides insights into how the lack of structured, quality data may be the biggest challenge for AI developers to create value through their efforts. While AI technology has reached a point where it is able to effectively process the required amount of data, it is currently being limited by factors related to the sensitivity of healthcare data. Providing AI developers with access to the datasets is inhibited by the bureaucratic structure of the Danish government, which is further reinforced by the strict regulations of the GDPR. Moreover, the data quality of healthcare data is often limited by clinical staffs' suboptimal use of the electronic health records, which leads to health-related datasets that are difficult to interpret by AI tools.

Value-creation from AI tools is also greatly limited by adoption challenges, as technologies that are proven to work well in testing, do not show the same results in clinical applications. Clinical staff do not see the value of these tools in their workflows, as they have not been sufficiently involved in the design process. This is further expedited by the black-box nature of many of these tools, as they do not provide clinical staff with explanations for their recommendations. Furthermore, artificial intelligence is not capable of doing abstract physician-related work, and AI developers must carefully consider these limitations when selecting which workflows to implement AI into.

The analysis of our data collection contributes to the field of participatory design, as it highlights the importance of correctly identifying and involving the stakeholders in AI implementations. Joint-responsibility programs between developers, clinical staff, hospitals, and the governing body are crucial in value-based implementations. We present how value in these initiatives can be achieved by utilizing a modified value-based healthcare implementation matrix, to categorize the important elements identified in our data collection, to create an implementation framework centered around AI-powered value-based healthcare (**Appendix A)**.

In the discussion section, we present how to address the challenges that were identified in the results section and provide actionable recommendations that AI developers must consider in future projects. A strong data platform is necessary to facilitate future AI implementations in healthcare. AI developers must cooperate with the Danish government in the recent initiatives towards increasing access to healthcare data, by stating the importance of structuring the data to let AI developers conform to GDPR regulations and medical standards. The developers must work closely with clinical staff and utilize their medical knowledge to help select which datasets are strong enough to be applied in AI, to create value and minimize the risks of biases against specific patient groups.

Collaborating with clinical staff is also crucial in ensuring the adoption of these tools, which our research reveals to be one of the largest limiting factors in clinical success. We propose that this can be achieved through properly managing the expectations from clinical staff in how these tools should be used, as well as establishing the limitations of AI, as it is not infallible, just like human physicians. This requires an iterative approach to development, where clinical staff are consulted before, during and after implementations, as they possess important knowledge regarding what constitutes patient-value, which is ultimately the goal of the implementations. We encourage AI developers to attempt to emulate the joint-responsibility programs we observed at the Medtronic-Rigshospitalet project, which enables them to create contracts based on value-based outcomes of the implementations.

Based on our understanding of the challenges and their underlying reasons, we propose that the application of the CRISP-DM methodology (**Figure 2**) and modified implementation matrix (**Appendix A**) should be used in addressing the challenges. Using the approach suggested in CRISP-DM and modified implementation matrix, we recommend developing a clear roadmap for implementing AI projects and driving realization of expected value. This roadmap consists of mobilizing internal forces through effective stakeholder engagement by assigning a mix of resources and competencies, where clinicians and administrative leaders work in tandem to develop AI tools. Creating a data platform that contains structured, quality data with clear guidelines for requesting access. The implementation efforts should be measured by iteratively evaluating and validating the tools using scorecards. AI developers must continuously benchmark and monitor their tools against traditional approaches and other technology. Successful transformations of healthcare using AI can only be achieved through adequate investments and strong external collaborations. Finally, different incentives must be provided to stakeholders, to ensure their participation in development and early adoption.

We highlight some of the practical and ethical considerations that should be addressed, to let Denmark succeed in restructuring their health care system around an

AI-powered value-based approach. The fragmentation of IT systems between the Danish regions results in data being scattered and stored in various formats. The Danish government should strive for alignment between regions in selecting IT suppliers, to facilitate beneficial communication between these systems. Clear frameworks for responsibility should also be established, as clinical staff are ultimately responsible for their decisions regarding patients, with or without the presence of AI. Addressing these implications are dependent on collaboration between the various stakeholders, to determine which stakeholders are responsible for which outcomes.

Finally, in reflecting on our research findings we highlight the limited applications of our recommendations due to the lack of primary data from the governing body. Our definition of value deviates slightly from the traditional definition, as we focus primarily on creating value for clinical staff, which we argue will ultimately benefit patients. The lack of existing successful applications of AI in Danish healthcare also limits our ability to prove that our recommendations will result in valuable outcomes. Furthermore, we highlight that future studies regarding patients' receptivity to these tools, as well as studies regarding societal implications would be beneficial in letting us expand our implementation model, to create a more holistic view of AI applications in Danish healthcare.

This thesis contributes to the scarce literature regarding AI implementation in the Danish healthcare industry. As artificial intelligence is still in its infancy within this research area, structuring projects around value early has the potential to position Denmark as a front-runner for healthcare AI in the world. Denmark is currently in a unique position, as the data that is available regarding patients far exceeds other countries. However, as other countries like China are rapidly building enormous data centers, this advantage will soon dissipate. While it is necessary to employ our recommendations in future projects to determine the effectiveness of our model, the comparative analysis between existing literature and our primary data makes a strong case for why a value-based approach is essential for AI-powered healthcare to succeed.

