Organizing a Competence Center at a Public Hospital to Increase Artificial Intelligence Impact

Key Learnings from a Comparative Study Across Six Large Organizations

Master's thesis in Management and Economics of Innovation

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Abstract

With the threat of overpowering healthcare demands, a significant funding gap and systematic failure to attend to the increasing portion of chronically ill in the near future, Artificial Intelligence (AI) is showing great promise as a possible remedy. Despite the national interest in AI's potential, Sahlgrenska University Hospital (SUH) are facing uncertainties regarding how to build AI into their organization, just like many others are. To help with this, SUH is pursuing an AI competence center (AICC) to help accelerate AI usage.

This study aims to provide SUH with actionable guidance on how to organize the new AICC and to contribute to the nascent and sparse academic field of organizing the implementation of AI in healthcare. To achieve this aim, a qualitative multiple-case study was carried out, with semi-structured interviews as the main mode of data gathering. Data extracted from 23 managerial interviewees across six organizations, SUH included, was analyzed through thematic groupings. Complementing this is an extensive literature review, ultimately synthesized into a theoretical framework around AI innovation, diffusion of innovation and healthcare culture.

The findings indicate that there are five major dimensions of approaching and organizing AI-enabled innovation in large organizations. To begin with, AI is argued to be highly complex, with unclear value, impact and boundaries. Organizations have subsequently constructed different degrees of direction for their AI work. Rather ubiquitous however, is the understanding of the large change and buy-in required. In addition, the value of external collaboration and knowledge is widely recognized. Finally, the organizational structure around AI plays a multi-faceted role in accelerating AI-enabled innovation.

Key considerations and learnings from the data and theoretical framework underbuilt complementary recommendations for how SUH can organize around the AICC. Firstly, it is recommended that the AICC should focus on enabling AI to overcome the operative dominance currently challenging AI usage in healthcare. Secondly, the AICC is recommended to prioritize administrative AI higher than clinical AI, as it is easier to accelerate while yielding large value. Lastly, it is recommended that the center should be placed near top management, have regional sanction, contain different competences and act as a boundary-spanner to accelerate AI at SUH.

Practically, the conclusions are valuable as guidelines for SUH moving forward with AI, possibly contributing to improving future healthcare delivery through AI impact. Theoretically, this study contributes to the field of healthcare AI implementation by exploring the ways a large hospital can organize around AI acceleration. The study's results are believed to address important aspects of accelerating AI in large organizations, applicable with caution to other university hospitals in particular but possibly other large organizations as well.

KEY WORDS: Artificial intelligence, innovation, healthcare, organize, accelerate, center

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Word List

Word	Written out	Meaning
AI	Artificial Intelligence	Technology used to build intelligent systems
Digitalization	-	Applied IT to increase value through digital solutions
SUH	Sahlgrenska University Hospital	University hospital in the Gothenburg area of Sweden
RVG	Region Västra Götaland	One of 21 regional governance structures in Sweden, containing SUH for example
AICC	AI competence center	The planned center at SUH that will focus on AI work
CIF	Care Informatics of the Future	Large IT project currently undertaken in RVG
NHS	National Health Service	The UK's government-funded single-payer healthcare system
NHSX	National Health Service X	Organization within NHS focusing on policy and best practice around technology and data
GOSH	Great Ormond Street Children's Hospital	Children's hospital in the London area, UK
DRIVE	Digital Research, Informatics and Virtual	A specialized unit at GOSH
LTHT	Leeds Teaching Hospitals Trust	A large university hospital in the Leeds area, UK
CIDD	Center for Information-driven Care	A unit within Region Halland focusing on developing healthcare delivery with data
CHAIR	Chalmers AI Research Center	Center at Chalmers University of Technology with research focused on applied AI

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1

Introduction

In this chapter the initial context of the study is explored. The background to the research questions and problems are detailed as well as the purpose, research questions and delimitations of the study.

1.1 Background

It is nothing new to state that healthcare is facing great challenges. Much is driven by demographic changes, where the number of people aged 80 or higher in Sweden are estimated to increase by 50% until 2029, compared to just a 7% increase for the entire population (SKR, 2020). Old age is naturally correlated with chronic illness, where around 80% of people aged over 80 are multi-sick, i.e., afflicted by at least two chronic illnesses (Socialdepartementet, 2016). The multi-sick, although a rather small group, account for half of total healthcare costs in Sweden, and chronic illnesses in general account for 80-85% (Socialdepartementet, 2016). This development is accelerating the total need for care, for which there will be a lack of healthcare resources, both in terms of professionals (Myndigheten för Digital Förvaltning, 2019) and financials (Finansdepartementet, 2019). In addition, the current reactiveness of healthcare (DeRienzo & Kaitz, 2019) is unfit for dealing with increased prevalence of chronic illnesses, pressuring healthcare to shift towards more proactive and behavioral measures (Panesar, 2019). The current decentralized structure with an industrial standardization logic, stemming from the dawn of New Public Management (Osborne, 2018; Eriksson et al., 2020), gives rise to obstacles for necessary collaboration, which means individual patient needs are often neglected (WHO, 2015; Socialdepartementet, 2016; Västra Götalandsregionen, 2018). This has helped put *person-centered care* in national focus (SKR, 2021; Socialdepartementet, 2020).

Information technology (IT) is frequently highlighted as an integral part of coping with the higher demand, different demand and personalization within healthcare (Lenz & Reichert, 2007; Omachonu & Einspruch, 2010), leading to digitalization and eHealth also rising on the national agenda (Regeringskansliet, 2014; Socialdepartementet & SKR, 2016). One of the fields receiving much attention within applied IT and digitization of healthcare is *Artificial Intelligence* (AI), which is a technology that is used to build intelligent systems[1] (Russell & Norvig, 2020). AI has also become an explicit focus in Sweden, with increasing research funding and a growing AI ecosystem[2] with

[1] Definition and details of AI are presented in the theoretical framework (see *3.1*)

[2] According to Vargo and Akaka (2012, p. 207), service ecosystems can be defined as: "relatively self-contained, self-adjusting systems of resource-integrating actors connected by shared institutional logics and mutual value creation through service exchange".

an increasing number of AI environments such as hubs (Vinnova, 2019; Österberg & Lindsköld, 2020). The increased interest is not without merit, where the Agency for Digital Government (2019, p. 9) estimates that AI, if "implemented exhaustively", could deliver 30 BSEK of value to the Swedish health sector each year. Vinnova (2018) goes as far as describing AI as a groundbreaking force within healthcare and medicine, with proactive measures, improved workflows and person-centered healthcare highlighted as possible outcomes. Likewise, Davenport and Kalakota (2019) explain that AI has an important role to play in healthcare. Better efficiency and more personalized care as a result of applying AI to healthcare problems, bodes well for tackling the challenges seen in Swedish healthcare today.

Despite the great interest at a national level, not much is happening at the hospital floors. Present achievements have been made in specialized use cases, such as radiology, and the large value gains are still far from being realized (Topol, 2019; E-hälsomyndigheten, 2020). According to the Swedish National Board of Health and Welfare, implementation is lagging behind the extensive research being done (Socialstyrelsen, 2019). The limited implementation despite dramatic statements about potential might appear paradoxical. However, there are indeed several obstacles, whose solutions are currently under investigation, that stand in the way of AI being widely adopted within the healthcare sector. These include ethical aspects such as bias (Topol, 2019; Rajkomar et al., 2019) and legal issues around data (Magnusson et al., 2019). However, a significant hurdle also lies in the organization, as the potential advantages require concurrent organizational changes (Österberg & Lindsköld, 2020; Socialstyrelsen, 2019). However, Wirtz and Müller (2019) highlight that conceptual models for how to merge AI into organizations are missing. Furthermore, Sun and Medaglia (2019) point out the lack of research within healthcare AI and how it could be governed in practice, indicating that the field of implementing healthcare AI is rather unexplored.

On a regional level[3], Region Västra Götaland (RVG) has deemed that "the development of digital healthcare and services" is one of four major areas necessary for meeting the future demands within healthcare (Västra Götalandsregionen, 2017, p. 5). One of the subareas touched upon in the RVG digital strategy, is indeed AI and its applications in healthcare (Västra Götalandsregionen, 2018). At the region's university hospital, Sahlgrenska University Hospital (SUH), there is *scattered* AI activity among researchers, and the aspect of organizing this activity to accelerate AI usage has been brought to attention. More specifically, the establishment of an *AI competence center* (AICC) is being pursued, while the details around how it should be organized is still uncertain and under discussion.

Lastly, AI has been recognized as highly valuable across sectors and nations, but the process of implementing AI does not come without challenges there either (Ericsson Industry Lab, 2020; Arpteg, 2018). Reasonably, much can be learned around organizational aspects and considerations, not just from other hospitals, but from a diverse set of large organizations attempting an AI acceleration similar to that at SUH.

[3] The governance structure in Swedish healthcare will be introduced in *4.1*.

1.2 Aims and research questions

Firstly, this thesis aims to provide SUH with actionable guidance on how to organize the new AICC to ultimately unlock the full potential of AI. Secondly, this thesis aims to contribute to the nascent academic field of implementing AI in healthcare, doing so by exploring the dimensions of accelerating healthcare AI at an organizational level. Lastly, in order to do this the study aims to leverage input from multiple large organizations on how they organize for AI implementation and acceleration. With these aims in mind, three research questions have been formulated:

1) *What are the main dimensions of approaching and organizing AI-enabled innovation in large organizations?*

2) *What key considerations and learnings for the AICC can be derived from other actors' AI work?*

3) *What are the recommendations for organizing the AICC?*

1.3 Delimitations

By virtue of the first research question, data from different organizations are collected. Nevertheless, the data subsequently is discussed from the perspective of what this means for SUH. Although this is in line with the second and third research, a clear delimitation of the study is to not discuss the data from all organizations' perspective, simply for the sake of clarity and keeping with the second and third research question.

Moreover, to achieve an abstraction level suitable for cross-organizational learnings, the study adopts a high-level focus, both organization- and theory-wise. The main dimensions of different organizations' approach to AI acceleration and organization will be explored, leaving details regarding e.g., individual technology adoption or specific AI technologies, both unnecessary and undesirable.

Lastly, the concurring COVID-19 pandemic yielded some limitations on the study. Data gathering turned completely remote, and pressured organizations (especially within healthcare) implied lower availability of informants.

1.4 Disposition

The thesis begins with a thorough description of its methodology, where case sampling, interview strategy, data analysis and literature review takes center stage. Following the methodology section, the theoretical framework that the study uses to analyze the findings and ultimately deliver recommendations will be presented. To provide the reader with an understanding of the studied contexts, descriptions of the studied organizations will be the next section. Subsequently, the first research question will be answered through the study's findings. Moving forward, the findings will then be synthesized with the theoretical framework in the discussion section, with the end goal being to answer the second research question. This discussion is then extrapolated to provide actionable recommendations for SUH in the recommendation section, hence answering the third and last research question. Finally, an overview of the study's main findings, implications and further research will be provided in the concluding section, i.e., conclusions.

2

Methodology

In this section, the methodology of the study is presented. The overall research strategy, case sampling, data collection methods, data analysis, literature review, research quality and ethics are discussed under separate subheadings.

2.1 Research strategy

Put shortly, the study is mostly of *explorative* character and then *normative* at the very end. Additionally, it is *qualitative* and *abductive* throughout the study. Lastly, multiple cases are leveraged to inquire in an epistemologically *interpretivist* way, based on a mostly *constructionist* ontological view of the studied field. These definitions and why the study is classified this way are put into context below.

In the beginning phases of the study, there was a need for exploration as the research setting had to be understood and scoped. This exploratory nature also meant that the ideas for research questions and relevant theory had to be adjusted iteratively. The research proposal was drafted together with SUH, but a key aspect in the early stages was continuing to conduct introductory interviews with people familiar with the research proposal and areas (detailed further in *2.3*). This feedback and guidance made it possible to find further direction. The research questions were also continuously evaluated against the criteria put forth by Bell et al. (2019), to make sure they were suitable. Their criteria include that the research questions should be clear, researchable, connected to established theory and research, and appropriately wide (Bell et al., 2019). Noteworthy here is that the research questions were allowed to remain wide in the beginning, in alignment with recommendations from both supervisors and Bell et al. (2019).

After having drafted the first version of the research questions, it became clear that the study had to continue in an exploratory manner. Initial literature review revealed that the field of *AI implementation in healthcare* (see *1.1* as well as *3.4*) is nascent and rather unexplored, which according to Edmondson and McManus (2007) calls for an exploratory approach with open-ended questions and a qualitative research strategy. Easterby-Smith et al. (2015) as well as Bell et al. (2019) also highlight the connection between exploratory research questions, phrased in terms of *how* and *why*, and a qualitative research inquiry, as qualitative data enable the capturing of nuanced data and perspectives that can help answer the open questions.

Maxwell (2005) underlines the importance of allowing the different parts of a qualitative study to influence each other with time as the author states that qualitative research cannot be pursued linearly. This continuous interplay between theory, data gathering, and analysis is similar to what Dubois and Gadde (2002) describe as abductive research, argued suitable for developing theoretical contributions. This way of triangulating, going back and forth between drawing conclusions from the data and reviewing literature, can according to Bell et al. (2019) be described as *interpretive* research. The study chose to adopt this abductive and interpretive approach, with a continuing theme throughout the study being *iterations*: collected data gave new perspectives on relevant theory and that theory was subsequently taken into account, whilst new theory gave new perspectives on what data to collect. The resulting research process is visualized in Figure 1 below.

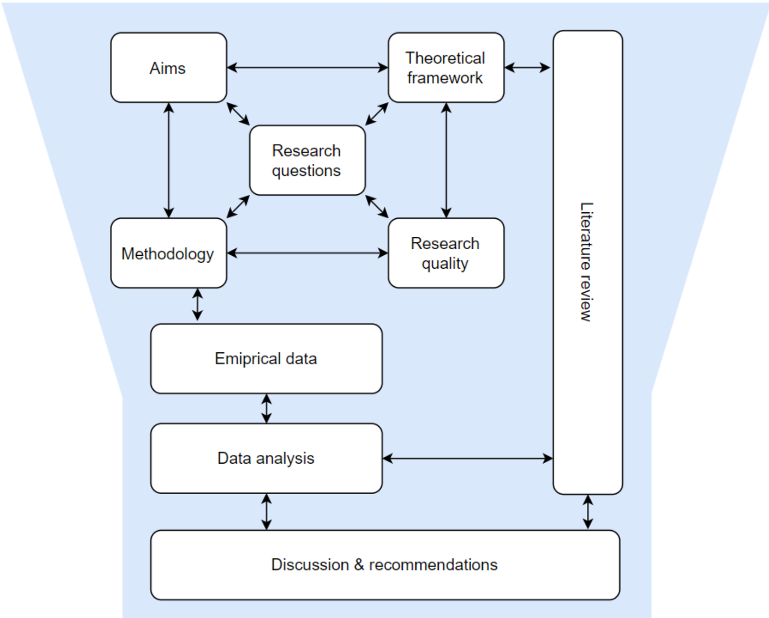

Figure 1: Illustration of methodological interconnections (adapted and expanded from Maxwell (2005)).

Taking a step back, Easterby-Smith et al. (2015) describe the research process as a multi-layered tree, where they regard ontological and epistemological considerations as the core layers of the tree. Without assuring that these considerations are consistent with the research strategy and methods, generation of valuable knowledge about reality is not likely (Bell et al., 2019). This study takes these core layers into account, and considers that, using the terminology from Bell et al. (2019), a *constructionist* ontological view and an *interpretivist* epistemological view are suitable[4]. Taking a constructionist view implies that there are believed to be many "truths", and that reality is crafted by human action and perceptions (Easterby-Smith et al., 2015; Bell et al., 2019). The way to inquire about this reality, i.e., the epistemological standpoint, then logically becomes to understand the different perspectives and subjective meaning of social phenomena, called interpretivism (Bell et al., 2019). These assumptions imply that the studied organizational structures, their approach to AI and the dynamic interactions within these, are not seen as fixed. Rather, these phenomena are viewed as human constructs that can have different interpretations and implications depending on how you view it. The study further expects that experiences and perspectives from different

[4] The terminology differs across literature, but the meaning stays the same. Easterby-Smith et al. (2015) for example, uses relativism as an ontological view instead of constructionism, and then social constructionism to represent the epistemological corresponding view. We chose the terminology of Bell et al. (2019) because of clear descriptions.

industries and nations might somewhat diverge, where capturing these differences could prove insightful. Bell et al. (2019) further propose that interpretivism is tied to interpretative research and abductive reasoning, which is in line with the study as a whole.

The qualitative character of the research questions points toward using a case study as a research tool. This is backed up by Yin (2014), who argues that case studies are suitable for research questions starting with *why* and *how*. Eisenhardt (1989) further motivates this study's case study approach by stating that theory-generating case studies are suitable for novel research areas. Fittingly, Yin (2014) also proposes that case studies are compatible with an interpretivist epistemological perspective, in line with the reasoning above that using multiple cases allow for further perspectives of reality, since opinions and perceptions can differ widely. Moreover, Yin (2014) clarifies that often, multiple-case studies are preferable over single-case studies as they have more analytical benefits. Multiple-case studies allow for comparisons and independent conclusions to come together, in line with the reasoning about triangulating the empirical reality with more data (Yin, 2014). Which cases were selected and why will be described in *2.2*.

In contrast to the mainly explorative nature of the study, the later phases were characterized by using theory and findings from the multiple cases interactively to produce concrete recommendations for SUH (the main hospital of study). The ultimate purpose of this was to propose key improvement points. This approach of valuing the findings and making suggestions for what to do or not, is defined by Wallén (1976) as *normative*. It also fits well with the fact that this is a master's thesis, in which it is common to apply acquired knowledge.

2.2 Case sampling

As detailed in *2.1*, the research design builds upon the use of different organizational cases to triangulate findings and eventually to provide well-grounded recommendations for SUH. Here, the reasoning and theoretical backing behind the selection of these organizations will be detailed. As pointed out by Gioia et al. (2013), case selection becomes foundational for potential transferability of results, something detailed further in *2.7.2*. In line with Eisenhardt (1989), the cases were selected for theoretical reasons such that they contribute to the study in a way that both extends the theoretical contribution while also reducing variation among the cases. Similarly, Yin (2014) recommends defining a set of criteria for case selection to guide and simplify the screening process. In the context of this thesis, the general criteria for consideration were:

1) A large organization, either a large hospital or a multidivisional large corporation, to yield a structural similarity with SUH.
2) Indications of being further ahead with AI than SUH. This in order for the process of interest, organizing around AI, to be transparently observable, in line with Eisenhardt (1989). Through being more mature with AI, applicable learnings can likely be identified.