8. References

Agency for Digitisation. (n.d.) *Denmark's National Strategy for Artificial Intelligence* Ministry of Finance. Retrieved from https://en.digst.dk/policy-and-strategy/denmark-s-national-strategy-for-artificial-intelligence/

Anderson, M. (2020). *How Value-Based Care is Being Impacted by AI Technology*. IEEE Computer Society. Retrieved from https://www.computer.org/publications/tech-news/trends/how-value-based-care-is-being-impacted-by-ai-technology/

ASAE. (2018). *Use Good Benchmarking Data to Your Advantage*. The Center of Association Leadership. Retrieved from https://www.asaecenter.org/resources/articles/foundation/2018/use-good-benchmarking-data-to-your-advantage

Ashworth, P. & Lucas, U. (2000). *Achieving Empathy and Engagement: A practical approach to the design, conduct and reporting of phenomenographic research*, *Studies in Higher Education*, DOI: 10.1080/713696153

Bajwa, J., Munir, U., Nori, A., & Williams, B. (2021). *Artificial intelligence in healthcare: transforming the practice of medicine*. Future Healthcare Journal, *8*(2), e188–e194. Retrieved from https://doi.org/10.7861/fhj.2021-0095

Baxter, P., Jack, S. (2008). *Qualitative case study methodology: Study design and implementation for novice researchers.* The Qualitative Report. pp. 544–559. Retrieved from https://nsuworks.nova.edu/tqr/vol13/iss4/2/

Bharadwaj, R. (2019). *Artificial Intelligence for Medical Billing and Coding.* Emerj: The AI Research and Advisory Company. Retrieved from: https://emerj.com/ai-sector-overviews/artificial-intelligence-medical-billing-coding/

Bjögvinsson, E., Ehn, P. and Hillgreen, P. (2012). *Design Things and Design Thinking: Contemporary Participatory Design Challenges*. Massachusetts: The MIT Press Journals. pp. 101-116

Blomberg, J. & Kensing, F. (1998) *Participatory Design: Issues and Concerns*. Palo Alto Research Center. Retrieved from https://link.springer.com/article/10.1023/A:1008689307411.

Blomberg, S. (2021). *Ph.D: Can a Computer Through Machine Learning Recognise Out-Of-Hospital Cardiac Arrest During Emergency Calls?* University of Copenhagen. Faculty of Health and Medicinal Sciences.

Bohr, A., & Memarzadeh, K. (2020). *The rise of artificial intelligence in healthcare applications*. Artificial Intelligence in Healthcare, 25–60. Retrieved from https://doi.org/10.1016/B978-0-12-818438-7.00002-2

Brandom, R. (2016). *Humanity and AI will be inseparable, says CMU's Head of Machine Learning.* Verge. Retrieved from https://www.theverge.com/a/verge-2021/humanity-and-ai-will-be-inseparable

Brown, T., Wyatt, J. (2010). *Design Thinking for Social Innovation*. Stanford Social Innovation Review. pp. 1-7.

Bryman, A. and Bell, E. (2007) *Business Research Methods.* Oxford: Oxford University Press.

Cattinelli, I., Bolzoni, E., Chermisi, M., Bellocchio, F., Barbieri, C., Mari, F., Amato, C., Menzer, M., Stopper, A., & Gatti, E. (2013). *Computational intelligence for the Balanced Scorecard: Studying performance trends of hemodialysis clinics*. Artificial Intelligence in Medicine. Retrieved from https://doi.org/10.1016/j.artmed.2013.04.005

Chatterjee, T. (2020). *Why using CRISP-DM will make you a better Data Scientist?* GreatLearning. Retrieved from https://www.mygreatlearning.com/blog/why-using-crisp-dm-will-make-you-a-better-data-scientist/

Chen, J. and Asch, S. (2017). *Machine learning and prediction in medicine - beyond the peak of inflated expectations*. New England Journal of Medicine. Retrieved from https://www.ncbi.nlm.nih.gov/pmc/articles/PMC5953825/

Chen, M., & Decary, M. (2019). *Artificial intelligence in healthcare: An essential guide for health leaders*. Healthcare Management Forum, *33*(1), 10–18. Retrieved from https://doi.org/10.1177/0840470419873123

Chen, P., (2020). *Essential Elements of Natural Language Processing: What the Radiologist Should Know.* ScienceDirect. Retrieved from https://www.sciencedirect.com/science/article/abs/pii/S1076633219304179

Christensen, M., Sturlason, A. (2019). *Blå blok vil droppe Sundhedsplatformen: »Har gjort det værre for sundhedspersonale og patienter i stedet for at gøre det bedre«*. Berlingske, pp. 1-3. Retrieved from https://www.berlingske.dk/danmark/blaa-blok-vil-droppe-sundhedsplatformen-har-gjort-det-vaerre-for

Ciriello, R., Richter, A., Schwabe, G., (2015). *PowerPoint Use and Misuse in Digital Innovation In: Twenty-Third European Conference on Information Systems.* Münster, pp. 1-15. Retrieved from https://www.researchgate.net/publication/279528708

ConnectedHealthInitiative. (n.d.). *Policy Principles for Artificial Intelligence in Health*. Published. Retrieved from https://actonline.org/wp-content/uploads/Policy-Principles-for-AI.pdf

Corti.ai (n.d.). *AI for Patient Consultations*. Retrieved from https://www.corti.ai/

Cortrium. (n.d.). *Our Story.* Retrieved from www.cortrium.com

Crigger, E. & Khoury, C. (2019) *Making Policy on Augmented Intelligence in Health Care*. AMA Journal of Ethics. Retrieved from https://doi.org/10.1001/amajethics.2019.188

DataRobot. (2021). *Humility in AI: Building Trustworthy and Ethical AI Systems. DataRobot AI Cloud.* DataRobot. Retrieved from *https://www.datarobot.com/resources/humility-in-ai/*

Djursing, T. (2017). *IBM's Watson i modvind: Foreslog livsfarlig medicin til danske patienter.* Version2. Retrieved from https://www.version2.dk/artikel/doktor-watson-modvind-foreslaar-livsfarlig-medicin-patienter-1081928

Doran, D., Schulz, S. & Besold, T. (2017). *What Does Explainable AI Really Mean? A New Conceptualization of Perspectives*. Cornell University. Retrieved from https://arxiv.org/abs/1710.00794

Drejøe, A., Frost, A. & Wichmann, C. (2019). *Improving the Adoption of Sundhedsplatformen: Utilizing Participatory Design and Super-users.* IT-University of Copenhagen. Bachelor Thesis.

Drysdale, E. et al. (2020). *Implementing AI in healthcare*. Vector-SickKids Health AI Deployment Symposium, Toronto, Ontario, Canada. Retrieved from https://vectorinstitute.ai/health-research/

Dudovskiy, J. (2018). *The Ultimate Guide to Writing a Dissertation in Business Studies: A Step-by-Step Assistance*. Research-methodology.net.

Egholm, C.L., Helmark, C., Doherty, P. et al. (2019). "*Struggling with practices" – a qualitative study of factors influencing the implementation of clinical quality registries for cardiac rehabilitation in England and Denmark.* BMC Health Serv Res 19. Retrieved from https://doi.org/10.1186/s12913-019-3940-5

EIT Health & McKinsey & Company. (2020). *Transforming healthcare with AI: The impact on the workforce and organisations*. McKinsey & Company. Retrieved from https://eithealth.eu/wp-content/uploads/2020/03/EIT-Health-and-McKinsey_Transforming-Healthcare-with-AI.pdf

EIT Health. (2020). *Healthcare Workforce and Organisational Transformation with AI – Enacting Change*. EIT Health think tank. Retrieved from https://thinktank.eithealth.eu/wp-content/uploads/2020/12/Think-Tank-Round-Table-Proceedings-2020_Denmark.pdf

EIT Health. (2021). *Funding an innovative future with AI in healthcare.* EIT Health Think Tank. Retrieved from https://thinktank.eithealth.eu/pharmacy/hot-topics-funding-an-innovative-future-with-ai-in-healthcare/

European Union. (2021). *European Union's Approach to Artificial Intelligence*. EEAS - European External Action Service. Retrieved from https://eeas.europa.eu/delegations/south-korea_en/75087/European%20Union's%20Approach%20to%20Artificial%20Intelligence%20(AI)

Evans, B. (2018). *Ways to think about machine learning.* www.ben.evans.com. Retrieved from https://www.ben-evans.com/benedictevans/2018/06/22/ways-to-think-about-machine-learning-8nefy

Federal Institute for Drugs and Medical Devices (BrArM). (2020). *The Fast-Track Process for Digital Health Applications (DiGA)*. A Guide for Manufacturers, Service Providers and Users.

Flick, U. (2015). *Introducing Research Methodology: A Beginner's Guide to Doing a Research Project*. Pp. 73-89. 2nd ed. SAGE Publications Ltd.

Fribo, A. (2013). *Epic og NNIT vinder milliardstor ordre på sundhedsplatform.* Version2. Retrieved from https://www.version2.dk/artikel/breaking-epic-og-nnit-vinder-milliardstor-ordre-paa-sundhedsplatform-54867

Fürstenau, Daniel & Auschra, Carolin & Gersch, Martin & Klein, Stefan. (2019). *A Process Perspective on Platform Design and Management: Evidence from a Digital Platform in Health Care*. Electronic Markets. 29. 581-596.