The introductory interviews (detailed further in *2.3*) with AI Sweden together with supervisor consultation and discussions with SUH gave guidance with these parameters in mind, which yielded Region Halland (henceforth simply Halland), Volvo Group (henceforth simply Volvo) and

Ericsson as suitable large Swedish organizations to study. On top of that, an international perspective was sought after, where AI Sweden highlighted the proficiency of the United Kingdom (UK) and their National Healthcare Service (NHS) within healthcare AI. From there, an introductory interview with a high-level NHS (described further in *4.3.2*) manager was facilitated, where two UK-based hospitals that arguably fit the criteria, Great Ormond Street Children's Hospital (GOSH) and Leeds Teaching Hospitals Trust (LTHT) were appropriated into the study's case selection. The process is visualized in Figure 2 below.

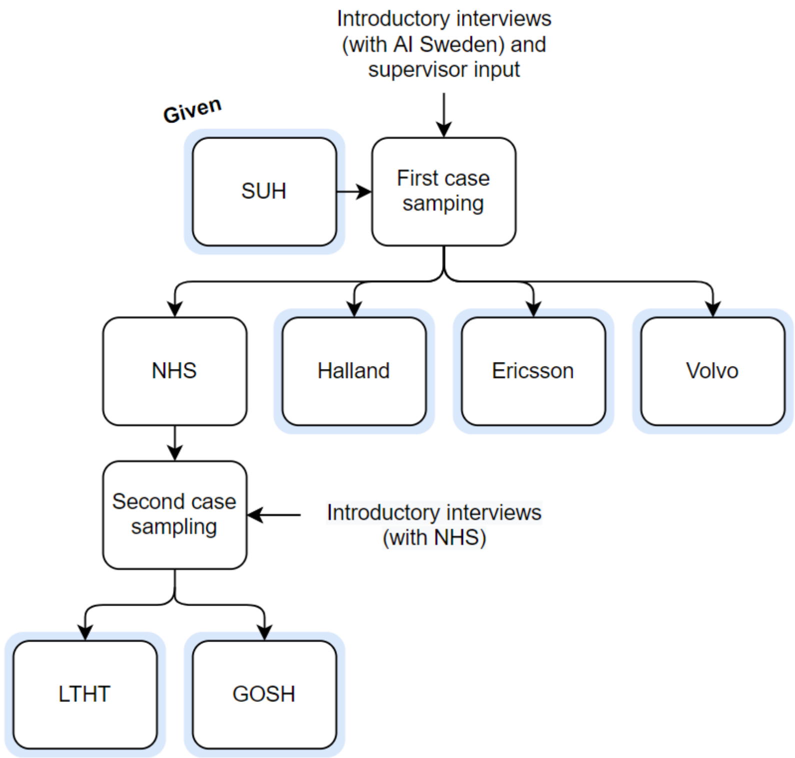

Figure 2: The case sampling process, with the final six case organizations highlighted in blue.

The selected cases, in what way they extend the study around SUH, and what considerations must be considered before applying learnings are presented in Table 1 below. Structural details and background on the studied organizations will be described further in *4*.

Table 1: Selected cases, how they extend the study and what differences became important to consider.

Case	Perspective and value	Considerations
Sahlgrenska University Hospital	Main case, receiver of normative recommendation	Basis for comparisons
Region Halland	Leaders within healthcare AI in Sweden	Significantly smaller region and hospital
Great Ormond Street Children's Hospital (GOSH)	International perspective, and leading healthcare AI development.	Smaller hospital and different macro structure
Leeds Teaching Hospitals Trust (LTHT)	International perspective	Different macro structure
Volvo Group	Private industry perspective	Different industry logics
Ericsson	Private industry perspective & well-established AI success	Different industry logics

Even though the difference between the other organizations and SUH increases as you go down the list in Table 1, there are arguably synergies to find within all. Moreover, the differences with regards to the study's focus, organizing around AI, does not become overwhelming, as motivated below. Halland is the most similar, and the regional size differences and its implication will be discussed further in section *6*. For the UK-based hospitals, GOSH and LTHT, the macro structure differs (detailed further in *4.3.2*) due to the single-payer healthcare system in the UK. However, due to the study focusing on organizational-level considerations, the overarching healthcare system and macro structure is argued to not affect the usability of findings to a significant degree.

Private industry organizations Volvo and Ericsson naturally present the largest difference in context, with clearly diverging industry logics as they are driven by profit and both operate with a product focus. Ericsson stands out as it is a high-tech company with IT-related products (more on this in section *4.4.2*), where AI arguably aligns easier with the current business. The structure, although multidivisional (which does approximate a hospital structure to a degree), also differs. As put forth in background (see *1.1*) however, not much AI has been implemented in healthcare. AI is attractive across industries, and due to the natural slowness of healthcare as pointed out by Arora (2020) (barriers to AI adoption in healthcare also described in *1.1*), much can be learned from other sectors. Especially so when it comes to organizational and overarching aspects of accelerating AI. Moreover, the nascent research of implementing AI in healthcare (Sun & Medaglia, 2019) means learnings from different industries give a richer context for discussions around how AI acceleration is contingent on different organizational conditions and what might be recurring themes throughout different contexts.

2.3 Interviews

The research design of the study, in terms of it being qualitative and abductive, called for in-depth interviews to collect qualitative data (Easterby-Smith et al., 2015). Furthermore, Yin (2014) highlights that interviews are appropriate for collecting data in case studies about organizations, and where data is collected from individuals. Hence, the source of the primary data was indeed interviews. The strategy for conducting these interviews is put forth below.

2.3.1 Interview characteristics

The interview agenda was twofold. Firstly, as a part of the research scoping, two rounds of informal interviews were conducted as a way to map the problem space as well as the informant network in the field. This way, these introductory interviews could be leveraged to get input on the sampling of individuals to interview and cases to study, see *2.2* and *2.3.2*. For that reason, the structure of these interviews was deliberately open and *unstructured*, allowing for input on a multitude of factors. Easterby-Smith et al. (2015) mention that unstructured interviews are used to stimulate conversation, a key aspect of gaining knowledge in the initial stages of the study, and Bell et al. (2019) mean unstructured interviews are often conversation-like in themselves. When it was perceived that these unstructured conversations had become saturated, a deliberate decision was made to stop and reevaluate how to continue. Even though these initial interviews were held in an unstructured way with a purpose of being explorative, they nevertheless generated data that became part of the study's findings.

After having mapped the problem space with the introductory interviews and having sampled both cases and a handful of interviewees, the second step in the interview agenda was conducting more structured interviews with the actors from the different cases. Going into these interviews, specified topics had been prepared for discussion as well as some loosely defined questions around these topics. According to the definition put forth by Bell et al. (2019), these could be described as *semi-structured* interviews. Bell et al. (2019) confirm that this type of interview fits with qualitative research. As further described by Bell et al. (2019), the semi-structured approach made it possible to systematically cover questions and topics, while it still allowed for flexibility in the form of more probing questions when appropriate or covering topics in an alternate order to preserve the flow of the interviews. The questions were open-ended to allow for expansive answers but became more focused toward the end of every interview. In contrast, the introductory phases of the interviews were characterized by questions designed to bring about a comfortable interview climate to not dive into the hard questions right away. Per the suggestion of Gioia et al. (2013), discretion of bringing pre-defined thoughts and assumptions into the interviews was important to not sway answers in any biased direction. This was especially important due to the previous experience of the authors. Though, at times there was a trade-off between avoiding projecting assumptions on interviewees and getting relevant data, as some aspects were interesting to explicitly cover when it did not come up without the authors having to prompt certain questions and provoke thoughts. This was thought to be within the confines of semi-structured interviewing, as they include an aspect of steering the interview still. Moreover, the approach allowed for data relevance between cases as well, something Bell et al. (2019) say is an advantage of semi-structured interviews over unstructured interviews; multiple case studies often need some structure to ensure compatibility among cases. See summary of introductory and main interviews in Table 2 below.

Table 2: The split between introductory interviews and main interviews and their structure.

	Introductory interviews	Main interviews
Structure	Unstructured	Semi-structured
Interviews	5	18

The length of every interview varied from 30 minutes to 90 minutes. Trost (2010) recommends letting the duration of interviews be at least 90 minutes, in order to gather enough information, but this was not always possible or desirable. Many interviewees were under strict time constraints due to their high-level position in combination with the (at the time of writing the report) ongoing COVID-19 pandemic and subsequent workload. Consequently, some interviews were conducted in collaboration with another research project, due to the time constraints of certain interviewees. Before these collaborative interviews, the loose questions and areas to address had to be coordinated between the research groups to ensure useful output for both studies. Many times, the semi-structured approach for the main interviews allowed for a good flow and pace throughout the interviews, leading to the 90-minute recommendation being neither desirable nor necessary. Occasionally, time yielded interviews non-exhaustive; in those cases, either a follow-up interview or clarifying questions via email was pursued.

By and large, the only two interviewers were the authors of this study. During every interview, the same researcher was designated as notetaker, whilst the other was responsible for driving the interview. This setup was flexible and served as a guideline, allowing both researchers to cooperate still, while still counteracting the difficulty Bell et al. (2019) mentions of actively listening and taking notes at the same time. In addition, as recommended by Trost (2010) and Bell et al. (2019), the audio of interviews was recorded to be able to replay and listen through the material for details, as to not miss anything important when taking notes. The notes were read through directly after the interviews, clarified and complemented with additional info from the recording where necessary. Not only the interviewee's words were noted, but also sentiment, silence and the atmosphere when deemed informative. The use of a designated notetaker, taking extensive notes that were quality checked right after the interviews and having recorded the interviews went into the decision of not transcribing the interviews, although recommended by Bell et al. (2019). The alternative cost of transcribing roughly 20 hours of interview material was deemed too high for the seemingly small value-added.

The fact that every interview took place in a virtual setting, as the COVID-19 pandemic hindered in-person interviews, needs to be elaborated on. All interviews were done through video conference tools, namely Zoom and Microsoft Teams. This meant the interviewees and authors could still see each other, though the details of the body language and atmosphere could not be as accurately sensed. However, the heightened use of video conferencing throughout society due to the COVID-19 pandemic meant that this was not out of the ordinary for any interviewee. This proved to be an advantage when setting up and conducting interviews nationally and internationally, as the threshold for doing so with a geographically distant subject was considerably lowered. As put by Bell et al. (2019), this also came with cost and time savings, beneficial for both pressured healthcare interviewees in general and the high-level interviewees across sectors having a high alternative cost. Additionally, recording through Zoom and Teams was readily available. For all the advantages, there were drawbacks with video interviews as well, as technical issues with quality of connection occasionally led to disturbance of the conversational aspect, argued a valuable part of qualitative interviews by Bell et al. (2019).

2.3.2 Interview sampling

The introductory interviews were purposely sampled, meaning the interviewees were selected due to their relevance for the research questions (Bell et al., 2019). Hence, for the introductory interviews the individuals were sampled due to their positions as key informants in the Swedish and UK AI ecosystems, working at AI Sweden and the NHS, respectively. The first interviewee with AI Sweden and the only introductory interviewee with the NHS were reached via email. From there, *snowball sampling* was used for selecting other introductory interviewees with AI Sweden, meaning that an interviewee is asked for another relevant interviewee to sample (Trost, 2010; Bell et al., 2019).

After having scoped the cases in question, as described in *2.2*, interviewees for the main interviews were also sampled. Independent of case belonging, the main interviewees were sampled purposively just like the introductory interviewees, but with other criteria. Namely, main interviewees who were in a managerial, overseeing or similar position and responsible for part of the case-organization's work with AI were sought after. The reasoning behind this was to keep the interviews on a sufficiently high abstraction level, as to not lose the big picture of the research questions.

The way the interviewees were initially sampled differed across the different cases as well. For interviewees at SUH, the supervisor at SUH was leveraged as a gatekeeper, meaning a list of interviewees fulfilling the criteria could be obtained and chosen from that way. Similarly, the supervisor's contact network was leveraged to get connected to an initial interview at Ericsson. The supervisor and introductory interviews also pointed to interviewees in Halland that fulfilled the criteria. Potential interviewees within Volvo, LTHT and GOSH were selected through scanning LinkedIn and websites. In all cases except SUH, snowball sampling was used for gaining access to more relevant interviewees in the same organization. For the final sample of all interviews conducted, please see Table 3 below.

Table 3: Sampling of interviews across cases and per role. As the organizational structures have yet to be described, the roles are presented in rather general terms. This is also done to preserve anonymity of the interviewees.

	AI Sweden	Ericsson	GOSH	Halland	LTHT	NHS	SUH	Volvo
AI Expert	3					1		
Middle/Support Manager		2		2			2	1
Strategist	1			2			1	
Top Management			1		1		4	2
Total	**4**	**2**	**1**	**4**	**1**	**1**	**7**	**3**
Grand Total Interviews	**23**							

As mentioned, a recurring approach was snowball sampling. According to Alvehus (2013), snowball sampling means that there is a risk that the same group of people are referred to over and over again. Although encountered, this was never deemed a problem during the study; due to the naturally occurring proximity of high-level individuals engaged in AI at each organization, this was expected. This also ties into the saturation achieved with the sampling above. Even though there are differing numbers of interviews per case, there was a pronounced data convergence at the later stages of the main interview phase around many questions of the same nature. However, pursuing full saturation ultimately became a question of difficulty to get more interviews and thesis time constraints, where the convergence and saturation levels achieved were deemed satisfactory. As put forth by Bell et al. (2019), it is very hard to know for certain that the sample size is appropriate, but saturation can be an indicator of an appropriate sample size. Though, Bell et al. (2019) also say a rule of thumb is that the more comparisons and cases in a study, the larger samples are required. To comment on the reasons behind the convergence and saturation seen despite the rather few interviews per case, this might have something to do with the field of AI acceleration in healthcare still being nascent (see *3.1.3* and *3.3.3*). If the field is nascent, the knowledge that does exist can reasonably be found rather quickly.

2.4 Secondary data

To get more data than interviews could provide alone, other data in the form of meeting protocols, company websites, documentation of organizational structures and slides from presentations was collected and studied. In particular, documents describing initiatives, plans and strategies were leveraged to complement data from interviews for the different cases. This in turn allowed for better use of time during interviews, where much of structural and historical information could be skipped to instead allow for more individual and targeted questions. Approaching the data collection like this, using secondary data from documents in combination with interviews, is advocated by Yin (2014) when doing case studies about organizations, the guiding principle being to use multiple sources of information. Two secondary data sources were of particular importance and relevance:

1) Halland's "handbook" on information-driven care, co-authored with AI Sweden. Due to yet being finished, a draft was received from AI Sweden via an introductory interview. This data source was deemed valuable as background data could be gathered here, yielding less time required for interviews with Halland stakeholders, instead allowing for more focused questions.
2) NHSX report "Artificial Intelligence: How to get it right" from 2019. This report was concise as it outlined NHS's view and approach to AI. This gave good background information for the interviews with the UK hospitals.

These two data sources were coded into data points along with the interviews, and hence included in the data structure and subsequent discussion. Other secondary data sources were mainly used for the organizational descriptions in section *4*, as these facts were not subject to further discussion.

2.5 Data analysis

Something clearly experienced during the thesis, and as highlighted by Bell et al. (2019), qualitative data and qualitative data analysis can be hard to navigate, where the volume and heterogeneity of the data can easily be overwhelming. Compared to quantitative analysis, qualitative analysis is less clear-cut and requires an iterative approach (Bell et al., 2019). This is also how this study chose to approach the data analysis, which was initiated in parallel to the data collection. Continuously reviewing the interview notes and secondary sources gave rise to discussions and thoughts as the data collection phase progressed. This concurrent approach is in line with the study's abductive approach (Dubois & Gadde, 2002). In fact, an even earlier analysis can be argued to have been made, where the lack of transcribing instead meant an initial screening of relevance took place during note-taking; while data integrity was maintained (original statements were rather intact), a data reduction did take place.

The sporadic and concurrent analysis during the data gathering phase transitioned into a more dedicated and formal analysis once the data gathering was complete. One of the only clear tendencies within qualitative data analysis is to adhere to a thematic approach, i.e., searching for themes within the data in some way (Bell et al., 2019). One of the more tangible methods of doing this is the one proposed in Gioia et al. (2013), which inspired the approach and terminology used in this thesis. The first step was to *code* the raw notes into distinct data points (short sentences explaining one interviewee sentiment each), where the coding attempted to maintain the integrity of interviewee terms, something also inspired from Gioia et al. (2013). In order to achieve agreement between the thesis authors as well as to reduce the risk of the codes misrepresenting the interviewee statements, the coding was reviewed by both authors before transferred into a digital post-it board[5]. For the sake of traceability, the data points were color-coded and tagged appropriately. The resulting data landscape is displayed in Figure 3 on the following page.

[5] Used a program called Miro: https://miro.com/

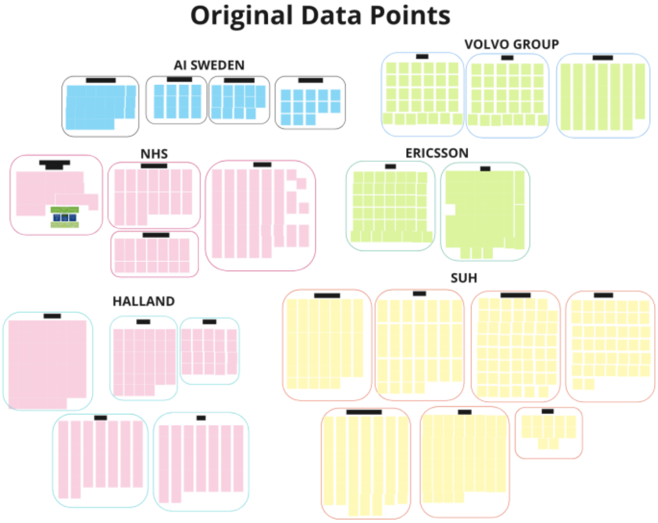

Figure 3: The result from the coding of raw notes into data points, each being represented by a small post-it in the image. Approximately 1000 data points were coded, here visualized with their original affiliative data source. Image from the analysis program.

Subsequently, the laborious task of grouping the data points into *first-order concepts* began, which in line with Gioia et al. (2013) were attempted to still largely maintain the interviewee terms. The first-order concepts eventually consisted of 5-25 data points each depending on how much data converged to a sufficient degree. The digital post-it board made it possible to easily duplicate data points that fit multiple groups, something occasionally utilized. Finally, after multiple iterations and rearrangements, the first-order concepts were each given a descriptive sentence. The resulting board is shown in Figure 4 below.

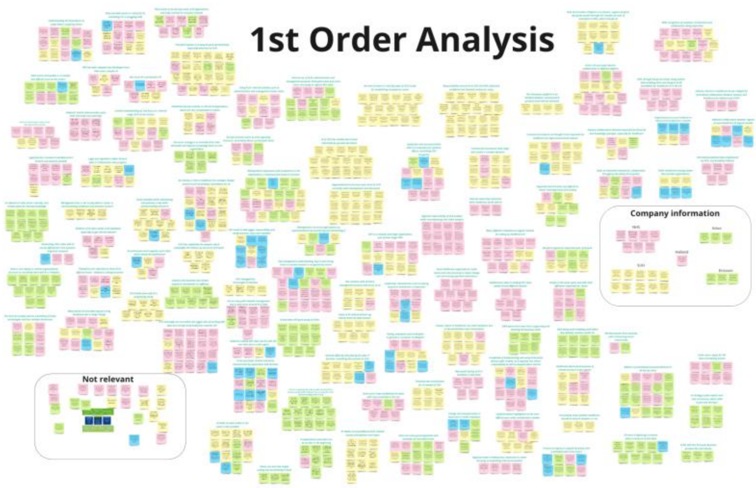

Figure 4: The result from the first grouping was around 100 first-order concepts. Some data points were identified as non-relevant for the discussion, hence placed in the *Company information* or the *Not relevant* group.

From there, the first-order concepts went through the second order analysis which entailed two additional groupings, raising the abstraction level each time. This time, the focus shifted from maintaining the integrity of initial codes, to thinking and grouping more with the theoretical framework in mind, as also suggested by Gioia et al. (2013). Following the terminology of Gioia et al. (2013), the first-order concepts were first grouped into 31 *second-order themes*, with 1-10 concepts in each. Lastly, these themes were gathered into five *aggregate dimensions*, visualized in Figure 5 below. These groupings were both done at the thesis authors' discretion, however with comprehensive discussion and agreement throughout, which Gioia et al. (2013) argues increases the analytical rigor. The aggregate dimensions serve as the answer to the first research question (see *1.2*) and become headings in the findings section, the second order themes serve as subheadings, and the first order concepts are displayed as a summary sentence in bold to start each paragraph. In this way, the findings uphold complete data structure integrity.

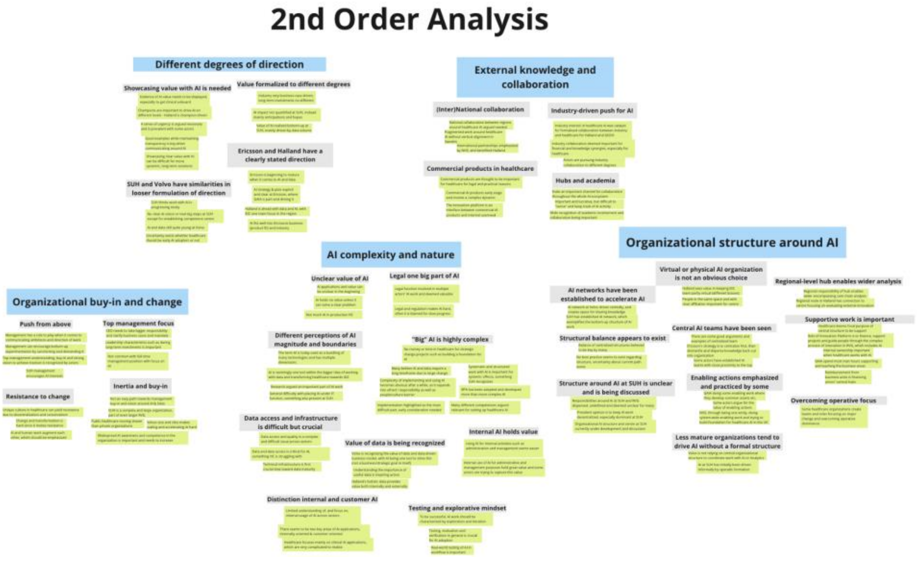

Figure 5: The second order analysis, which yielded both second-order themes (grey highlight) and aggregate dimensions (blue highlight). The first-order concepts are highlighted in green.

The final and likely most significant analysis in the study regards the one that then synthesizes the main dimensions and themes from findings together with the theoretical framework to answer the remaining research questions. This process and its results are recorded in section *6*. During this synthesis, some groups in findings (mostly isolated first-order concepts) were found superfluous for the main reasoning in this thesis. These findings can be found in *Appendix A* for the interested reader.

2.6 Literature review

A critical part of any thesis is the literature review (Bell et al., 2019; Easterby-Smith et al., 2015). This is where the understanding of previous work is developed, and the topic of the study is refined (Easterby-Smith et al., 2015). Bell et al. (2019) also highlight that the study's significance should be displayed through this interaction with previous research, where both coherence and problematization should be strived for. Therefore, the literature review needs to be characterized by critical thinking, hence go beyond just a summary (Bell et al., 2019). The details of the approach, scope, evaluation method and how the thesis authors' previous knowledge played a part, will be described in this section.

2.6.1 Approach

The exploratory nature of the study was apparent during the literature review, as this task naturally involves a comprehensive search as described by Bell et al. (2019). One of the defining features of an abductive approach is to allow for and make use of continuous interplay between literature and empirical findings to drive the research forward (Bell et al., 2019). Due to this and the qualitative character of the study, it was difficult to produce a conclusive list of topics and theoretical areas at the onset. Instead, the approach was more flexible to allow for an evolving understanding of concepts and limitations. The literature review was progressive, starting early on and continuing throughout the study in an iterative way, where empirical findings could guide the search for theory and vice versa. Easterby-Smith et al. (2015) argue that most research projects have the literature review ongoing for the entire duration.

In the very beginning, it was actually discovered that the understanding of the research area was moderate due to previous experience and education. To exemplify, many concepts and much of the theory that appeared during the first exploratory search for literature was recognizable. This led to mind-mapping of relevant terms, areas of interest and keywords, based on previous experience. The mind map, in line with Easterby-Smith et al. (2015), served as a base to start the literature review from, allowing for a more structured approach and loosely defined boundaries. Three major areas and their respective keywords were identified and mind-mapped, see Figure 6.

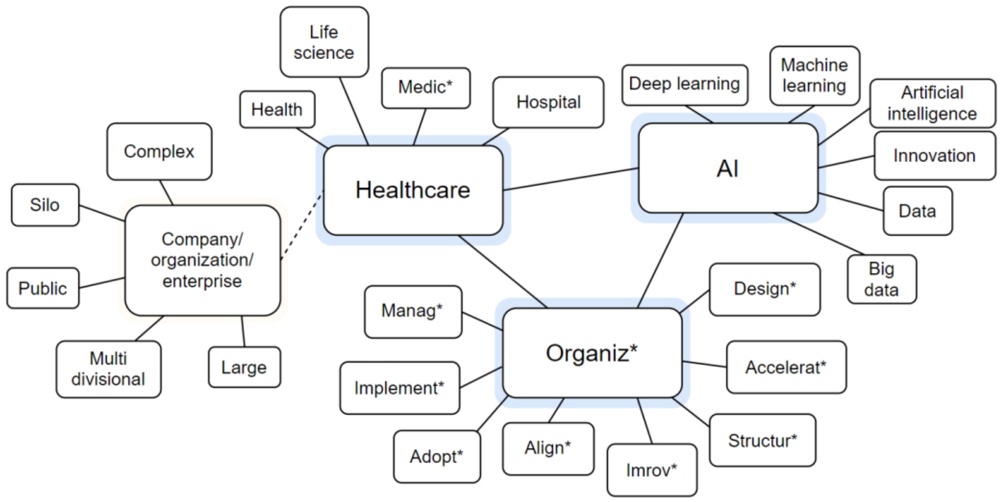

Figure 6: Mapping of keywords that lay the foundation for the initial literature search.

This mind map was leveraged to perform a wide sweep based on the keywords in it. A wide sweep, or *trawling*, is a procedure for collecting information in order to make it easier to get an overview over a field, according to Easterby-Smith et al. (2015). Using one word from each of the three different clusters, a list of all such keyword combinations (720) was produced. An example of one such combination would be: *hospital* + *organize* + *artificial intelligence*. Each combination of keywords in the list was searched for on Google Scholar using an automated script, as Gusenbauer (2019) describes Google Scholar as the most comprehensive search engine for academia. The script collected the ten top results for every keyword search, which were then saved and concatenated.

The end result of this process was a list of preliminary relevant literature with 7,200 entries. In the terminology of Easterby-Smith et al. (2015), this also doubled as a *summary record* of keywords and sources for the literature review, something they highlight as beneficial in order to easily track and compare a vast number of sources.

Removing duplicates from this list led to 3,218 unique entries remaining. By going through every entry title and roughly evaluating the relevance, a list of 784 potentially relevant sources was produced. In turn, these relevant sources were scanned and literature that stood out was read in more detail and summarized. In the end, 20 highly relevant sources stood out and were used as a basis for further literature review as the study progressed.

This process resembles the one described by Easterby-Smith et al. (2015) and Bell et al. (2019) as a *systematic review*. However, the criteria for selection and the evaluation process were not as stringent as they describe, mostly because of the risk highlighted by Bell et al. (2019) as well as supervisors of being overwhelmed with literature if choosing the systematic approach. The study adopted a more flexible but yet comprehensive approach, more in line with what Bell et al. (2019) call a *narrative review*, which encompass a wider scope with looser and less explicit criteria for inclusion than a systematic review. Bell et al. (2019) also emphasize the connection between a narrative approach and an interpretive epistemology and research design, since this approach is then a good fit to the overall research goal, i.e., generating deeper understanding of the topic rather than making sure new knowledge is added. This connection solidifies a narrative review as appropriate for this study.

Further cementing the narrative approach, auxiliary searches were made and input on other literature was taken into account. For example, certain literature was recommended by the supervisors, which was subsequently scanned. Review articles, such as Greenhalgh (2004), were considered with extra care, since these allow for efficient scanning and tracing of relevant citations (Easterby-Smith et al., 2015). If concepts, areas or keywords of interest were found in the literature, standalone searches were made to cover these areas as well. In line with the abductive approach, standalone searches were made drawing upon empirical findings as well. In that way the review was continuous and progressive in nature throughout the study. Easterby-Smith et al. (2015) argue for this approach, where collection of relevant keywords and subsequent searches should be allowed to expand as empirical findings generate new insights as the study progresses. This is deemed a crucial component of the study's iterative abductive research approach.

2.6.2 Scope

Because of the study's healthcare focus, literature directly concerned with this setting was considered primarily. However, due to the complexity of the topic and relative sparsity of relevant research, studies regarding innovation in general were gathered as well, in cases where theoretical synergies were identified. This is in line with how Greenhalgh (2004) performed their comprehensive review, and necessary for this study since it aims to compare different settings, therefore not only including healthcare but also private industry companies.

2.6.3 Information evaluation

Starting with a wide and automatically generated literature base, being critical of literature was paramount in narrowing this down to relevant and useful literature. The beginning stages of the literature review was characterized by surface-level evaluation, due to the sheer amount of literature generated by the automatic search. Much in line with what Bell et al. (2019) mention about reading around topics and what Yin (2014) says about not forcing literature into a review just because it has been uncovered, this made it possible to only pursue literature which was deemed utmost relevant. Once much of the literature from the initial search had been discarded and 784 entries remained, a more thorough information evaluation was necessary. The decisiveness of the information evaluation is implied by the narrowing down of literature from 3,228 pieces to ultimately 20 pieces remaining. The following stages of the literature review, meaning review of recommended articles and literature from auxiliary searches inspired by empirical data, was subject to the same critical approach as well.

The thoroughness of evaluation of sources built on exploring several dimensions of credibility inspired by Easterby-Smith et al. (2015): purpose, authorship, type of publication, accuracy and timeliness. Purpose behind literature became a necessity to evaluate as it became evident that the field is subject to different views of what AI means for healthcare. This is in line with what Bell et al. (2019) say about considering the motive behind literature. Authorship was used as an indicator for credibility as there are prominent authors that are more critically acclaimed than others within the field. Furthermore, where some literature built on other authors' literature it became important to double check the original work. Type of publication was considered as Bell et al. (2019) propose that articles published in peer-reviewed journals can serve as an indicator for legitimacy and Easterby-Smith et al. (2015) say that academic books are an important source of knowledge as well. Moreover, this became a natural part of the literature review as literature from several sources was continuously navigated. Accuracy was strictly considered for automatically sourced literature as described above and continued to be strict throughout the study as to not build an irrelevant theoretical framework, again mentioned by Bell et al. (2019) as well. Timeliness was considered as well, often a non-issue however due to the novelty of the applied AI field. Where older sources were still used, or a source was used heavily[6], credibility was established through either citation counts, supervisor consultation or the fact that the source was used as literature in courses leading up to this very thesis.

2.6.4 Previous experience and knowledge

The thesis authors had previous practical experience from the research setting, as both authors wrote a bachelor's thesis for the same hospital, albeit a different division, on the subject of leadership in the intensive care unit. Although this was an asset at times, it also made for a source of bias which had to be constantly questioned. With a preunderstanding of what could be relevant dimensions in this thesis, the literature review had to be done with caution as to not get locked-in, especially because the abductive method calls for an openness to change (Easterby-Smith et al.,

[6] For example, Glouberman and Mintzberg (2001a; 2001b) and O'Connor (2008).

2015). Lastly, this bias was countered in part by the automatic literature search and by asking for recommendations on literature from the supervisors.

2.7 Research Quality

Different research quality measures will be discussed here. Bell et al. (2019) highlight that literature is not unified when it comes to which measures are suitable for qualitative research, where some argue that equal terms can be applied to quantitative and qualitative research, while others deem that adjusted measures are needed. There seems to be a connection again to epistemological standpoints, where constructionists argue for specialized measures (Bell et al., 2019). Easterby-Smith et al. (2015) also highlight the connection between epistemology and appropriate definitions of research quality. Based on this, the study adopts the four dimensions of *trustworthiness* put forth by Lincoln and Guba (1985), as they go well together with an interpretivist view of there being no *one* correct account in qualitative research (Bell et al., 2019). The four dimensions, namely *credibility*, *transferability*, *dependability* and *confirmability*, are elaborated on below.

2.7.1 Credibility

What is traditionally referred to as internal validity, Lincoln and Guba (1985) calls credibility. More precisely, credibility can be seen as a parallel to internal validity according to Bell et al. (2019). Building on the idea of there being alternative accounts of reality, credibility means to what degree the *specific* account presented by researchers is plausible and acceptable. Consequently, credibility is a product of how well the research has been conducted according to best practices and guidelines. For this study, this means the presence and involvement of an academic supervisor strengthens credibility as the study has been subject to constant methodological evaluation.

Furthermore, this study utilizes theoretical conceptualizations, such as creating its own grouping *big innovation* (see *3.1.3*), to better synthesize literature into a cohesive and applicable theoretical framework. In order to be transparent and maintain credibility, footnotes highlight what terminology the original source uses in cases where an abstraction has been made.

Another thing that increases credibility is member validation (Bell et al., 2019), which entails the research participants taking part of the findings as presented by the researchers, to give feedback on their correctness. During this study, the preliminary conclusions were presented before SUH interviewees, after which feedback was received. This in addition to going back and listening to the exact recordings of interviews to be sure of data integrity, mean the credibility of this study is underbuilt further. Lastly, Bell et al. (2019) highlight triangulation of data as a means of further improving credibility; the study employed triangulation in terms of using multiple cases, but also through utilizing secondary data to back up the primary interview data.

2.7.2 Transferability

Transferability, a parallel expression to external validity, regards how the results of a study can be applicable and transferred to other contexts than the one studied (Bell et al., 2019). This becomes tricky for qualitative research such as this thesis, as the qualitative inquiry focuses on depth using small samples rather than breadth using large samples, the latter being the focus of quantitative inquiry (Bell et al., 2019). According to Lincoln and Guba (1985), determining transferability requires information on both the original context and the potential application context. Since it is impossible for the inquirer (the thesis authors) to understand all possible application contexts, a *thick description* of the studied context is instead recommended by Lincoln and Guba (1985), to allow for readers to themselves assess the congruence between that and their potential application context. The study attempted to provide such rich accounts of the studied organizations through creating a full section dedicated to contextual information (section *4*) in addition to indirectly presenting information about the organizations' settings through the findings.

However, the thesis's multiple-case approach allows for some noteworthy transferability implications. Gioia et al. (2013) argue that case studies can be transferred if the generated results provide clear relevance to other contexts, but that it all depends on the case selections. With the normative recommendations being customized for SUH, other university hospitals provide the most straightforward applicability. Furthermore, with a degree of theoretical abstraction, results can be generalized even wider, as argued by Easterby-Smith et al. (2015) for studies of this character. In concrete terms, the essence of the discussion and subsequent recommendations is believed to plausibly apply to many large organizations attempting to approach AI-enabled innovation. In general, the studied organizations (see *2.2*) span multiple nations and sectors, and the applicability of the results could arguably do the same. However, this should naturally not be done before thoroughly examining the provided contextual information together with the results.

2.7.3 Dependability

Dependability as presented by Lincoln and Guba (1985) rests on how well the process of performing the research has adhered to reliable methods. Dependability describes how the methodology impacts the variability of the results, much the same way reliability does in quantitative research (Bell et al., 2019). Lincoln and Guba (1985) suggest extensive records can help in establishing dependability, as the methodological choices can then be audited. However, Bell et al. (2019) highlight the disfavor of this approach as it is very resource-intensive, which is why this study chose to avoid it. However, halfway through the study there was an informal opposition session with two other thesis projects, meaning that some form of auditing took place during the study. Moreover, chapter *2* tries to meticulously outline the course of the study to achieve a desirable level of replicability, hence dependability.

2.7.4 Confirmability

Confirmability is a parallel concept to objectivity in quantitative research, but as suggested by epistemological interpretivism, this holds little relevance if there is thought to be no objective reality (Bell et al., 2019). Instead, confirmability is concerned with how the researchers have acted as to not skew the data or outcomes of the research (Lincoln & Guba, 1985). Lincoln and Guba (1985) mean that the use of triangulation once again improves confirmability of the study. Moreover, *reflexivity* is an important aspect for confirmability, where researchers are encouraged to reflexively question their impact on the study in terms of biases, personal values and prejudices (Lincoln & Guba, 1985; Bell et al., 2019). Through openly describing less admirable aspects of the study, such as the skewed distribution of interviews across the cases and the influence of previous knowledge, the study tries to showcase confirmability this way.