Gaultier, D. (2021). *The key to Data Science success is the CRISP methodology*. Business & Decision. Retrieved from https://en.blog.businessdecision.com/the-key-to-data-science-success-is-the-crisp-methodology/

Gaultier, D. (2021). *The key to Data Science success is the CRISP methodology. Business & Decision*. Business Decisions Blog. Retrieved from https://en.blog.businessdecision.com/the-key-to-data-science-success-is-the-crisp-methodology/

GDPR.eu. (2021). *What is GDPR, the EU's new data protection law?* European Union. Retrieved from https://gdpr.eu/what-is-gdpr/

Geller, M. (2020). *The Pros and cons of Artificial intelligence in healthcare*. Aidoc.com. Retrieved from https://www.aidoc.com/blog/pros-cons-artificial-intelligence-in-healthcare/

Gerke et al, (2020). *Ethical and legal challenges of artificial intelligence-driven healthcare.* Artificial Intelligence in Healthcare, 295–336. Retrieved from https://doi.org/10.1016/B978-0-12-818438-7.00012-

Gioia, D. & Corley, K. & Hamilton, A. (2013). *Seeking Qualitative Rigor in Inductive Research.* SAGE Journals. Retrieved from: https://journals.sagepub.com/doi/10.1177/1094428112452151

Giordano, Chris & Brennan, Meghan & Mohamed, Basma & Rashidi, Parisa & Modave, Francois & Tighe, Patrick. (2021). *Accessing Artificial Intelligence for Clinical Decision-Making*. Frontiers in Digital Health. 3. 645232. 10.3389/fdgth.2021.645232.

Goebel R. et al. (2018). *Explainable AI: The New 42?.* In: Holzinger A., Kieseberg P., Tjoa A., Weippl E. Machine Learning and Knowledge Extraction. Springer, Cham. Retrieved from https://doi.org/10.1007/978-3-319-99740-7_21

Hatherley, J. J. (2020). *Limits of trust in medical AI.* Journal of Medical Ethics. pp. 478–481. Retrieved from https://doi.org/10.1136/medethics-2019-105935

HBR. (2016). *Event Summary: Costs and Outcomes in Health Care.* Harvard Business Review. Retrieved from https://bullseyeresources.com/wp-content/uploads/2018/03/Event-Content_Types-of-Events_Customer-Conference.pdf

Healthcare Denmark. (2021). *Three Danish regions have chosen the same supplier of electronic health record systems · Healthcare Denmark*. Retrieved from https://www.healthcaredenmark.dk/news/three-danish-regions-have-chosen-the-same-supplier-of-electronic-health-record-systems/

Healthcaredenmark. (2021). *Healthcare Data*. Ministry of Health. Retrieved from https://www.healthcaredenmark.dk/healthcare-in-denmark/population-health-management/healthcare-data/

Hemamalini, S. (2014). *Patient Management Scorecard Checks Health of Hospital*. ISixSigma. Retrieved from https://www.isixsigma.com/implementation/success-factors/patient-management-scorecard-checks-health-hospital/

Hult, C. (2019). *Fakta om Sundhedsplatformen. Region Hovedstaden*. RegionH. Retrieved from https://www.regionh.dk/til-fagfolk/Sundhed/sundhedsplatformen/om-sundhedsplatformen/Sider/Fakta-om-Sundhedsplatformen.aspx

Humankinetics.com. (2021). *Steps of the research process*. Human Kinetics. Retrieved from https://us.humankinetics.com/blogs/excerpt/steps-of-the-research-process

iEduNote.com. (2021). *Research Process: 8 Steps in Research Process*. IEduNote. Retrieved from https://www.iedunote.com/research-process

Imran, N., & Jawaid, M. (2020). *Artificial intelligence in medical education: Are we ready for it?*. Pakistan Journal of Medical Sciences, pp. 857–859. Retrieved from https://doi.org/10.12669/pjms.36.5.3042

Intellishore. (2019). *Sustaining a healthy data platform*. Intellishore. Retrieved from https://intellishore.dk/service/data-platform/?gclid=Cj0KCQjww4OMBhCUARIsAILndv6zQhUDBPjYu_L2HksLYWXI5J7tWNhTkolCspf9WVzZo3GKK3RPpJQaAh0MEALw_wcB

Jean, S., Cho, K, Memisevic, R. and Bengio, Y. (2015). *On using very large target vocabulary for neural machine translation*. arXiv preprint. Retrieved from https://arxiv.org/abs/1412.2007

Jiang F, Jiang Y, Zhi H, et al. (2017). *Artificial intelligence in healthcare: past, present and future.* Stroke and Vascular Neurology. DOI:10.1136/svn-2017-000101

Kambli, R. (2020, March 30). *Collaboration is the key to disruption in healthcare.* Express Healthcare. Retrieved from https://www.expresshealthcare.in/strategy/collaboration-is-the-key-to-disruption-in-healthcare/417973/

Kaplan, J. (2016). *Artificial Intelligence: What Everyone Needs to Know*. Oxford: Oxford University Press

Katz, G. (2020). *Implementing Value-Based Health Care in Europe: Handbook for Pioneers.* EIT Health. Retrieved from https://eithealth.eu/wp-content/uploads/2020/06/Implementing-Value-Based-Healthcare-In-Europe.pdf

Kelly, C.J., Karthikesalingam, A., Suleyman, M. et al. (2019) *Key challenges for delivering clinical impact with artificial intelligence*. BMC Med 17, 195. Retrieved from https://doi.org/10.1186/s12916-019-1426-2

Kerry, C. F. (2020). *Protecting privacy in an AI-driven world*. Brookings. Retrieved from https://www.brookings.edu/research/protecting-privacy-in-an-ai-driven-world/

Kimpen, J. (2019) *Here's how to make 'value-based healthcare' a reality.* WeForum. Retrieved from https://www.weforum.org/agenda/2019/02/here-s-how-to-make-value-based-healthcare-a-reality/

Kong H. J. (2019). Managing Unstructured Big Data in Healthcare System. Healthcare informatics research, 25(1), 1–2. Retrieved from https://doi.org/10.4258/hir.2019.25.1.1

Kumar, G., Basri, S., Imam, A., Khowaja, S., Capretz, L., Balogun, A. (2021). *Data Harmonization for Heterogeneous Datasets: A Systematic Literature Review.* Applied Sciences. Retrieved from https://doi.org/10.3390/app11178275

Kushniruk, A. & Nøhr, C. (2016) *Participatory Design, User Involvement and Health IT Evaluation*. Stud Health Technol Inform. 2016;222:139-51. PMID: 27198099.

Lagasse, J. (2019). *As benchmarking in healthcare becomes more common, artificial intelligence is poised to facilitate it*. Healthcare Finance News. Retrieved from https://www.healthcarefinancenews.com/news/benchmarking-healthcare-becomes-more-common-artificial-intelligence-poised-facilitate-it

Lapach, Y. (2021). *Getting started with AI: How much data do you need?* 2021.AI. Retrieved from https://2021.ai/getting-started-ai-how-much-data-needed/

Lee, N. T., Resnick, P., & Barton, G. (2019). *Algorithmic bias detection and mitigation: Best practices and policies to reduce consumer harms*. Brookings. Retrieved from https://www.brookings.edu/research/algorithmic-bias-detection-and-mitigation-best-practices-and-policies-to-reduce-consumer-harms/

Letourneau-Guillon, L., Camirand, D., Guilbert, F., & Forghani, R. (2020). *Artificial Intelligence Applications for Workflow, Process Optimization and Predictive Analytics*. Neuroimaging Clinics of North America, 30(4), e1–e15. Retrieved from https://doi.org/10.1016/j.nic.2020.08.008

Lindskow, T., Ibrahim, R. M., Thomsen, M. V., Bell, B., & Kruse, C. R. (2020). *Kunstig intelligens i det danske sundhedsvæsen*. Ugeskrift for Laeger, 182(16). Retrieved from https://ugeskriftet.dk/videnskab/kunstig-intelligens-i-det-danske-sundhedsvaesen

Long, M. (2019). *PACS RIS and AI: a fully integrated radiology workflow*. Aidoc. Retrieved from https://www.aidoc.com/blog/pacs-ris-ai-workflow/

Long, M. (2020). *Artificial Intelligence in Medical Diagnosis | Healthcare Insights*. Aidoc. Retrived from https://www.aidoc.com/blog/artificial-intelligence-medical-diagnosis/

Longoni et al, (2019). *AI Can Outperform Doctors. So Why Don't Patients Trust It?* Harvard Business Review. Retrieved from https://hbr.org/2019/10/ai-can-outperform-doctors-so-why-dont-patients-trust-it

Longoni, C., Bonezzi, A., & Morewedge, C.K. (2019). *Resistance To Medical Artificial Intelligence*. Consumer Decision-Making. Retrieved from https://www.semanticscholar.org/paper/Resistance-To-Medical-Artificial-Intelligence-Longoni-Bonezzi/028d026be997ebf1f1c762407d216ff35a81ca73

Lubarsky, D. (2021). *AI Can Increase Efficiency in Healthcare, Even in a Pandemic*. Technology Solutions That Drive Healthcare. Retrieved from https://healthtechmagazine.net/article/2021/02/ai-can-increase-efficiency-healthcare-even-pandemic

Marr, B. (n.d.). *How Is AI Used In Healthcare - 5 Powerful Real-World Examples That Show The Latest Advances*. Forbes. Retrieved from https://www.forbes.com/sites/bernardmarr/2018/07/27/how-is-ai-used-in-healthcare-5-powerful-real-world-examples-that-show-the-latest-advances/

Mazor, J. (2019). *Læger massivt utilfredse med Sundhedsplatformen, viser ny undersøgelse.* Tv2lorry. Retrieved from https://www.tv2lorry.dk/lorryland/massiv-utilfredshed-med-sundhedsplatformen-blandt-laeger-viser-ny-undersoegelse

McKinsey & Company. (2019). *AN AI NATION? Harnessing the Opportunity of Artificial Intelligence in Denmark*. Innovationsfonden. Retrieved from https://innovationsfonden.dk/sites/default/files/2019-09/an-ai-nation-harnessing-the-opportunity-of-ai-in-denmark.pdf