2.8 Ethical considerations

The ethical considerations of the study, highlighted as important to consider in general by Bell et al. (2019), became especially tangible due to the healthcare setting ultimately being connected to life-and-death situations. By virtue of this, even though no patient or medical data was handled, the information handled during the study was sensitive still. Moreover, the data concerned high-ranking individuals, reasonably heightening the sensitivity of the information further, as it represents not only individuals but whole organizations in a sense. This made for an ethical grey area as the purpose of the study is to highlight organizational aspects. In this context, not only was it important *what* interviewees said, but sometimes *who* said something was of importance. To stay firmly on the ethical side in this grey area, it was decided to not disclose information that could reasonably pinpoint an individual and what that individual said. This is in line with what Bell et al. (2019, p. 114) state as important ethical considerations, namely "protection of privacy through confidentiality" and "avoidance of harm". This meant there was an occasional loss of detail in the findings, though this did not outweigh the ethical gains. Moreover, Bell et al. (2019, p. 114) suggest that "preventing deception" is an ethical aspect to consider. Congruent with the comments on confirmability under *2.7.4*, there was an active effort made to be transparent, both when conducting the study and when detailing it.

Lastly, due to the COVID-19 pandemic, actual at the time of performing the study, the necessity of lengthy interviews within the pressured healthcare environments were carefully evaluated as to be efficient with high-ranking individuals' time. One dedicated adjustment was to perform joint interviews at SUH with an adjacent master's thesis, reducing the time required for those interviewees and hence, ethical implications of the study.

3

Theoretical framework

The theoretical framework will be presented in three sections: *Defining AI*, *Diffusion of innovations and major change*, and finally *Healthcare specifics*, also visualized in Figure 7 below. This way, the framework starts narrow with the details of AI, widens its way towards AI as an innovation, moving over to general innovation theories, and finally narrowing back down towards the healthcare context and the specifics of innovation and AI in this environment. First off, some characteristics of AI will be presented.

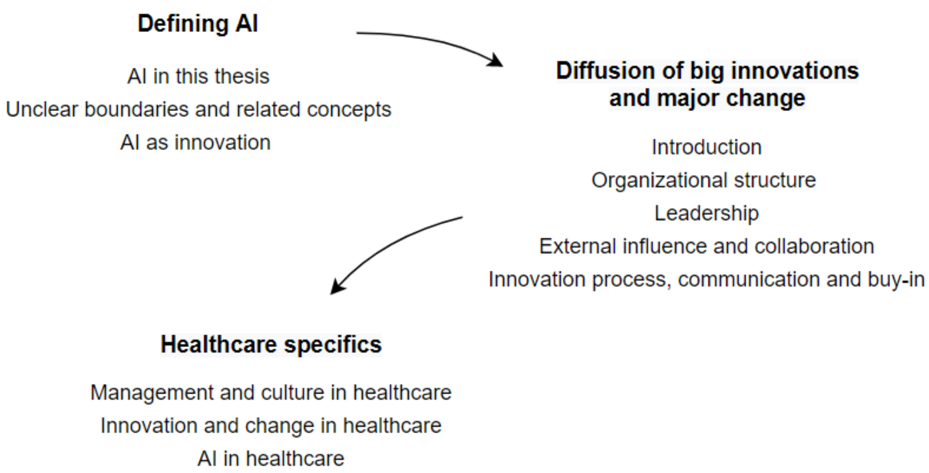

Figure 7: Theoretical framework structure in this thesis.

3.1 Defining AI

In this section AI and how it is approached in this thesis will be laid out. Definitions will be discussed, along with fundamentals of AI and how AI relates to the broader term of innovation.

3.1.1 AI in this thesis

No *one* official definition of AI exists according to the University of Helsinki and Reaktor (2021), why it is important to discuss what is meant by AI in this thesis. IBM (2021) defines AI as any human-like intelligence embedded in machines, computers or robots, while the European Commission (2019, p. 1) mentions that "Artificial intelligence (AI) refers to systems that display intelligent behavior by analyzing their environment and taking actions – with some degree of autonomy – to achieve specific goals". NHSX (2019, p. 14) highlights that definitions are also contingent on the context in which AI is applied, as they chose to rely on the following definition due to its good fit with health and social care: “the science of making machines do things that would require intelligence if done by people”. Even though finding an exact and detailed technical definition bears little importance in the context of this thesis, the one selected by NHSX, originally from the field's founding document (McCarthy et al., 1955), is deemed appropriate.

The term itself, *AI,* can also mean different things in different contexts, by the judgement of the thesis authors. AI can refer to a set of specific technologies, but at other times refer to how the actual technology impacts the way of doing business; an example being how AI is used to discuss transformation in businesses and be a component in business strategies. In such business contexts, the foundation of what is being discussed as AI risks becoming abstract. Therefore, in an effort to be precise about what is meant by the term *AI* in this thesis, AI is defined as the *technology* that enables *innovation* and in turn gives rise to *business impact*, see Figure 8 below.

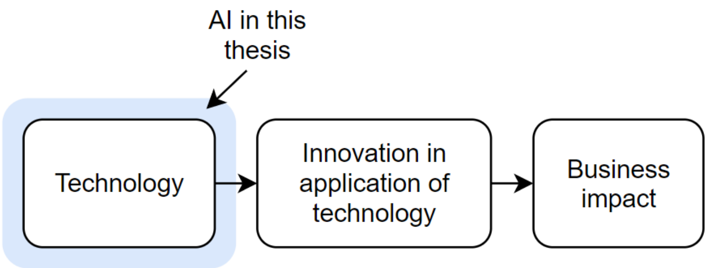

Figure 8: Illustration of how this thesis defines AI.

This conceptual model builds upon the interpretation of what AI is put forth by the European Commission (2018); they classify AI as one of six *key enabling technologies* that enable multidisciplinary innovation. The separation of the terms innovation and business impact is done on the thesis authors’ prerogative to paint a clear picture of how the idea of enabling technology ultimately connects to higher level business effects. It is also in line with how Reddy et al. (2019) reason about AI being incorporated into healthcare, as they suggest such a health system could be characterized as *AI-enabled*. Furthermore, the conceptualization fits in with what both Grant (2018) and O’Connor (2008) put forth about how technology enables innovation, which in turn has the potential to generate a competitive advantage.

Separating the technology, innovation and business impact in this way also makes it easier to approach the complex field of AI in a systematic way. By overlooking overly technological details, and at the other end not only seeing the concept of AI as a business transformation, allows for focusing the thesis on trying to understand how to *realize* business impacts *by* using AI technologies. The thesis authors believe that this separation and concretization is especially important as to not be blinded by the enthusiasm Lorica and Loukides (2018) mention the field has experienced.

3.1.2 Unclear boundaries and related concepts

Because of the easily confusing situation with different definitions of what AI is and what to use the term for, the boundaries of what AI is are equally blurred. Again, especially when many uses of AI refer to something more business-oriented and not specific technologies. Therefore, these boundaries have to be explored.

Starting with the more technical view of AI, machine learning (ML) is one term that is often used interchangeably with AI when speaking of how an intelligent system works at a more detailed level. ML techniques and models are often components in an intelligent system that would be called an AI system (Russell & Norvig, 2020). That way, what can be classified as AI technologies and as ML technologies overlap. Though, there are systems not built with ML technology that could be said to show intelligent behavior or could reasonably be called AI systems, ultimately meaning that the field of ML is thought of as a subfield of AI (Russell & Norvig, 2020). Many other terms are used to categorize these congruent AI and ML technologies further, often to differentiate between different detailed system characteristics and applications (Panesar, 2019). To exemplify, such terms include unsupervised learning, supervised learning, natural language processing, vision systems, and deep learning. Moreover, many new techniques are being invented and explored (Jordan & Mitchell, 2015). For the sake of keeping discussions on an appropriate abstraction-level throughout this thesis, focus will not lie on such detailed technological characteristics. Instead, AI technologies will be discussed on a level in line with the previous Figure 8.

What is clear is that data is indeed needed for AI technologies to be used. This is because, in order to function, AI-enabled systems need to be trained using example data, or in other ways use data as an input (Russell & Norvig, 2020). From this input data, key patterns can be extrapolated and applied to new data, thereby displaying a form of intelligence. A crucial takeaway is that this means access to data is a prerequisite and requirement for AI technologies to be of use. Somewhat paradoxically, this raises questions about whether the data infrastructure is included within the boundaries of AI technology as depicted in Figure 9. Speaking in favor of this is Sculley et al. (2015), who argue that data processing is a part of AI-enabled systems, and that very little of the system is the actual code (which in itself could be thought of as the technology). The author argues that, in contrast, the infrastructure and data aspects around such systems are vast and complex, see Figure 9 below.

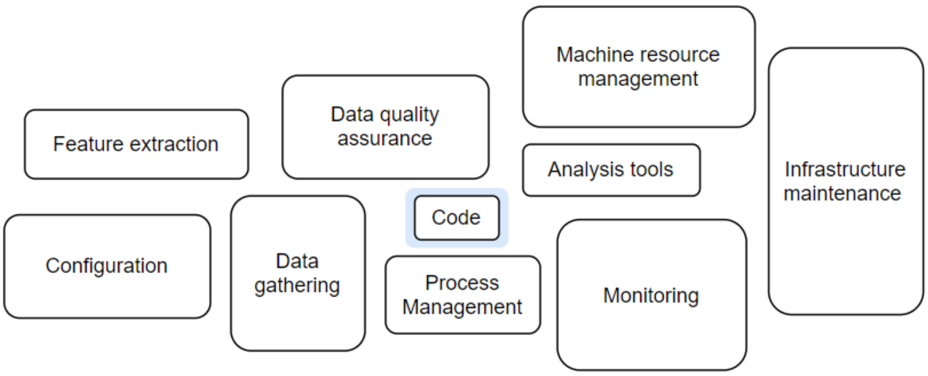

Figure 9: Software code in comparison to surrounding system architecture, adapted from Sculley et al. (2015).

Lee et al. (2019) corroborate this reasoning, as they state that 80% of the work lies in data preprocessing due to the "garbage in, garbage out" rule that applies when it comes to AI and data analytics. Data acquisition and data infrastructure, therefore, become vital elements in applying AI at a wider scale (Lee et al., 2019). Jordan and Mitchell (2015) further mention that there is a growing focus on the system architecture in which AI operates, stating that it is becoming more complex with multiple collections of software running in parallel on distributed platforms. In one sense, this means the term *technology* may account for the entire technical system in Figure 9 above as well, whilst the surrounding system might also be viewed more as a prerequisite for AI. The above reasoning implies that the extent to which an organization is *data-driven* holds great relevance for leveraging AI.

3.1.3 AI as an innovation

This technical and conceptual complexity described above has implications on how to classify AI as an innovation as well. As explored, the term AI means different things in different contexts. Therefore, it is important to also explore the different approaches to classifying AI as an innovation.

Assink (2006) states that the idea of innovation is multi-faceted. The author outlines that innovation can concern products and services, processes, organization, management style and business models. What innovation entails is a continuum, on different levels where whole value chains at a company level can be affected, just as on a more individual level (Assink, 2006).

It seems appropriate to start with Christensen's (1997) distinction *sustaining* and *disruptive* innovation as one way to think about AI as an innovation. Sustaining innovation, meaning an innovation that only improves existing products according to Christensen (1997), can be an example of where AI improves existing processes and products. In turn, it is conceivable that disruptive innovation, innovation that meets minimum requirements with new technologies, gaining traction and ultimately outcompeting existing sustaining innovation, may also be achievable through AI. Though, because this distinction by Christensen (1997) explains highly specific situations when applied to AI, it does not paint the whole picture.

Another class of innovation would be *radical* innovation. O'Connor (2008) states that a previously used definition of radical innovation is: a product, service or process that creates new markets or transforms existing ones by the means of new features, unprecedented leaps in performance of existing features or major cost-savings. However, such innovation projects are of a longer horizon, and tangible returns can be years away (Leifer et al., 2001). Hence, radical innovation means high uncertainty for firms, as they must incorporate new technological competences, that in turn give rise to more management challenges than incremental innovation does (O'Connor, 2008; Grant 2018). Therefore, these uncertainties are not only technical, but also organizational and resource-related. Drawing a parallel to AI, this definition captures more of the complexity AI technologies entail. The role of new technological competences in radical innovations seems like an extra appropriate dimension to take into account when discussing AI in this thesis.

Grant (2018) connects the ideas of technological competences to a firm's business models, saying that although new technological capabilities are characteristic for radical innovations, new business models are not. Instead, when new technological capabilities are accompanied by a new business model, Grant (2018) calls this *architectural innovation*. Such architectural innovation requires configuration of whole strategy and activity systems, which in turn constitutes great difficulties for established firms according to the author. The direct opposite of architectural innovation is *component* innovation. To exemplify further, Grant (2018) calls the hybrid automobile engine a component innovation as it did not require reconfiguration of the whole car design, whilst the electric engine did just that. The electric engine also introduced another dimension of building charging infrastructure, qualifying it for being labeled an architectural innovation by Grant (2018). The difficulty of drawing the boundaries around what AI is and what the specific technologies involved are (presented in the above sections), ties in with the concept of innovation at a more architectural scale; take for example the data infrastructure prerequisites for AI-enabled systems.

A related label for innovations that is concerned with something bigger than component innovation is *systemic* innovation (Takey & Carvalho, 2016; Chesbrough & Teece, 2002; Teece, 1986). Systemic innovation regards an innovation that is not standalone, but instead is accompanied by *complementary* innovations. The authors contrast the term systemic innovation against autonomous innovation, described by Chesbrough and Teece (2002) as something that cannot rely on other innovations being developed, thereby allowing it to be independently developed. Systemic innovation on the other hand, brings with it changes in business processes and the business system in itself (Takey & Carvalho, 2016). In general, cooperation and coordination are important parts for such innovations and changes since they depend on complementary assets as part of the system (Teece, 1986). Takey and Carvalho (2016) expand the reasoning further, as they state that systemic innovation often expands outside the company, making cooperation in the external value network an aspect for systemic innovations as well. Ultimately, systemic innovation typically is more long-term in its value, but can bring initiation costs for some parts of the organization, hence making adoption and diffusion more complex (Taylor & Levitt, 2004). Again, as with architectural innovation, systemic innovation explains the complexity of AI quite fittingly.

Yet another dimension of innovation is described by Damanpour (1996): the distinction between *administrative* innovation from *technical* innovation. The author says that administrative innovation is related to the organizational structure, administrative processes and human resources, whereas technical innovation is concerned with products and technology in products or services. Kimberley and Evanisko (2017) supports this argument by also making the same distinction between technological and administrative innovation.

O'Connor (2008) means that when new value chains are required to exploit an innovation, *business models*, i.e., how an organization creates and captures value (Chesbrough, 2007), come into question. Grant (2018) also highlights that it is important to assess the implications that an innovation has on the organization's capabilities and business model. For AI technologies specifically, Lee et al. (2019) mean that AI is the most powerful when it is used to create innovative business models. Business model innovation is a term Chesbrough (2010) uses when describing how business models can change or be actively changed in this way.

While AI can enable all of the innovation definitions above, the concepts that have big change potential, i.e., radical, systemic, architectural, administrative and business model innovation are together thought to nicely include many complex dimensions in which AI technologies can foster innovation with big impact. As to not use the exact wording of previous innovation definitions and risk confusion or improper use of established terms, an umbrella term coined by the researchers, *big innovation*, will encompass the ideas of the dimensions covered by the more wide-encompassing innovations listed above. As put by Grant (2018), innovations often require many complementary resources outside of the core know-how in order to be realized. The definitions put forth above all do just that as they encompass a big leap forward, a complex big change and are deemed suitable to use in this thesis, as it aims to provide recommendations for how to achieve large-scale impact through organizing AI-enabled innovations. Using an umbrella term for these higher-level complexities and definitions helps make formulations concise and understandable, enabling a red thread throughout while still allowing for details to be discussed when needed. See Figure 10 below for an illustration of the umbrella term *big innovation* and what it includes.

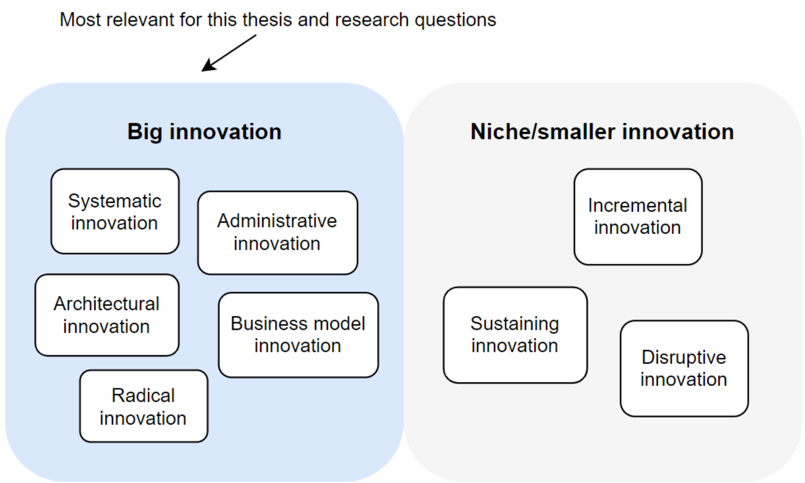

Figure 10: Visualization of how the innovation terms deemed most relevant for this study are bundled.

As elaborated on, big innovation stemming from AI technology inherently means that more than the very technology has to be taken into account. Crawford and Calo (2016) write that AI as a concept presents a cultural shift in addition to a technical one, meaning social-system analysis is crucial to deploy AI safely. Further emphasizing the cultural and social aspects of AI-driven innovation, Lorica and Loukides (2018) exemplify the difficulty of applying AI technologies in practice, saying that the path toward AI is unclear for many organizations. Ericsson Industry Lab (2020, p.4) supports this as well, as one key finding from surveying organizations about their AI adoption was that "eighty-seven percent faced more people/culture challenges than tech or organizational challenges". Moreover, achieving a data-driven culture, where leveraging AI technology can enhance the potential value, is a larger challenge currently being undertaken by many companies, where Davenport and Bean (2018) argue that a joint and coordinated effort is necessary. In line with this, Lee et al. (2019) propose that widely adopting AI entails major organizational change, and should be treated as such. This reasoning suggests that the act of implementing AI is complex as well and has significant cultural and organizational aspects to it. In line with this, Wirtz and Müller (2019) argue that benefits from AI require a sophisticated strategy to be achieved.

The difficulties of defining AI technologies, what innovations follow and the cultural and organizational associated with implementing AI technologies can be explained partly by the conceptual model Afuah (2003) details; a highly complex technology that is in the early stages of its evolution is characterized by high uncertainties and is influenced by non-technical factors. AI technologies could be complex, while in early stages of its evolution, as Kelly et al. (2019) and Yu et al. (2018) argue that the field of AI is making fast paced progress and accelerating rapidly, hence it is not in an era of marginal improvements, see Figure 11 below.