Medtronic. (n.d.). *Measuring value in terms of longitudinal patient-centric outcomes rather than short-term transactions.* Medtronic Global. Retrieved from https://global.medtronic.com/xg-en/e/response/value-based-healthcare.html

Mehrotra, R., Ansari, M., Agrawal, R. & Anand, R. (2020) *A Transfer Learning approach for AI-based classification of brain tumors.* ScienceDirect. Retrieved from https://www.sciencedirect.com/science/article/pii/S2666827020300037

Melnikovas, A. (2018). *Towards an Explicit Research Methodology: Adapting Research Onion Model for Futures Studies*. Retrieved from https://doi.org/10.6531/JFS.201812_23(2).0003

Meske, C., Bunde, E., Schneider, J., Gersch, M. (2020). *Explainable Artificial Intelligence: Objectives, Stakeholders, and Future Research Opportunities.* Information Systems Management. Retrieved from https://www.tandfonline.com/doi/full/10.1080/10580530.2020.1849465

Miliard, M. (2018). *What hospitals need for successful AI: a digital base*. Healthcare IT News. Retrieved from https://www.healthcareitnews.com/news/what-hospitals-need-successful-ai-digital-base

Ministry of Finance & Ministry of Industry, Business and Financial Affairs. (2019). *National Strategy for Artificial Intelligence*. Retrieved from https://en.digst.dk/media/19337/305755_gb_version_final-a.pdf

Ministry of Foreign Affairs of Denmark. (2016). *Copenhagen Initiates New Collaboration to Promote Research on Healthcare*. InvestInDK. Retrived from https://investindk.com/insights/copenhagen-initiates-new-collaboration-to-promote-research-on-healthcare

Minto, B., & McKinsey & Company. (1968). *Barbara Minto: "MECE: I invented it, so I get to say how to pronounce it"*. McKinsey Alumni Center. Retrieved from https://www.mckinsey.com/alumni/news-and-insights/global-news/alumni-news/barbara-minto-mece-i-invented-it-so-i-get-to-say-how-to-pronounce-it

Mohan C., SM (2018). A*rtificial intelligence in radiology - Are we treating the image or the patient?*. The Indian Journal of Radiology & Imaging, 28(2), 137–139. Retrieved from https://doi.org/10.4103/ijri.IJRI_256_18

Morgan R. Frank, David Autor, James E. Bessen, Erik Brynjolfsson, Manuel Cebrian, David J. Deming, Maryann Feldman, Matthew Groh, José Lobo, Esteban Moro, Dashun Wang, Hyejin Youn, Iyad Rahwan. (2019). *Toward understanding the impact of artificial intelligence on labor.* Proceedings of the National Academy of Sciences. DOI: 10.1073/pnas.1900949116

Ng, K. (2021). *AI to help doctors develop personalized treatments*. IBM Research Blog. Retrieved from https://www.ibm.com/blogs/research/2020/12/ai-personalized-treatments/

OECD. (2020). *TRUSTWORTHY AI IN HEALTH*. OECD organization. Retrieved from https://www.oecd.org/health/trustworthy-artificial-intelligence-in-health.pdf

Panch, T., Mattie, H. & Celi, L.A. (2019). *The "inconvenient truth" about AI in healthcare.* npj Digit. Med. 2, 77. Retrieved from https://doi.org/10.1038/s41746-019-0155-4

Panesar, A., (2021). *Machine Learning and AI for Healthcare*. Springer, eBook. [2nd ed]. Retrieved from: https://link.springer.com/book/10.1007%2F978-1-4842-6537-6

Porter, M. & Teisberg, E. (2006). *Redefining Health Care: Creating Value-Based Competition on Results.* Boston, Mass: Harvard Business School Press.

Pritchard, J. (2021). *How Artificial Intelligence is Improving Value-Based Care*. Share Moving Media. Retrieved from https://sharemovingmedia.com/how-artificial-intelligence-is-improving-value-based-care

PwC. (n.d.) *Artificial intelligence in health*. PwC NL. Retrieved from https://www.pwc.nl/en/publicaties/sherlock-in-health.html

Randall, D., Harper, R. and Rouncefield, M. (2007). *Fieldwork for Design.* London: Springer, pp. 1-14 , pp. 59-88, pp. 135-200, pp. 209-254.

Reddy, M. (2021). *Digital Transformation in Healthcare in 2021: 7 Key Trends*. DAP. Retrieved from https://www.digitalauthority.me/resources/state-of-digital-transformation-healthcare/

RegionH. (2021). *Finansiering og Fonde.* Region Hovedstaden. Retrieved from https://www.regionh.dk/til-fagfolk/Forskning-og-innovation/finansiering-og-fonde/Sider/default.aspx

Rice, M. (n.d). *The Growth of Artificial Intelligence (AI) in Healthcare*. Health Recovery Solutions. Retrieved from https://www.healthrecoverysolutions.com/blog/the-growth-of-artificial-intelligence-ai-in-healthcare

Richards, 1., & Monie,J. M. (2013). *Read me first for a user's guide to qualitative research methods* [2nd ed]. Thousand Oaks, CA: Sage.