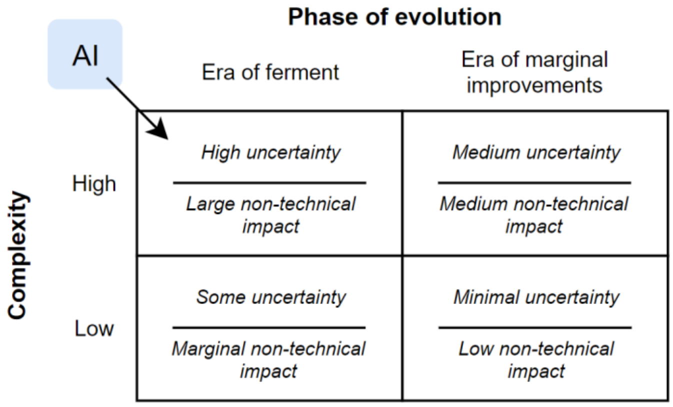

Figure 11: How the phase of technological evolution and complexity affects uncertainty and non-technical impact of the technology and where AI places within this. Adapted from Afuah (2003).

To summarize, AI is a technological enabler of big innovation and subject to cultural and organizational challenges. Hence, theories of how to spread and implement big innovations and overcome such challenges in general are relevant for properly understanding the dynamics of how to leverage AI techniques for big innovation and to ultimately achieve a large-scale impact.

3.2 Diffusion of big innovations and major change

In this section, theories within the wide fields of innovation diffusion, big innovation[7] and change management will be presented. Normally, these concepts are treated separately, but within the confines of this thesis, the theories overlap and are hence presented through their common components as identified by the thesis authors: *organizational structure*, *leadership*, *external influence and collaboration,* and lastly *innovation process, communication and buy-in*. Before that, an introduction to the topic and its relevance will be given. The overall section will draw on literature from the general fields, with specific sources regarding healthcare where suitable. The specific issues that pertain to the healthcare setting will be described further in the subsequent section *3.3*.

[7] In this theoretical synthesis, innovation types that fall inside the conceptualization of big innovation will be presented as such, however with a footnote showcasing the original term of the authors in question.

3.2.1 Introduction

Growth and renewal through big innovation is crucial for any organization's long-term survival (O'Connor, 2008). However, previously successful and established organizations are generally bad at renewing themselves and staying relevant when technologies and markets change (Bower & Christensen, 1995; Christensen, 1997). This inertia usually stems from the previous success, which leads to an inability to question the status quo (Assink, 2006). Leonard-Barton (1992) similarly argues that when organizations strive towards efficiency within their core competencies through scale and scope, these competencies ultimately turn into core rigidities. The critical factor here, according to Christensen (1997), is when the necessary change is not deemed attractive by current customers. This phenomenon is argued by Chesbrough (2010) to be synonymous to what he describes as a barrier stopping organizations from experimenting with business model innovations. It is highly difficult for organizations to invest into future customer needs, while prioritizing away current customers, which often leads to incumbents falling victim to new entrants (Bower & Christensen, 1995).

This tension between the organization's operating and innovating part is inevitable, as the novel nature of innovation instinctively threatens routines and the status quo (Grant, 2018). This tension is described in literature as the trade-off between exploitation (of current lines of business) and exploration (of future opportunities) (see e.g., March, 1991; O'Connor, 2008; O'Reilly & Tushman, 2004). This trade-off gets more difficult to balance the more proficient an organization becomes with its daily business, as the opportunity cost to experiment and explore then increases (March, 1991). Organizational innovativeness and renewal is a process which, especially when driven by technology, is characterized by uncertainty, technological interrelatedness and irreversibilities (Teece, 1996). Big innovation[8] similarly needs experimentation, as it otherwise has no data to justify it (Chesbrough, 2010). Exploiting the current mode of business on the other hand, is according to March (1991) characterized by safe, clear and fast feedback that inhibits exploration and innovation through initiating cumulative learning and an organizational lock-in towards the current direction. However, March (1991) also argues that a balance between exploitation and exploration is needed for a firm to succeed long-term. Assink (2006) similarly argues that in order for an organization to survive and grow in the long run, innovation is key, where big innovation[9] is highlighted as an especially powerful catalyst.

Grant (2018) writes that technology and innovation continues to generate many new industries and also has the potential to transform many existing ones, including healthcare. He further argues that continuous renewal is possible, where companies that succeed in this are said to possess *dynamic capabilities* (Grant, 2018). In the words of Teece et al. (1997), dynamic capabilities are a firm's ability to *sense* what renewal is relevant, *seize* it and subsequently *transform*. Furthemore, as strengthened by Damanpour (1996), with innovation comes change, a change that an organization has to manage properly in order to succeed. Gustafson et al. (2003) emphasizes that resistance can be expected when changes appear to interfere with current conditions. Further, Grant (2018) argues that resistance to innovation is positively associated with the stability of the operative and

[8] Originally business model innovation.

[9] Originally radical innovation.

administrative organization, as the social and political power structures threatened by the innovation are then firmly cemented.

The change management field is rich with comprehensive theories that aim to explain why change so often fails and give guidance on how to succeed. Two of these include Kotter's 8 change principles (see Kotter, 1995; Kotter, 2012) and the ADKAR model (Hiatt, 2006). Common components of these theories, combined with those of theories regarding innovativeness in general and big innovation in particular, have been synthesized and will be presented below. Both O'Connor (2008) and Assink (2006) argue for the systemic interconnectedness between the different factors towards innovativeness and change. Hence, even as the factors are presented individually, a holistic approach is needed.

3.2.2 Organizational structure

Much of the literature regarding big innovation comments on specialized organizational structure in one way or another. In order to cope with the need for dual focus mentioned earlier, partly towards exploiting current business and partly towards exploring opportunities for renewal and big innovation[10], O'Reilly and Tushman (2004) pioneered the later popularized term *organizational ambidexterity*. The authors, corroborated by Grant (2018), argue that ambidexterity is the reconciliation between the otherwise conflicting activities of exploration and exploitation, and has been shown to be positively associated with performance, innovation and survival (O'Reilly & Tushman, 2013). To achieve it, a clear structural distinction between the activities, with the sole integration appearing in the top management team, is needed to allow for the completely different processes and cultures called for (O'Reilly & Tushman, 2004). Bower and Christensen (1995) similarly argue for complete independence for this unit, mainly to shield the exploratory unit from the dominant logic and incentives in the mainstream organization. Separation could aid resource-wise as well, as a separate pool of money and internal protection is probably needed to allow experimenting with big innovation[11] (Chesbrough, 2010). Further adding to this notion, O'Connor (2008) states that in order to make big innovation[12] happen, a clear organizational structure with explicit responsibility for this activity is needed. However, as O'Connor (2008), Börjesson and Elmquist (2011), as well as Grant (2018) argue, if the results they generate are to be diffused throughout the organization, greater integration than solely at top management level is needed to avoid rejection. In particular, the exploration unit should be clearly and explicitly differentiated from the organization's normal innovation activities, as well as tightly connected to the overall strategy, both to prevent alienation and clarify its role in the organization (O'Connor, 2008).

In general, centralization and other organizational design parameters that regulate division of labor and coordination should be chosen carefully in order to be internally consistent (Mintzberg, 1989). With this in mind, Mintzberg (1989) states that centralization does offer the greatest potential for coordination, but that it can also be achieved through liaison devices such as committees and task forces. In fact, Greenhalgh (2004) found that one of the only structural determinants that clearly

[10] Originally discussed in terms of innovation that will bring large change to an organization.

[11] Originally business model innovation.

[12] Originally radical innovation.

enables innovation and its implementation is establishing what the author calls *semi-autonomous multidisciplinary project teams*. This is corroborated by Grant (2018), who states that such teams enable integrating exploration with effectiveness. When the goal is to achieve major change, a similar team, or *guiding coalition*, with a mix of vertical and horizontal leading positions is needed, especially in the early phases (Kotter, 1995; Kotter, 2012). Taking it one step further, Leifer et al. (2001) argue for a permanent structural formation, a *hub*, to deal with big innovation[9] and the complex process it entails. Here, legitimacy could be built, and uncertainties reduced through gathering human resources, cumulative know-how and facilities (Leifer et al., 2001). It also appears that diffusion of complex technology is positively influenced by a central formation of this kind (Hottenstein et al., 1999). This reasoning applied to AI can be seen in the paper by Lee et al. (2019), as they argue for an in-house AI team to help facilitate AI-based big innovation[8], as gathering a team enables more efficiency and larger impact. Moving even closer to the topic of this thesis, Cosgriff et al. (2020) argue that a hospital AI department is needed if AI is to find its way safely and efficiently into medical practice, as this unit could take charge on standardizing processes around data issues, model evaluation, policy compliance, ethics and workflow integration. The authors refer to the introduction of radiology as precedent for this way of bringing a new tool into wide healthcare usage, visualized in Figure 12 below.

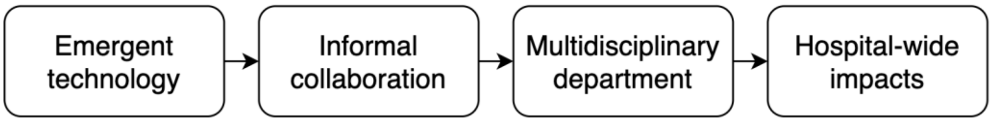

Figure 12: Visualization of how Cosgriff et al. (2020) argued that radiology came about in the beginning of the 20th century, exemplifying how they argue that AI should also be assimilated.

3.2.3 Leadership

Quite naturally, and as already highlighted in the previous section regarding organizational structure, leadership has big implications on how innovation and change manages to progress. However, the extent to which top management should intervene is not obvious, as the continuum between diffusion and dissemination of innovation displays (Greenhalgh, 2004). Diffusion is natural and hence characterized by unpredictability, self-organizing and spread through social networks, while dissemination on the other hand is managerially controlled and largely planned, orderly and usually spread through vertical hierarchies (Greenhalgh, 2004), see Figure 13 below.

Figure 13: The diffusion-dissemination-continuum. Figure adapted from Greenhalgh (2004).

With this in mind, some kind of responsibility over big innovation or change initiatives needs to be established. Chesbrough (2007) found that, in the case of big innovation[13], the strategic apex of the organization needs to embrace this task, as authority and capability will be too weak otherwise. Similarly, Greenhalgh (2004) argues that complex innovation, where assimilation by the system as a whole is often needed, may require organization-wide decisions from the top. However, authoritative decisions do come with the risk of being rejected and hindering sustained innovation use (Rogers, 1995).

While it is important that leaders assume responsibility over change, it does not equate to them doing the actual work. Instead, O'Connor (2008) emphasizes that if a separate innovation team is created, the team should have full endorsement from top management in order to gain authority. In general, top management support, commitment and involvement is widely regarded as essential for successfully driving change and implementing innovation (Meyers et al., 1999; Gustafson et al., 2003; Afuah, 2003; Takey & Carvalho, 2016; Berwick, 2003). These characteristics can be hindered by the *dominant logic* of an organization, under which management has normally risen to its current ranks (Chesbrough, 2010; Afuah, 2003). This dominant logic of how the organization creates and captures value often lies cemented subconsciously, and acts as a cognitive barrier to big innovation[14] that falls outside this logic (Chesbrough, 2010; Assink, 2006).

One way leadership can contribute against organizational inertia such as dominant logic and cemented routines, is to create perceptions of crisis and hence a clear urgency for change (Grant, 2018; Greenhalgh, 2004). In fact, Leonard-Barton and Kraus (1985) found that when the need for change was clearly defined at the top of an organization, the chance of success was greater. Strengthening this argument further is Kotter (1995, p. 2), as he puts "establishing a great sense of urgency" as the first step in his change management framework. This step is not easy, as 50% of the changes the researcher observed underestimated the strength of urgency as a catalyst for transformation or simply lacked sufficient courage, ultimately leading to a failed change effort (Kotter, 1995). Hiatt's (2006) ADKAR framework also touches these aspects, as both **A**wareness (of the needed change) and **D**esire (to participate in the change) can be achieved through clearly communicating the prevalent urgency for change.

Building on the established need for change, it is widely argued in literature for a vision accompanied by goals and a strategy to guide the change. Grant (2018) highlights that establishing a clear vision and ambitious goals helps further with counteracting embedded inertia within the organization as it can instill a sense of purpose among the employees. Without a concise vision that sets the direction of change, individual sub-projects can seem incoherent and alienate staff from the change (Kotter, 1995; 2012). Further, Pisano (2015) argues that organizations need an innovation strategy to start building a capacity to innovate and align different interests internally, a responsibility that falls on senior management. He further highlights the tangibility required, as insipid wordings in the likes of "innovation is important for us"[15] does not provide much direction

[13] Originally business model innovation.

[14] Originally business model innovation and radical innovation from the two sources, respectively.

[15] Interpretation by the thesis authors

to align towards (Pisano, 2015). With regards to establishing a clearly distinguished big innovation team and system[16], O'Connor (2008) accentuates alignment with overall strategic intent, often realized through a board overseeing big innovation project selection. McAfee and Brynjolfsson (2012) show that the reasoning in this paragraph also applies to the specific change of becoming more data-driven; organizations require leadership to set clear vision and goals, and just having data is not enough. Lee et al. (2019, p. 8) further argue for an AI strategy, where quality, quantity and infrastructure of data should be the first order of business, as to not build a "palace on quicksand". Also, embedded in any innovation strategy should be clear resource allocation, as big innovation[17] might need an earmarked budget to avoid internal competition (Chesbrough, 2010; Pisano, 2015).

Due to the long-term nature of big changes, maintaining urgency and commitment through systematically planning and facilitating "short-term wins" becomes necessary (Kotter, 1995; 2012). Tangible effects make the progress unambiguous, likely increasing the likelihood of employees staying invested in the transformation, and anchors the changes into organizational culture (Kotter, 1995). If these signs of progress are communicated clearly, the commonly existing mindset barrier could gradually be broken down as well (Assink, 2006; Gustafsson et al., 2003). Rogers (1995) mentions that this communication is especially effective if the communicator is an opinion leader. Lee et al. (2019) similarly highlight initial focus on readily feasible smaller projects when it comes to AI acceleration, as this enables increased familiarity and enthusiasm towards the concept within the organization.

3.2.4 External influence and collaboration

"The evidence that boundary spanning stimulates innovation is overwhelming" (Grant, 2018, p. 241). With innovation in general, external influences play a big part in how an organization succeeds (Greenhalgh, 2004; Rogers, 1995). To achieve dynamic capabilities as described by Teece et al. (1997), the first step is sensing the environment in a systematic way, also argued as the first step towards organizational change according to Grant (2018). *Absorptive capacity,* entailing systematic identification and integration of new knowledge and described by Zahra and George (2002) as a dynamic capability that enables organizational change, helps an organization assimilate innovations (Greenhalgh, 2004). Mapping and participating in the wider ecosystem has also been seen to facilitate both systemic innovation (Takey & Carvalho, 2016) and implementation of innovation in general (Meyers et al., 1999).

Connecting the reasoning above to the earlier one regarding unique organizational structure, O'Connor (2008) recommends the innovation team to have an external interface to facilitate knowledge generation. The researcher also highlights that the necessary entrepreneurial capabilities could be unavailable within the organization, hence further strengthening the need to raise the gaze over the organizational horizon. Continuing on the theme of external competence, Grant (2018) highlights that organizations are increasingly seeking, exploiting and applying knowledge from outside the organization to generate innovation. This phenomenon is called *open innovation*,

[16] Originally discusses a team and system focusing on radical innovation.

[17] Originally business model innovation and innovation in general by the two authors, respectively.

which Chesbrough (2003) argues to be fundamentally about utilizing the abundant knowledge that exists in our modern, connected world. McAfee and Brynjolfsson (2012, p. 8) refer to Joy's Law: "Most of the smartest people work for someone else", as they urge organizations to open up their work around data and AI to the outside world.

3.2.5 Innovation process, communication and buy-in

Moving towards a formalized change procedure, there are many aspects to consider in order to enable internal assimilation. Pisano (2015) suggests that an innovation process cannot be done ad-hoc, but that organizations instead need a well thought out innovation system with a set of coherent processes and structures leading from search to funding and beyond. This system benefits from being infused with an experimental mindset, as this is required for big innovation [18] (Chesbrough, 2010).

Within this internal change process, communication becomes a cornerstone. Meyers et al. (1999) suggest that effective cross-departmental communication enhances probability of success. This is corroborated by Greenhalgh (2004), who argues for intraorganizational multi-professional networks where a foundation (e.g., common vision, terminology and meaning of innovation) can be established, which then accelerates adoption. The change vision should be communicated widely, as a transformation requires buy-in despite possible short-term losses; Kotter (1995, p. 7) found that most failed change initiatives under-communicated the vision "by a factor of ten". In addition, the role of the unique innovation structure (if one is established, see section 3.2.2 for its arguments) ought to be communicated clearly, as to minimize resistance and display the value it holds for the organization (O'Connor, 2008). Communication should also be directed towards achieving overall organizational awareness and knowledge, as the change is doomed from the start if a clear understanding of why it is needed fails to be established (Hiatt, 2006). Successful routinization of innovation necessitates high levels of motivation and competence of individuals (Gustafson et al., 2003) and Lee et al. (2019) hence recommend providing broad AI training if undertaking an AI transformation. One way of doing this is through formal facilitation such as workshops, as diffusion and implementation is positively influenced by such modes of knowledge spread (Meyers et al., 1999; Hottenstein et al., 1999).

To facilitate effective communication and organization-wide buy-in to change, literature describes the importance of special roles. For example, Grant (2018) highlights *champions*, as he writes that organizations skilled with innovation and change have learned to utilize individual drive and commitment. He further depicts that through them, resistance can be overcome, and enthusiasm spread (Grant, 2018). Champions have also been found highly relevant for successful implementation (Meyers et al., 1999). Another role often mentioned is the boundary-spanner (Rogers, 1995; Zahra & George, 2002), as they help bring ideas and knowledge from external actors and networks. Stimulating the formation of these roles support innovativeness, as boundary-spanners can create a link to leading actors with regards to the innovation.

[18] Originally business model innovation.

3.3 Healthcare specifics

For the sake of providing a sound base for discussing the above concepts of AI and innovation diffusion in healthcare, specifics of the healthcare setting are presented below. More specifically, the dimensions detailed are *management and culture in healthcare*, *innovation and change in healthcare* as well as *AI in healthcare*.

3.3.1 Management and culture in healthcare

The healthcare sector is uniquely complex due to the ecosystem of different stakeholders: government agencies, IT-firms and public hospitals (Sun & Medaglia, 2019). Furthermore, Mintzberg (1989) means that hospitals are complex organizations in themselves, characterized by a decentralized structure with high autonomy. The operating core of hospitals is well trained and takes most decisions, something Mintzberg (1989) calls a *professional bureaucracy*. This professional bureaucracy is supported by a large support staff, suitable in a complex but otherwise stable environment. Similarly, Harris (1977) suggests that the hospital organization is in effect two organizations. It is divided into an administrative side and a clinical side, where the administrative side is supplying what clinicians demand (Harris, 1977). The concept of clinicians demanding things ties into what Harris (1977) mentions about physicians and their special relationship to the hospital organization in general. Namely, physicians have much responsibility and are in a unique position to demand all types of necessary things for their patient, often resulting in an atmosphere where physicians are thought to know best (Harris, 1977).

Glouberman and Mintzberg (2001a)[19] takes this idea of divisions within the hospital organization further, proposing a framework with four distinct dimensions to explain the difficulties in organizing healthcare. The dimensions at play are *community*, *control*, *care* and *cure* according to the authors; *community* representing society having a stake in healthcare through the hospital board and elected trustees, *control* meaning the managerial and administrative hierarchy, *care* referring to nursing as a way to coordinate workflows around patients, and lastly *cure* that represents the separate world of medical intervention carried out by physicians. This way of categorizing showcases the complexity of the hospital organization and Porter (2010) similarly mentions that healthcare stakeholders often have conflicting goals. Glouberman and Mintzberg (2001a) continue by stating that the relationship between managers in administrative hierarchies (world of control) and physicians (world of cure) is skewed, much like Harris (1977) describes. While managers have de facto control over budgets and processes, in life-or-death situations their control is undermined and instead the physicians get the last say. This means managers end up controlling "a patchwork quilt of more or less autonomous enclaves", making it very difficult to exercise control or manage the hospital in general (Glouberman & Mintzberg, 2001a, p. 62). The authors mean that, in this way physicians work *in* a hospital and not *for* it. This is summarized by Herzlinger (2006), who says that integrating healthcare activities is not easy. Glouberman and Mintzberg, (2001a) go on to say that the dimension of community is even further removed from the problems at the hospital floor, meaning it is more powerful on paper than it is actually able to affect the situation in the hospital.

[19] Although inspired by US healthcare, the narrative from these researchers is comprehensive and recognizable in the Swedish context as well, by the discretion of the thesis authors.

Still, Glouberman and Mintzberg (2001b) mean that hospitals coordinate through specialization. Somewhat paradoxically, through easily identifiable and highly specialized units and individuals, an automatic coordination arises due to standardized communication and expectations. This works when everyone does what is expected, but as problems arise that cannot be predicted the system fails to coordinate by these means (Glouberman & Mintzberg, 2001b). Because the hospital organization is so strongly built on traditions of specialization and physician autonomy, interventions to fix the system through putting a manager in charge does little to actually improve the situation (Glouberman & Mintzberg, 2001b). Instead, Glouberman and Mintzberg (2001b) state that managers at hospitals are better off *facilitating* self-management within the different clinical specializations, in contrast to trying to control it technocratically[20]. Glouberman and Mintzberg (2001b) mention one concrete example of facilitatory action: that of physical reorganization being more powerful than rewriting the organizational tree on paper.

Another key point illustrated by Glouberman and Mintzberg (2001a) is that the world of cure prefers to focus on incursions and ingestion of medicine, over manipulation through touch or talking. Glouberman and Mintzberg (2001b) point out that healthcare does not equal medicine or incursion to other possibly helpful approaches to curing disease such as physiotherapy, nursing or even more alternative practices like chiropractic. The reason is that physicians often regard these approaches as being of a lower status. This means that caring measures that can help prevent disease in the first place, be it physiotherapy or nursing, are often overlooked (Glouberman & Mintzberg, 2001b). The authors also point out that the practice of medicine has been very beneficial, but question medicine as the only legitimate focus in healthcare.

3.3.2 Innovation and change in healthcare

The above cultural specifics could very well be described as one type of dominant logic (see Afuah, 2003; Chesbrough, 2010) within healthcare. AI technologies challenge this culture and logic, let alone the technical capabilities of the organization, through big innovation as described above. Therefore, it is useful to understand how healthcare handles changes arising from innovation in general. Several key aspects of innovations and change in healthcare recur in literature.

Firstly, the organization of hospitals is fragmented due to specialization in silos, decentralization and skewed power balances as described by Glouberman and Mintzberg (2001a). Mannion and Davies (2018) suggest that the many and complex nets of subcultures in healthcare can undermine improvement initiatives. Along the same line, Ferlie et al. (2005, p. 117) mean that innovation spread in multi-professional organizations such as in healthcare is difficult as they write: "strong boundaries between professional groups at the micro level of practice slow innovation spread". As put forth by Berwick (2003, p. 1970), "In healthcare, invention is hard, but dissemination is even harder". Extrapolating from what Herzlinger (2006) says about healthcare on a macro level, the siloed healthcare structure could also result in financial sub-optimization, as analyzing costs in silos may lead to disapproval of technologies that ultimately reduce total costs. Similarly, Eriksson et al. (2020) argue for increased coordination between the different levels of healthcare providers,

[20] Where the primary management principle is expertise, i.e. the manager has the last say as they are *more* knowledgeable.

currently operating in silos. Even though Herzlinger (2006) and Eriksson et al. (2020) do not refer to the hospital-level of organization, any individual hospital is inevitably embedded in the larger healthcare system it operates in, hence reasonably making the researchers' concepts at least partly applicable. Furthermore, all change is not equal as it too can be bifurcated; one type being technological change focused on by physicians, while administrative change driven by administrative managers is distinctly different (Glouberman & Mintzberg, 2001a).

The second aggregate dimension of innovation in healthcare is related to how innovation is prioritized overall, or rather how it is not. Varkey et al. (2008) point out that there is a natural tension between productivity and innovation in healthcare, where daily operations are prioritized over innovation. Once again this is reflected in the financials, as there is little room in healthcare budgets to allow for innovation diffusion according to Berwick (2003). Moreover, when it comes to diffusion of innovation in healthcare, Berwick (2003, p. 1974) highlights that "slack for change", translating into time and money, as necessary for leaders to facilitate. This is key to understanding how to approach innovation in healthcare, where Varkey et al. (2008) propose to align the innovation process to this reality by letting innovations take a parallel path until maturity is demonstrated. This holds value due to the inherent high risks with change in the mission-critical environment that is healthcare (Varkey et al., 2008).

A third prominent aspect of healthcare innovation concerns the policy in healthcare. As big innovation is concerned with business models in part, what Hwang and Christensen (2008) say about policy in healthcare applies: regulation is a barrier and key challenge for new healthcare business models. According to Herzlinger (2006), legislation can hinder innovation in healthcare and other times aid it, meaning that it is important for innovators to understand the legislative landscape properly.

3.3.3 AI in healthcare

Just as it is important to understand how innovation in general is approached within healthcare, it is important to understand how AI technologies are approached more specifically. Below, some specifics around AI technologies in healthcare are presented.

Topol (2019) states that bringing AI to medicine has just started, whilst Russell and Norvig (2020) say that the number of formally approved[21] AI applications for healthcare are few but rising in numbers. Likewise, Sun and Medaglia (2019) mention that there is a hype around AI in healthcare but that it is in the early stages in terms of implementation. Meskó et al. (2018) gives concrete examples of how AI technologies can be used in healthcare, such as in mining medical records and designing treatment plans. In more specific medical areas such as radiology, pathology and dermatology, AI shows large potential within image diagnostics and analysis as well (Topol, 2019). Moreover, AI programs can be on par with healthcare professionals in specific work according to Liu et al. (2019), while Arora (2020) highlights that AI techniques can significantly outperform other feature extraction methods in recognizing patterns within large amounts of data. AI technologies can also be used in ways that are not immediately affecting patients medically, for

[21] They refer to approvals from the US Food and Drug Administration office (FDA).

example smarter bed allocation, staffing and workflow optimization (Arora, 2020). Taking things even further, Arora (2020) states that AI has the potential to redefine healthcare capabilities, disrupt healthcare organizations and markets in a transformative manner.

Alas, with all this potential and promise there are obstacles and pitfalls as well (Topol, 2019). For instance, the researcher continues saying that ethical aspects constitute a challenge in using AI and algorithms in healthcare. Topol (2019) mentions that transferring responsibility from physicians to algorithms presents a hurdle, especially when reasons behind results from certain AI algorithms are inexplicable, also called the black-box problem. In addition, avoiding building in systematic human bias into algorithms is also a formidable challenge (Topol, 2019). According to Cosgriff et al. (2020), the performance of AI algorithms is questionable too, as few algorithms have actually been evaluated on patients, and in these few cases they have even displayed unimpressive results. Instead, the authors state that many published algorithms have been developed in silos by researchers (Cosgriff et al., 2020).

Apart from challenges with ethics and performance of AI technologies, technical obstacles exist as well. For example, Kelly et al. (2019) mention that medical data is often stored in silos and therefore hard to aggregate. The authors mean that existing IT infrastructure has to be updated and changed drastically before AI technologies can be implemented; they draw a parallel to the NHS in the United Kingdom where it has been recognized that new systems and new standards are a must (Kelly et al., 2019). Arora (2020) draws the same conclusion about IT systems needing reconfiguration but highlights that this may be hard to prioritize over investments that directly improve short-term patient care, especially for politicians subject to public opinion.

In reality, even AI technologies that are highly effective and overcome infrastructural difficulties are vulnerable to human opinion about AI and the challenge this presents (Kelly et al., 2019). In order to combat human barriers, the authors put forth that patient value needs to be emphasized and that peer-reviewed articles are needed for AI technologies to gain trust in the healthcare community. Moreover, practical issues of accountability, safety and utility must be discussed in such terms that the actual implementation stage of AI is in focus (Kelly et al., 2019). Arora (2020) adds that the introduction of AI has to be gradual and well thought-out, mentioning proactively adopting organizational practices in anticipation of the potential large-scale impact of AI technologies as an example.

Lastly, Cosgriff et al. (2020, p. 1) argues that actually, “the lack of clinical results is the byproduct of a lack of coherence, leadership and vision”. The problems of implementing and deploying AI into clinical practice have so far been neglected, Seneviratne et al. (2020) claim. Sun and Medaglia (2019) as well as Wirtz and Müller (2019) similarly claim there is little empirical research to rely upon for guidelines on AI adoption in the public sector.

3.4 Theoretical summary and research gap

AI is a rather immature technology, and great complexities arise when the time comes to leverage it towards an innovation and ultimately business impact. The technology brings both a technical and a cultural peripheral that need to be accounted for, especially if AI is to be leveraged for big innovation with big change potential. Big innovation does not come naturally to organizations, and a dedicated effort through devoted structure, clear vision, extensive external collaboration and continuous internal alignment is required to complete the renewal each organization needs. But these types of innovations, complex and difficult no matter the context, become even more so when approached within the healthcare setting. Unique characteristics such as cultural clashes, public funding and constraining legislation make managerial efforts and big innovation highly intricate to undertake. AI is no exception, where complex obstacles yield applied AI in healthcare scarce, despite the great potential of AI to remedy many of the growing problems in healthcare. Research in the field of AI implementation and how hospitals more practically can approach and counteract this slow development, is emerging but still nascent. The hope is that this thesis can contribute to this research gap by viewing AI through the lens of big innovation applied in the healthcare setting, hence focusing on the practical acceleration of AI in healthcare.

4

Description of the studied organizations and contexts

Before diving into the results of the study, some background information on the studied organizations will be provided. For details regarding the selection of these organizations, please refer to *2.2*. In this section, basic organizational details such as size, mission, hierarchical structure and other relevant information (that is not subject to further discussion, hence not deemed relevant to present in section *5*) will be detailed. These details were partly gathered from interviews and partly from secondary sources. After an introduction to the Swedish healthcare system comes the main case of the study, *Sahlgrenska University Hospital*, followed by *Other healthcare organizations*, and finished off with *Private industry organizations*.

4.1 Introduction to the Swedish healthcare system

Governance and responsibility of healthcare in Sweden is mostly decentralized, where the 290 municipalities, 21 regions and the state share responsibility (Socialdepartementet, 2016). The national government mainly sets guidelines and principles, while the regions account for implementation and the actual provision of care. Municipalities are in turn responsible for social services such as elderly care, aid for disabled, education, among others (Socialdepartementet, 2016).

4.2 Sahlgrenska University Hospital and RVG

Sahlgrenska University Hospital, henceforth called SUH, is one of the largest hospitals in northern Europe and the largest in Sweden with around 17,000 employees (Sahlgrenska, 2018). Thereby, the organization is very sizable, where an interviewee adds that they are spread out over four main locations and approximately 2000 beds. Under the Hospital Director, the line management structure is divided into six areas responsible for different operational foci as well as research within their specialties. Besides the traditional hierarchy, several staffing functions under the Director support different aspects of the business, such as HR or R&D. This means the sub-organizations and reporting paths are siloed, but cross-functional formations are not uncommon as a way of breaking out of the line management structure. Subsequently, the organization around AI naturally involves many units and individuals. As highlighted in interviews, SUH is a university hospital, meaning it has a mission to perform academic research and innovate in parallel to providing care. Hence, there is complexity subject to discussion, why it will be presented under section *5*. Though, basic structural aspects around AI are depicted in Figure 14 on the next page, with further descriptions gathered from interviews of the depicted components following below.

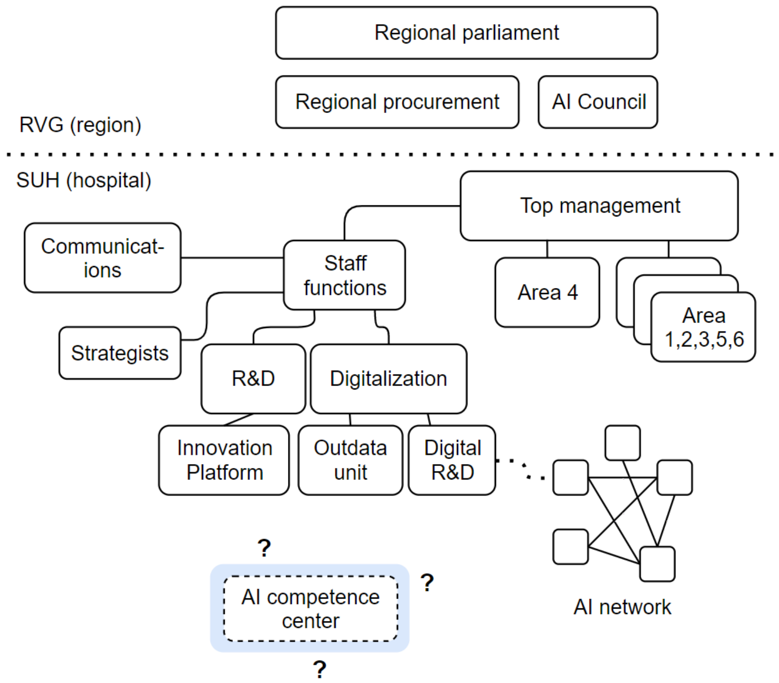

Figure 14: The relevant organizational structure of SUH and RVG.

Starting at the hospital level, the previously mentioned sub-areas under the Director (top management) are visualized. Area 4 has been broken out to emphasize its importance in regard to AI; Area 4 is very involved in AI management questions and among other things the area focuses on radiology and pathology, two fields where AI technologies are thought to be highly useful. The staffing functions are also involved in the work with AI at SUH, where the communications function is trying to spread information about AI use at SUH and strategic functions are looking into how AI use can be accelerated. Moreover, the staffing function *digitalization* is involved in AI work through multiple units; the cross-functional *Digital R&D* unit is responsible for developing digital health overall and the Outdata unit extracts and composes relevant data from the large influx of data from throughout at SUH. The Digital R&D unit is also responsible for starting, connecting and hosting meetings with the *AI network* at SUH. The AI network itself focuses on connecting researchers, sharing project learnings and sharing competence among AI projects. Under yet another staffing function, R&D, the Innovation Platform is situated, whose mission is to clarify the healthcare innovation process and help innovators find the right way, not only at SUH but also at a regional level. Again, SUH has decided on setting up a cross-functional AI competence center (AICC) to gather competences in a common unit, but are in discussions about where to place it, why it is surrounded by question marks in Figure 14 above.

SUH's parent organization is Region Västra Götaland, henceforth called RVG, and the two organizations naturally interact to a great extent. RVG itself employs 55,000 people, which includes SUH and other hospitals, primary care, culture, jobs and public transportation as well (Västra Götalandsregionen, 2015). The region's affairs are subject to influence from political powers, as there is a regional parliament with the ultimate say in the region. On the regional level there are also staffing functions such as procurement. One regional group of particular interest is the *AI Council*, which according to interviews is a counselling board for questions around AI in the whole region where many individuals involved with AI at SUH also partake.

4.3 Other healthcare organizations

Here, the other studied healthcare organizations will be described. First off is Region Halland, followed by the NHS, where two hospitals were part of the interviews: Leeds Teaching Hospitals Trust, and Great Ormond Street Children's Hospital.

4.3.1 Region Halland

Region Halland, henceforth simply Halland, is the neighboring region of RVG, and similarly has responsibility over not just healthcare, but also infrastructure, jobs, culture and the environment. As gathered from an interview, Halland is significantly smaller than RVG (55,000) and even SUH (17,000) with its 7,500 employees. Halland has one joint organization, Halland Hospital, for all the specialized somatic care in the region. The hospital is spread out over two acute hospitals and two facilities for planned care, where in total 3,500 out of the region's 7,500 are employed (Region Halland, 2021).

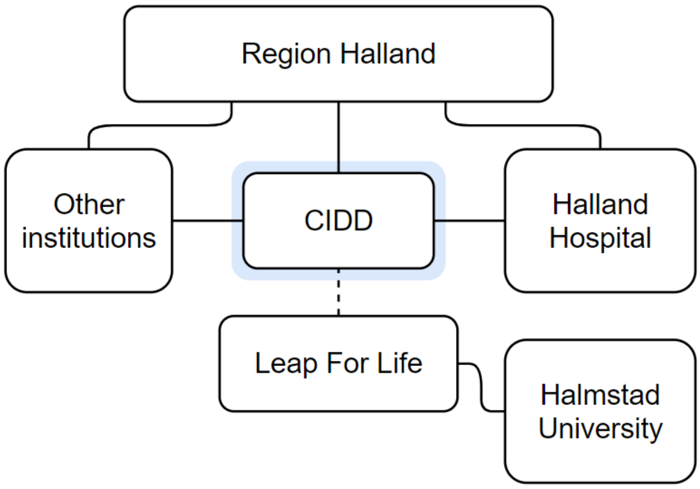

Figure 15: Connections between CIDD and the rest of the regional structures in Halland.