Richardson et al. (2021). *Patient apprehensions about the use of artificial intelligence in healthcare*. Npj Digital Medicine. Retrieved from https://doi.org/10.1038/s41746-021-00509-1

Rigby, M. J. (2019). *Ethical Dimensions of Using Artificial Intelligence in Health Care.* Journal of Ethics | American Medical Association. Retrieved from https://journalofethics.ama-assn.org/article/ethical-dimensions-using-artificial-intelligence-health-care/2019-02

Robson, C. (2002). *Real World Research: a Resource for Social Scientists and Practitioner-Researchers* (2nd ed.). Oxford: Blackwell Publishers Ltd.

Rosenberg, M. (2021). *Artificial Intelligence Tools Can Help Clinicians Spend More Time with Patients*. Managed Healthcare Executive. Retrieved from https://www.managedhealthcareexecutive.com/view/artificial-intelligence-tools-can-help-clinicians-spend-more-time-with-patients

Saldana, J. (2016). *The Coding Manual for Qualitative Researchers* (3rd ed.). SAGE Publications Ltd.

Sandeep, R., Sonia, A., Simon, C., Paul, C. (2019). *A governance model for the application of AI in health care*. Journal of the American Medical Inpanchfasossoformatics Association. pp.491–497. Retrieved from https://doi.org/10.1093/jamia/ocz192

Saunders, M., Lewis, P., & Thornhill, A. (2016). *Research methods for business students*. 7th ed. Pearson Education: India.

Schmidt, M., Schmidt, S. A., Sandegaard, J. L., Ehrenstein, V., Pedersen, L., & Sørensen, H. T. (2015). *The Danish National Patient Registry: a review of content,* *data quality, and research potential*. Clinical epidemiology. Retrieved from https://doi.org/10.2147/CLEP.S91125

Schmitt, M. (n.d.). *Artificial Intelligence in Medicine | The Top 4 Applications*. DataRevenue. Retrieved from. https://www.datarevenue.com/en-blog/artificial-intelligence-in-medicine

Shaptunova, Y. (2021). *AI in Healthcare: 8 Major Ways It Is Innovating the Industry in 2021*. SaM Solutions. Retrieved from https://www.sam-solutions.com/blog/ai-in-healthcare/

Shinners, L., Aggar, C., Grace, S., & Smith, S. (2019). Exploring healthcare professionals' understanding and experiences of artificial intelligence technology use in the delivery of healthcare: An integrative review. *Health Informatics Journal*, *26*(2), 1225–1236. Retrieved from https://doi.org/10.1177/1460458219874641

Siwici, B. (2019). *Tech Optimization: Getting the most out of AI.* Healthcare IT News. Retrieved from https://www.healthcareitnews.com/news/tech-optimization-getting-most-out-ai?fbclid=IwAR2j_cOWH5WY83YZ-YsCScDj7LUAfXyhBKnzRoJqN-mikDCiMyN6rl-5e6s

Siwicki, B. (2019). *Tech Optimization: Getting the most out of AI*. Healthcare IT News. Retrieved from https://www.healthcareitnews.com/news/tech-optimization-getting-most-out-ai

Smith, P., Sagan, A., Siciliani, L., Panteli, D., McKee, M., Soucat, A. and Figueras, J., (2020). *Building on value-based health care Towards a health system perspective.* Copenhagen, Denmark: WHO Regional Office for Europe UN City

Spatharou, A., Hieronimus, S., & Jenkins, J. (2021). *Transforming healthcare with AI: The impact on the workforce and organizations*. McKinsey & Company. Retrieved from https://www.mckinsey.com/industries/healthcare-systems-and-services/our-insights/transforming-healthcare-with-ai

Stahl B. C. (2021). *Ethical Issues of AI: Artificial Intelligence for a Better Future: An Ecosystem Perspective on the Ethics of AI and Emerging Digital Technologies*. pp. 35–53. Retrieved from https://doi.org/10.1007/978-3-030-69978-9_4

Study.com (2015) *Interactionism in Sociology: Definition & Examples*. Study.com. Retrieved from https://study.com/academy/lesson/interactionism-in-sociology-definition-examples-quiz.html.

Sundblad, W. (2021). *Why Your AI Must Be Humble*. Forbes. Retrieved from https://www.forbes.com/sites/willemsundbladeurope/2021/03/15/why-your-ai-must-be-humble/#:%7E:text=His%20suggestion%20is%20%E2%80%9Chumble%20AI,path%20of%20learning%20and%20familiarity

Sundhedsministeriet. (2021). *Danmark vil være førende i brug af sundhedsdata*. sum.dk. Retrieved from https://sum.dk/nyheder/2021/oktober/danmark-vil-vaere-foerende-i-brug-af-sundhedsdata-

Sundhedsministeriet. (2021). *Vision: Strategisk samarbejde for bedre brug af sundhedsdata*. sum.dk. Retrieved from https://sum.dk/Media/637698890887354228/Vision%20-%20strategisk%20samarbejde%20om%20bedre%20brug%20af%20sundhedsdata.pdf