In 2019, Halland took a decision to formalize the creation of the *Center for Information-driven Care* (also called CIDD[22], which will be used henceforth) (Region Halland, 2019). The decision came after a three-year collaboration project with a US hospital, and meant a dedicated budget, organizational placement and mission (Region Halland, 2019). CIDD is connected, through regional management, to both the region's hospital and other institutions such as primary care and ambulance, visualized in Figure 15 above. A related structure is one located at the region's main university, Halmstad University, called *Leap for Life* (LFL). This center is focused on *information-driven care*-related innovation in the region, where regional growth and external collaboration are the main activities being pursued (Leap for Life, 2021). Understood from interviews is that Halland has received attention in the media and in the healthcare community for their work on this topic. Further details regarding CIDD, LFL and the work being done there will be detailed in *5*.

[22] The abbreviation comes from the Swedish name of the center: **C**entrum för **I**nformations**D**riven Vår**D**.

4.3.2 United Kingdom's National Health Service

One key distinctive feature of the United Kingdom's (UK) healthcare system is that it consists of one large entity, the National Health Service (NHS), making it a single-payer system compared to the regional-based system (effectively a 21-payer system) operating in Sweden. The detailed structure of the National Health Service (NHS) is not within the scope of this thesis, however some aspects are worth mentioning. One example is the national demonstration of strength with regards to AI that this tight hierarchical structure has enabled; to deliver the changes set up by the NHS long-term plan and the political leadership's vision around technology, NHS set up *NHSX*, a joint team working to accelerate digitalization and technological innovation throughout the NHS (NHSX, 2019). Within this, £250M is being invested towards AI through the creation of the *NHS AI Lab*, which focuses on enabling and supporting AI-based innovation, much through setting standards and adjusting national policies (NHSX, 2019). Another cross-institutional national structure concerning AI in the UK is one called *AI Centre for Value Based Healthcare*. This organization focuses more on technological infrastructure, where one project is about developing a federated learning interoperability platform for national usage (AI Centre, 2021). Although being part of the national entity NHS, the hospitals within it are argued by a high-level interviewee to be highly autonomous and not experiencing much help (yet) from the large national initiatives. The UK hospitals part of this study will now be described.

4.3.2.1 Leeds Teaching Hospitals Trust

Leeds Teaching Hospitals Trust, henceforth LTHT, is one of the largest hospitals in England, with around 18,000 employees and 2000 beds divided between seven locations across the Leeds region (Leeds Teaching Hospitals Trust, 2021). LTHT, similarly to SUH, is a university hospital, making research and innovation part of their mission. LTHT does not, according to an interviewee, have a dedicated organizational structure for AI. What they do have, is a Research Data and Informatics Team, which aids researchers in identifying, collecting, and anonymizing data from throughout the hospital's systems.

4.3.2.2 Great Ormond Street Hospital

Great Ormond Street Hospital, from here on out written GOSH, is a children's hospital located in the London area. GOSH constitutes around 4,000 staff and 400 beds, through which they provide specialist children's care, often to patients referred from other local hospitals across the London area and across the UK (Great Ormond Street Children's Hospital, 2021).

GOSH has received increased attention due to the establishment of a specialized unit within the hospital called the *Digital Research, Informatics and Virtual Environments Unit*, or as more commonly referred to, *DRIVE*. In this dedicated space, new technologies and everything that comes with them are tested, with a clear focus on digital innovations such as AI (DRIVE, 2021). DRIVE will be detailed further under *5*.

4.4 Private industry

Below, the private organizations from outside of the world of healthcare are presented in terms of their basic organizational structure, namely *Volvo Group* and *Ericsson*.

4.4.1 Volvo Group

Volvo Group, henceforth only referred to as Volvo, is a multinational organization headquartered in Sweden with roughly 100,000 employees, manufacturing vehicles and transport technologies in 19 countries and selling them in 190 countries (Volvo Group, 2021). Traditionally a vehicle and technology manufacturer with focus on products such as trucks, buses and construction machines, Volvo is now becoming more service-oriented and offers *transport solutions* according to a high-level interviewee. Volvo has many divisions under the group level, corresponding to entire businesses focusing on different transport solutions such as trucks or construction vehicles. The organizational structure (elements elected for relevance to AI) represented by Figure 16 below.

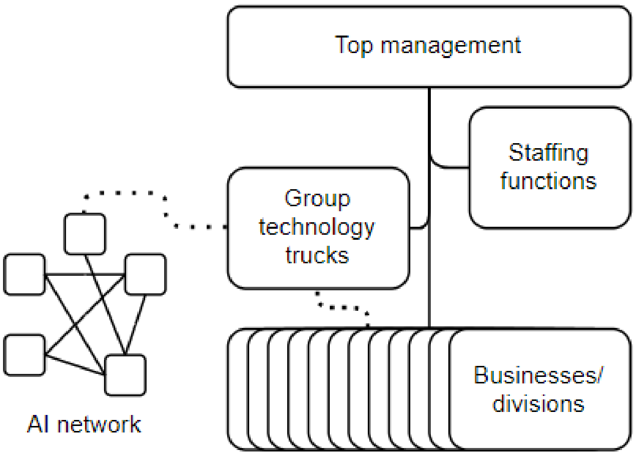

Figure 16: Volvo's basic organizational structure around AI.

Group Trucks Technology (GTT) is a group function at Volvo headed by the Chief Technology Officer (CTO) but was found in an interview to not be a regular group staffing function per se, hence the visual choice of isolating it. Hereinunder, common and strategically important technology development for the whole of Volvo is concentrated, not only for truck divisions despite the name. Technologies having to do with electromobility or connectivity, are examples of things being worked on in GTT. Connectivity has a close connection to data and therefore AI, which has led to strategic AI work at Volvo being primarily driven and owned by the GTT as well. It does this by supporting AI work in many businesses or divisions, one example being that an AI network has been started by GTT, where businesses can interact and learn from each other. In contrast to AI being led by GTT, what Volvo calls advanced analytics is owned by each business, whereas it was previously owned by GTT as well.

4.4.2 Ericsson

Ericsson is also an international firm headquartered in Sweden with roughly 100,000 employees that manufactures information and communication technology and equipment (Ericsson, 2021). The organization around AI at Ericsson is depicted in the following Figure 17.

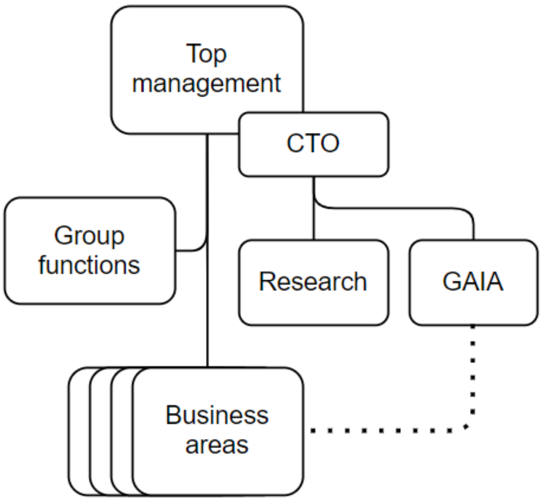

Figure 17: Ericsson's relevant organizational structure around AI.

Further contextual information was gathered from interviews with managers from Ericsson, detailed hereafter. The four business areas are part of the line management structure, and herein AI is used within the products and services that Ericsson produces and sells. Though, under the CTO in top management there are centralized structures that focus on AI as well. One example would be the central research department under the CTO, where AI is said to be one explicit focus area to perform cutting-edge research in. The most explicit structure in regard to AI at Ericsson can also be found under the CTO, namely *GAIA*, or **G**lobal **AI A**ccelerator. Non-surprisingly, GAIA focuses on accelerating AI at Ericsson, meaning it can be described as a central internal consulting unit that helps business areas with their AI projects. For this mission, 300 employees have been employed in 4 locations for GAIA specifically. GAIA and the work being done there will be detailed further in section *5*.

4.5 AI Sweden

AI Sweden, or the Swedish National Center for applied Artificial Intelligence, is different from the other organizations in this study as it is working to accelerate applied AI in Sweden through a number of hubs (AI Sweden, 2021). Being a partly partner-owned organization, it does this through coordinating work and sharing knowledge between its partners (AI Sweden, 2021). In addition to the partner firms, the Swedish government also finances AI Sweden through Vinnova, further highlighting its transnational nature. AI Sweden is a common denominator for all above actors (in section 4) that are based in Sweden, as SUH, Halland, Volvo and Ericsson are all partners of AI Sweden (AI Sweden, 2021). As such, it has not been subject to the same type of interviews as the other firms in this study, due to AI Sweden not being interesting as an organization in itself. Instead, the knowledge AI Sweden has of applied AI and how its partner firms approach AI was highly relevant.

It contributes to the Swedish AI ecosystem by running projects of national interest, some of which are healthcare specific. For example, the *information-driven healthcare* project looks into how data can be used to improve healthcare, while another project named *SCAPIS AI platform* focuses on heart image analysis.[23] Noteworthily, the first involves Halland in the core team, while the latter one is led by the university branch of SUH (AI Sweden, 2021). Lastly, AI Sweden also has technical infrastructure in place for partner firms to make it easier to access computing power and data (AI Sweden, 2021).

[23] Read more at https://www.ai.se/en/projects-9.

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5

Findings

In this section, the findings of the study's data collection will be presented. This is done to answer the first research question:

What are the main dimensions of approaching and organizing AI-enabled innovation in large organizations?

The findings have been grouped into five themes: *AI complexity and nature*, *Different degrees of direction*, *Organizational buy-in and change*, *External knowledge and collaboration* and lastly *Organizational structure around AI*. Throughout these themes and subheadings, the main theme of a group of data points (corresponding to first-order concepts, see *2.5*) is marked in **bold** to increase readability. For potentially interesting data that was deemed superfluous for the subsequent discussion and the overall coherency of this thesis, see *Appendix A*.

5.1 AI complexity and nature

Initially, findings show a clear tendency toward leveraging AI being highly complex, with different perceptions of what it is, what it could be and what is needed to move forward. To start off, the value of AI was not clear for all organizations.

5.1.1 Unclear value of AI

AI applications can be unclear in the beginning. For Volvo, AI started as something new they wanted to understand and had limited knowledge of. Initially, the potential value was thought to be isolated to self-driving vehicles, but they have now realized that the "applications are endless". In hindsight, Volvo argues that they could have pushed AI more while stating their intentions more clearly from the start. For Ericsson and Region Halland, the process was similarly tentative; Halland states that the potential has revealed itself over time, while Ericsson highlights that skepticism and uncertainty preceded the current higher levels of maturity.

AI is not considered valuable if no real problem can be solved through it. For Volvo, this translates to customer value: ""If the customer does not need it, it doesn't matter if it is AI, it should be beneficial for the customer". Ericsson argues in a similar way, while SUH also highlights that they want to see a clear problem that AI can solve before moving forward. For one of SUH's AI initiative leaders, AI is thought of as a tool, and AI value needs to be clearly identified before formalizing the initiative further as the interviewee states "you don't build a house without knowing what's supposed to be in it". Members of SUH top management further argue that solutions must be tightly tied to a pressing problem, where one interviewee wants to create impact for patients and colleagues "now, not in 5-10 years". This was also a consistent finding from introductory interviews with AI Sweden, as well as from Region Halland, as they both advise against "pushing" AI and instead identifying a need that AI can proficiently solve. At the same time, AI Sweden describes that you cannot always rely on customers to demand these improvements. GOSH provides an interesting perspective to counter the above reasoning, stating that there is almost an obsession with showcasing value through small pilot projects, even though results from these cannot fully showcase the long-term value of AI investments.

Not much AI in production in healthcare. Following the yet unclear value of AI, it is not surprising that implemented AI applications in healthcare are scarce. This was true for all healthcare actors, as they all state that AI remains mainly in the research phase. GOSH and Halland have come somewhat farther than SUH, as some smaller-scale deployments and exploratory projects utilizing AI are being carried out. Still, besides some alleged mammography applications at LTHT, hospital-wide applications remain more or less uncharted territory, and AI Sweden believes that operationalizing AI in healthcare in this way is quite far off.

5.1.2 Different perceptions of AI magnitude and boundaries

Research is argued to be an important part of AI work. SUH and healthcare in general is very research-driven, and interviewees highlight the importance of research also in the case of AI. In GOSH's DRIVE unit, one key focus is researching around data and technology, and SUH also emphasizes that research has to be stimulated. Ericsson values research highly, as unique value comes from investing in this long-term perspective, contrasted to the business areas' more short-term goals. Eriksson's central AI R&D unit is also in charge of sensing the market trends, done through academia collaboration.

AI is seemingly one tool within the bigger idea of working with data and transforming healthcare. NHSX states that the number of medical or care-related tasks that can be automated into AI-enabled systems is significant. Halland agrees but also argues that great value can be achieved simply by gathering and viewing the data, where applying AI technologies on top can enhance the analysis but does not determine the entire value. Truly understanding the dynamics of the organization through a fact-based approach based on data can break down long-lived assumptions and aid with communicating the potential of this bigger concept, which they call information-driven care (IDC). IDC relies completely on the data warehouse that has been continuously built during the past 5+ years, on top of which AI can be applied to enhance IDC's potential due to AI's ability to handle large volumes and complexity. CIDD (the team in charge of developing IDC in Halland) has already done this, both to predict mental illness as well as to optimize bed availability. Halland as well as AI Sweden highlights that IDC and AI makes it possible to move towards a more proactive healthcare practice. Some at SUH are also thinking with these bigger strokes in mind, although still in the idea-phase; AI is considered by these interviewees to bring large changes when the way-of-working shifts towards a data-driven one.

5.1.3 Data access and infrastructure is difficult but crucial

Data and data access is critical for AI, something healthcare is struggling with. "[Succeeding with AI is] fundamentally about understanding the importance of data and data infrastructure, because without that, all the other stuff becomes completely irrelevant" says the interviewee from GOSH. LTHT struggles greatly with this, where the top management interviewee argues: "The quality of data on the back-office side is so poor, there's no point to apply AI on top of it" as well as "old-fashioned would be generous" with regards to the data characteristics. One example is their "live bed state report", where LTHT currently has to phone the departments to check how many beds are available due to the live data not being trustworthy (as it is not updated with appropriate frequency by staff). SUH also recognizes that data is the foundational problem with AI in healthcare, but has similar struggles as LTHT, where e.g., pathology discs are still in the digitization process. Halland emphasizes that holistic data from across the care chain is a common obstacle.

Data access and quality is a complex and difficult issue across sectors. Halland testifies that data access outside of research settings becomes tricky in healthcare as regulation presents a big barrier. AI Sweden strategist corroborates by saying that it is "extremely difficult" to use healthcare data today. Halland tries to solve it partly by utilizing a sandbox solution at the local university, as well as having researchers on a shared employment basis between the university and the hospital. But issues around data access and quality are not isolated to the healthcare sector. Data and data access is something that Ericsson still struggles with, and it is the first criteria when GAIA evaluates a prospective AI project. Ericsson further emphasizes that data truly is key, where ethics and legislation necessitates a clear data strategy. Also at Volvo, data quality is one great obstacle, where data cataloguing is argued a key step towards "high-value AI".

Technical infrastructure is the first crucial step toward data maturity. Within LTHT, there are around 550 different IT systems, and even though a few serve as main, the complexity is high. SUH is also recognizing technical infrastructure as one obstacle, something a massive project called Care Informatics of the Future (CIF) (Swedish "Framtidens Vårdinformationssystem") which will implement a region-wide system, is hoped to remedy. Halland has their data warehouse on local hard drives to avoid the legislative uncertainties around cloud solutions, something that took a long time to actualize. In general, GOSH argues that healthcare is poor at gathering data; the interviewee believes that by using data the operational structure, logistics and supply chain could be transformed, but that the data and infrastructure does not exist. GOSH continues that they: "for sure know that AI will be important", and if SUH agrees then proper infrastructure is necessary first, otherwise there is no point to proceed. The interviewee adds that a team around the data infrastructure is also needed, "not just a big data warehouse with loads of [swearword] in it".

5.1.4 Value of data is being recognized

Volvo is recognizing the value of data and a data-driven business model, with AI being one tool to drive this. AI is naturally one part of Volvo's service offering, due to the advent of autonomous mobility. In connection with this, they focus on connected vehicles and leveraging connectivity to gather data faster and thereby shortening test-cycles. The ambition is to become "a data-driven company" and Volvo recognizes that the trend is going towards complete solutions rather than traditional products such as cars or trucks. They have started their journey to become data-driven, where making use of AI is one aspect. AI is thought to fit in well with their existing advanced analytics capability and that it, similar to advanced analytics, is a tool in the bigger picture; "AI is not a business endpoint, but rather a method to help us with our business". One interviewee points out that the firm is not a data company yet but is learning and maturing fast when it comes to data. Compared to five years ago, they now capture more data and know more about how to use it.

Understanding the importance and value of data is inspiring action among multiple actors. Ericsson has realized the value of data access and are subsequently investing in this. One source says they have had problems with the complexity of data access and have worked hard to connect data streams. This realization is also present at SUH, as they state that data access and data sharing is critical and that this is being worked on. One concrete example is that they have established a so-called "Outdata unit" to help with extracting relevant data from the large influx of data. LTHT has also taken measures to help with data access by establishing a research data team to collect data from the hospital's systems, in order to supply research projects with quality data. Moreover, there is an ongoing project at LTHT that aims to build a data platform in order to evolve from the current process of manually digging into databases. Similarly, Halland has integrated much data, saying that complete information is needed and that they are almost there. For example, they have realized that through using data from the salary system they can use the method *patient encounter costing*[24] to better analyze costs. They say that it is crucial to integrate the different systems and to add them sequentially, starting with medical journal systems, followed by financial systems, HR systems, and so forth. Furthermore, they have demanded that private actors use the same medical journal system as the region's public hospitals to homogenize the data further and are looking into incorporating municipality data as well. Halland argues that they have had good prerequisites for this as well, having a common journal system and a basic data warehouse since many years back.

Halland's holistic data provides value externally as well. The holistic data in Halland is interesting and useful for external actors, in addition to being valuable internally for the region. This is because the data is real and non-synthesized, meaning that it can effectively be used for research as well as test or validation of commercial products.