Sutskever, I., Vinyals, O and Le, QV. (2014). *Sequence to sequence learning with neural networks*. Advances in neural information processing systems. Retrieved from: https://arxiv.org/abs/1409.3215

Svaneborg, R. (2018). *Sundhedsplatformen har stort potentiale – men den er også ramt af store problemer*. Information. Retrieved from https://www.information.dk/indland/2018/02/sundhedsplatformen-stort-potentiale-ogsaa-ramt-store-problemer

Takyar, A. (2021). *The Impact of Digital Transformation in Healthcare*. Leewayhertz. Retrieved from https://www.leewayhertz.com/digital-transformation-in-healthcare/#:~:text=Digital%20transformation%20in%20healthcare%20is,offer%20a%20better%20user%20experience.

ThesisMind. (2019). *Analysis of Saunders Research Onion*. Retrived from https://thesismind.com/analysis-of-saunders-research-onion/

Thoning Callesen, J. (2021). *Engineers and doctors join forces: New Danish center for AI and health.* Syddansk Universitet. ritzau.dk. Retrieved from https://via.ritzau.dk/pressemeddelelse/engineers-and-doctors-join-forces-new-danish-center-for-ai-and-health?publisherId=12056383&releaseId=13607803

Tiwar, M., Mukherjee, P., & Singh, A. (2015). *A Survey on Data Mining Methodologies for Healthcare*. International Journal of Engineering and Management Research. Retrieved from https://www.ijemr.net/DOC/AsurveyOnDataMiningMethodologiesForHealthcare(355-358).pdf

Tripathi, M. (2020). *Underfitting and Overfitting in Machine Learning*. Data Science Foundation. Retrieved from https://datascience.foundation/sciencewhitepaper/underfitting-and-overfitting-in-machine-learning

Veradigm.com (2020). *What is Value-based Healthcare? A Comprehensive Guide*. Veradigm. Retrieved from https://veradigm.com/what-is-value-based-healthcare/.

Verger, R. (2021). *Artificial intelligence creates better, faster MRI scans*. Popular Science. Retrieved from. https://www.popsci.com/story/technology/artificial-intelligence-fast-mri-scan-time

Villamil, D.R. (2011). *Process model for data mining in healthcare sector.* Retrieved from https://www.semanticscholar.org/paper/Process-model-for-data-mining-in-health-care-sector-Villamil/c12677e137e03dd3cbacbd216a6fd7038a704f78

Wehrstein, L. (2020). *CRISP-DM ready for Machine Learning Projects - Towards Data Science*. Medium. Retrieved from https://towardsdatascience.com/crisp-dm-ready-for-machine-learning-projects-2aad9172056a

Wessel, L. K., Baiyere, A., Ologeanu-Taddei, R., Cha, J., & Jensen, T. B. (2021). *Unpacking the Difference between Digital Transformation and IT-enabled Organizational Transformation*. Journal of the Association for Information Systems. Retrieved from https://doi.org/10.17705/1jais.00655

Wicks, D. (2017) *"The Coding Manual for Qualitative Researchers (3rd edition)", Qualitative Research in organizations and Management:* An International Journal, Retrieved from https://doi.org/10.1108/QROM-08-2016-1408

World Health Organisation. (2021). *Guidance for Post-Market Surveillance and Market Surveillance of Medical Devices, Including in Vitro Diagnostics*. WHO. Retrieved from https://www.who.int/publications/i/item/9789240015319

Wu E, Wu K, Daneshjou R, Ouyang D, Ho DE, Zou J. (2021) *How medical AI devices are evaluated: limitations and recommendations from an analysis of FDA approvals*. Nat Med. DOI: 10.1038/s41591-021-01312-x.

Yanqing, J., Edwards, S., Dwivedi Y. (2019). *Artificial intelligence for decision making in the era of Big Data – evolution, challenges and research agenda.* International Journal of Information Management. Volume 48. pp. 63-71.

Yin, R. K. (2009). *Case Study Research Design and Methods*. Thousand Oaks, CA: SAGE Publications Ltd.

Zefeiti, S. M. B. A., & Mohamad, N. A. (2015). *Methodological Considerations in Studying Transformational Leadership and its Outcomes*. International Journal of Engineering Business Management. Retrieved from https://doi.org/10.5772/60429

Zicari, R. V., Ahmed, S., Amann, J., Braun, S. A., Brodersen, J., Bruneault, F., Brusseau, J., Campano, E., Coffee, M., Dengel, A., Düdder, B., Gallucci, A., Gilbert, T. K., Gottfrois, P., Goffi, E., Haase, C. B., Hagendorff, T., Hickman, E., Hildt, E.,

.Wurth, R. (2021). *Co-Design of a Trustworthy AI System in Healthcare: Deep Learning Based Skin Lesion Classifier*. Frontiers in Human Dynamics. Retrieved from. https://doi.org/10.3389/fhumd.2021.688152

Zimmermann, T. M. W. (2016). *Perspectives on Data Science for Software Engineering* Morgan Kaufmann.