5.1.5 "Big" AI is highly complex

Many different competences argued relevant for setting up healthcare AI. Due to the eclectic nature of AI and IDC, the necessity of multidisciplinary and cross-functional work is emphasized by all healthcare actors. Computer science and analytics, health economics, change management, and procurement are highlighted, with special emphasis on the role of clinical expertise. In the DRIVE unit at GOSH, competence within research, medicine and computer science are gathered under the same roof. In Halland's corresponding CIDD unit, similar

[24] A method for analyzing costs through pinpointing resource usage with data from multiple systems. For more details, please refer to Yasin (2017) and the Halland handbook on IDC.

competence collaborates, with an addition of health economics. Due to clinical AI often being incorporated into commercial products, understanding the external interface is also highlighted, further highlighted under section *5.4.2*.

Complexity of implementing and using AI becomes obvious after a while, as it expands into others' responsibilities as well as a cultural barrier. A consistent finding is that AI is a very complex field, and that the barriers to acceleration become more and more pronounced as you move forward. The distinction between technology and innovation is highlighted by NHSX, as they argue that innovation in large is about culture. As AI Sweden puts it: "a thousand things" have to get done before a model can be trained, and one SUH manager corroborates that technical development is the smallest issue. Instead, as argued in unison by Halland, GOSH, NHSX and AI Sweden, the main issues are of organizational and cultural nature. As put by GOSH, as new workflows and relationships disturb the status quo: "It becomes a human problem, the same as 'I'm going to move your sofa'".

Implementation highlighted as the most difficult part, with early consideration needed. Expanding on the previous point, implementation is emphasized as the most intricate and complex phase when it comes to AI development in healthcare. GOSH argues that implementation is "without a doubt the rate-defining part". SUH recognizes this as well, and highlights that implementing innovations has no strong tradition in healthcare, and that more effort and research is needed. With Halland's early use case, mental health prediction, they highlight the implementation difficulty that arises due to new patient dynamics: "how do you say to someone that they risk falling mentally ill without making it self-fulfilling?". This is said to be one of the key learnings from GOSH's work with AI; think about implementation and all the dependencies that will arise, and do it early.

Many believe AI and data require a long time frame due to large change. SUH believes it is a long journey ahead, and suspects that large-scale AI is far off, with the exception of RPA and imagery applications. Key stakeholders within SUH find themselves on this long road and have taken on an apathetic attitude to navigate the uncertainty, as quotes like "you have to start somewhere", and "you keep on working" exemplify. Halland has been on this journey for about 5 years; they are not finished but the data warehouse is operational which puts them further ahead than many. In general, as Halland points out in their handbook, rigorous quality demands make AI more slow-moving in healthcare. However, that is not an excuse to put off investments, as the top manager at GOSH argues for the opposite: "I can guarantee that in 10-15 years, the ones investing [in AI] will be dramatically better off than those that aren't". The long-term nature of an AI transformation applies in industry as well as Volvo, after recognizing that although easier than in healthcare, AI is still far from being a natural part of Volvo's culture.

Systematic and structured work with AI is important for systemic effects. AI Sweden advocates strongly for a systematic approach to accelerating AI instead of the bottom-up, ad-hoc one currently dominating in healthcare. Similar thoughts are also put forth by NHSX, who has established a clear action plan[25] to reach the potential of healthcare AI in the UK. GOSH states that a key learning and recommendation for others (after tackling the data issue, see *5.1.3*) is to formalize and plan who will carry out foundational AI work. Halland has done so, as they have the CIDD team who operates according to a 9-step evaluation process for each AI project. SUH aims to move in this direction, as the key driver within the hospital wants more structure to move forward, both for overall work as well as for more specifically for off-the-shelf AI product procurement, as this activity in itself poses significant challenges. Ericsson corroborates by being pleased with their work, arguing that investing and having an organization around AI is "clearly good".

No money or time in healthcare for strategic change projects such as building a foundation for AI. "There will be no value [of AI] in the short-term, first have to build the foundation properly" states the GOSH interviewee, mentioning the short-sightedness that is hindering healthcare from investing in necessary infrastructure for AI. To prove the point, analogies such as "giving bread to starving countries instead of investing in their agriculture" are presented. The interviewee continues: "As an executive in industry you are expected to have a 5-, 10- and 20-year strategy and you're also expected to put 20% of the revenue into the long-term plan. Healthcare puts 0%. It only pays for this year". This strategic-operational trade-off is a "real problem in healthcare not seen in other industries", as GOSH further recognizes that it is really difficult to invest in data infrastructure when the money is taken from e.g., employing additional nurses. However, the top manager continues: "if you can never make the jump, you can never leverage AI". SUH executives are experiencing this struggle first-hand, where one says that strategic work gets pushed aside due to operational overload (especially now during the COVID-19 pandemic), and another says: "We're too busy pushing the square wheel to stop and consider making it round", meaning they know things could be done better. The same SUH executive further emphasizes the difficult trade-off with: "Proactive health is better than reactive, but it is difficult for an emergency hospital to see the value in that when people are dying right next to you". Individual departments struggle to stimulate innovation, as the tight budget does not allow for expensive technology investments. SUH, through RVG, tries to rectify this by earmarking annual investments into hubs such as AI Sweden.

5.1.6 Legal one big part of AI

Legal and regulation makes AI hard and is often blamed for slow progress. Although Ericsson also finds that legislation complicates data usage, this is especially true in the healthcare sector due to sensitive data. Halland highlights that confidentiality laws hinder them from utilizing data from private care providers in their region, and that frustration can arise as their mission is interfered with. Multiple SUH interviewees also highlight the legal aspect of data access as a problem, and that the path forward requires carefulness. However, an interesting perspective is provided by one high-level employee, who gets the sense that people use the legal difficulties as an excuse: "patient safety is a safe bet that no one will argue against", where the real driver is fear. The interviewee continues that, based on experience, rules actually have to be broken if radical change is to be pioneered.

[25] See NHSX (2019, p. 17) for more information.

Legal function involved in multiple actors' AI work and deemed valuable. Both Halland and NHS put great emphasis to include legal competence in the work around AI and to do so early, as the landscape is currently complicated to navigate. Today Halland has continuous collaboration with industry partners within the context of IDC, where legal competence is key to do so; they further argue that people will not feel safe without the IDC team having good knowledge about integrity and confidentiality. In Volvo's AI network, the legal department participates, displaying the same tendency within industry. For SUH, IT-related legal competence appears to reside within the Innovation Platform.

5.1.7 Distinction internal and customer AI

There seems to be two key areas of AI applications: internally- and customer-oriented. This is highly explicit in Halland, as IDC is said to have two components: personalized precision *care* and precision *management*, where the latter is concerned with identifying and acting on holistic organizational patterns. The Halland strategist further believes that this distinction of clinical versus non-clinical will become ever clearer as the field moves forward. NHSX expands by defining five application fields: diagnostics, knowledge generation (such as pattern and causality recognition), public health (such as epidemiology), system efficiency (such as predicting demand to optimize staffing & care pathways) and lastly what they call P4 medicine (next-generation healthcare characterized by prediction, prevention, personalization and participation). Within industry, a similar distinction appears, as both Ericsson and Volvo highlight that customer-facing AI and related data carries different requirements for verification and protection.

Healthcare focuses mainly on clinical AI applications, which are very complicated to realize. When asked about possible effects of AI, top management at SUH mention clinical applications such as diagnostics and radiology, where diagnostics is especially emphasized due to the big potential of AI within image analysis. However, as pointed out by Halland, clinical AI applications require CE markings and the road towards implementation is bumpy and long. SUH is also recognizing this, as one knowledgeable interviewee highlights that clinical AI is subject to many more compliance constraints as legislation is lagging behind the clinical development. Halland states that clinical applications are of more interest to external companies than internal applications. CIDD, being Halland's internal team with AI, does work on clinical applications but works on internal issues as well.

Limited understanding of, and focus on, internal AI across sectors. At SUH, discussions regarding internal AI for administrative and management purposes are sparse and early stage. When asked, top management are positive towards the idea as potential value can be seen, but it is not a recurring discussion point. A similar situation exists at Volvo, where internal use is not discussed or explored as much as usage towards customers. The lack of focus on internal AI is, according to both Halland and one interviewee from SUH, a great shame, as there is much value to gather (more on this in *5.1.8* below). At GOSH there are some internal AI projects underway, such as optimizing billing, predicting length of stay as well as implementation of equipment tracking infrastructure, however the still relatively low levels of funding are highlighted. Finally, internal AI is not completely problem-free either; the interviewed NHS manager points out that system down-time within pressured organizations can make implementation tricky.

5.1.8 Internal AI holds value

Using AI for internal activities such as administration and management seems easier. Several data points from different actors converge on this being the case. SUH hypothesizes that there are fewer ethical considerations for administrative use of AI. Using AI for precision management feels easier to implement and is needed, adds another interviewee from SUH. The Halland strategist adds that AI for administration or management, mentioning prognosis of patient influx and patient flows specifically, is a lot faster to implement and easier to handle than clinical AI as no CE marking is required for analyzing patterns that does not affect individuals. In addition, Halland means that AI for administrative or management use "works perfectly fine to develop internally" and that SUH are big enough to develop this themselves. LTHT also states that AI for non-clinical use seems easier to implement, as physicians are trained to be autonomous whilst IT-personnel "do what they are told in a way that doctors do not". At Volvo, they have gotten further with internal AI as the demand for testing and verification is lower there than for customer-oriented AI. For healthcare, the NHSX recommends starting with AI for administrative use or back-end operations solutions to prove the benefits of AI. On the other hand, GOSH states that while there are many problems that can be easily solved within administration and management (e.g., scheduling and logistics), healthcare simply does not collect the data to do so.

Internal use of AI for administrative and management purposes holds great value and some actors are trying to capture this value. Ericsson sees value in AI for internal uses and uses AI e.g., to predict how many error reports they will receive from customers. They have even used it to optimize the use of their office space. According to one Ericsson manager, there is more automation internally than in Ericsson's products. Volvo is using AI internally to clean data, automate processes to simplify work and enhance robotized production. One interviewee at Volvo mentions that internal use of AI could create indirect value as well, as it can build trust in and normalize AI, thereby paving the way for more customer-facing uses as well. The strategist in Halland states that for healthcare, using AI to predict emergency flows and being able to adjust staffing accordingly is "incredibly value-generating". Meanwhile, one interviewee at SUH highlights that the administrative workload is enormous, saying that "you cannot even imagine". To ease this workload, Halland uses AI for administrative tasks such as predicting patients' care damages before they happen and optimizing the number of beds needed.

5.1.9 Testing and explorative mindset

Testing, evaluation and verification in general is crucial for AI adoption. "How can we trust the systems?" is one question commonly received by AI Sweden, highlighting trust issues for many organizations with regards to AI. Some of this is justified due to black-box character and risk of built-in bias with AI. To cope with the former, AI Sweden says more work needs to be done; to cope with the latter, NHSX argues for rigorous anti-bias tests. In general, NHSX believes that scaling up testing environments such as sandboxes are needed to reach the adoption stage, as well as to cool down common "overhype" with AI. For SUH, intricacies with procuring commercial AI products are argued to depend on the high degrees of evaluation and testing required.

Real-world testing of AI in workflow is important. To fully understand the implications and system-wide effects, both NHSX and GOSH have realized the importance and difficulty of testing AI solutions in a real-world setting and modeling the impact on clinical workflows, compared to the controlled settings of a pilot or research project. In line with this, Halland claims that Leap For Life (Halland's externally-faced IDC hub) offers a "sharp" clinical testing environment to external companies, with access to clinical expertise. GOSH is taking this even further, as they are currently developing a "future ward": an actual live ward with professionals and patients that will act as the "staging post" for new technologies to achieve "controlled deployment".

To be successful, AI work should be characterized by exploration and iteration. AI Sweden puts great emphasis on the exploration, testing and iteration needed to effectively implement AI; they believe in putting AI to the test in one department to trial and showcase value before scaling up. Volvo has come to the same realization, as they in hindsight believe that ordering a couple units to pilot AI could have been beneficial, instead of tackling the biggest hurdle (self-driving cars) immediately. Volvo also mentions that they could have tried applications in less sensitive areas. Similarly, Halland believes in starting small to get going and figure out the path forward. Halland allows CIDD to experiment with data and argues that this has allowed potential to reveal itself over time. SUH appears to be on board with this reasoning, as they also argue that initiating *something* is critical, as put by one top manager: "you have to start somewhere". Volvo argues similarly that immature technology such as AI demands putting exploration in focus: "you have to try it out", something currently done with their external partners.

5.2 Different degrees of direction

The second category of findings concern the perceived direction of AI work and its importance. Direction of work ties into visions, plans and how homogenous the perceptions of the path forward is in the different organizations.

5.2.1 Showcasing value with AI is needed

Value clearly needs to be demonstrated to achieve more adoption, especially for clinical acceptance. GOSH states that involving people with clinical background is important for clinical acceptance of AI-related projects, saying that everyone in the DRIVE board is still clinically active. Likewise, Halland spoke on clinical personnel being inherently skeptical and that clear value of AI needs to be displayed to get them onboard. Showcasing the benefits of AI within every area is important to top management of SUH as well. According to the interviewed NHS manager, clinical champions of AI are an important piece of this puzzle due to the recognized weight of displaying the value of AI.

Champions are important for driving AI, where Halland is a prominent example. Much like the interviewed NHS manager, SUH top management mentions that "there is a need for clinical champions to drive [AI adoption] by showing its advantages", which is why SUH has established the AI Forum. Moreover, the researchers need to participate in communicating and driving AI according to one top manager at SUH. Several data points from Halland describe how it is driven by champions; one individual was described as "their messiah" and was said to be integral to CIDDs connection to hospitals in the region as well as international connections. AI Sweden corroborates by arguing that change agents and facilitators are important.

A sense of urgency is argued necessary for AI acceleration and is prevalent with some actors. Healthcare as a whole is up against big challenges with an aging population and an increasing prevalence of multi-sick patients. Halland realized the potential for IDC to help with this and subsequently started to work with setting it up. When GOSH realized they were in the bottom 10 percent of digital maturity they acted and set up their DRIVE unit. Ericsson did something similar; when they realized that they had an AI competence gap they set up GAIA. Data points from Volvo point to them sensing an urgency as well, where they highlighted its importance for the future and that "we must do it".

Being transparent and fronting with good examples is key when communicating around AI. GOSH means communication and demonstrations can create enthusiasm and awareness, but that the risk is that it comes off as braggadocious. Converging data points from SUH imply that they believe success cases and the good aspects of AI should be leveraged in communication, but that being transparent is important to ultimately gain trust among employees. AI Sweden suggests that communication must be strategic and take human behavior into account.

5.2.2 Value formalized to different degrees

Industry is very "business case"-driven and even long-term investments that are properly evidenced get funding. As Ericsson is a profit-driven company, everything is driven by business cases; they saw business value in AI and therefore pursued it. Likewise, in order to understand the value of projects clearly, GAIA requires that when business units apply for support, they submit a business case. Volvo works with business cases as well, as they do things because they "see a need for it and have prioritized it when financing it". If AI has a solid business case, Volvo argues that they are not afraid to pursue it.

AI impact not is not quantified at SUH. SUH says hopes and anticipations for the potential of AI are high. Multiple data points from SUH highlight the fact that there are discussions and speculation going on about what AI can bring. At the same time, one interviewee says few understand the potential of AI, meaning rough estimations are used to describe the potential and impact of AI. One data point in particular summarizes how SUH perceives the impact of AI: "We hope it will work great".

Value of AI is understood from the bottom up at SUH. "Islands within the organization have adopted AI", says one person at SUH. The source at SUH continues, saying that there is much research activity going on within AI at the hospital. Furthermore, the value of AI applications is seen on the hospital floor through shortage of personnel and higher workloads due to large data volumes. In general, areas such as diagnostics, pathology and radiology have received attention due to the clear use case of AI to unburden the workforce, something that could be used as a success case for the rest of SUH, says one interviewee at SUH.

5.2.3 SUH and Volvo have similarities regarding looser formulation of direction

SUH thinks work with AI is progressing nicely. SUH top management mentions that "there is a lot happening with AI right now", expressing pride in what they have done so far, the most recent activity being initiating a discussion regarding an AI competence center. Similarly, another manager at SUH says their progression with AI "feels good". SUH is in the beginning phases of integrating AI, approaching AI with curiosity, welcoming it and taking small steps towards AI holism through supporting and recruiting people, says one SUH interviewee.

No clear AI vision or plan for next steps at SUH, except for establishing an AI competence center. The data points concerning comments on SUH's AI vision converge on the fact that the vision is not clear-cut. Several high-ranking people have not heard of an AI vision, exemplified by the following comment: "Maybe there is one". Meanwhile, there is a draft vision that is being worked on in collaboration with the SUH communication office, other data points confirm. Though, it is not very concrete and more along the lines of "we should be leading the development of AI", says one high-ranking individual at SUH. Moreover, when asked about an AI vision, top management suggests that SUH should "use AI much more than they do today". Neither is there any next steps plan or timeline looking past the ongoing formalization of the AICC according to another interviewee. In the interim, the sentiment is that formal visions will follow (after the center formation) and that the road is long. However, the time has come to formalize the AI initiative, says one high-ranking SUH interviewee.

AI is still in the early stages at Volvo. Although quite mature in regular analytics, AI is not deemed a natural part of Volvo's business and the AI maturity differs throughout the firm. They have some AI competence, but it is not centralized, nor do they know how they would organize such a centralization. More advancements within AI are planned, but at the moment only some simple AI technologies in products.

Uncertainty exists whether healthcare should be early adopters of AI or not. One high-level SUH interviewee in particular raised a question about the assumption that healthcare should be at the forefront of AI development. It is a question of balance between letting other actors take on the early risks versus evolving alongside other actors to stay relevant and be ready when the technology matures. Even though there are major risks with being early, the adoption of AI technologies at SUH needs to speed up, says the interviewee. In addition, SUH is a university hospital with a lot of research power and a parallel mission to be innovative, further complicating this balance and trade-off.

5.2.4 Ericsson and Halland have a clearly stated direction

The AI strategy and plan is explicit and clear at Ericsson, where central structure GAIA plays a big part. There is a separate AI strategy at Ericsson, ultimately owned by the CTO. In the beginning, GAIA was a component in this strategy, but after its conception GAIA took over much of the strategic work around AI at Ericsson by collaborating with the research division and each business area. Moreover, there is one central AI strategy alongside AI strategies for each business area. Lastly, Ericsson is following their clear plan for GAIA to go from zero to 300 employees.

Halland is ahead with data and AI, with IDC as one main focus in the region. One SUH interviewee commented on the perceived data maturity in Halland, saying that Halland's work with gathering data in a warehouse is "absolutely amazing". In the same way AI Sweden means that Halland is leading within healthcare AI, having data infrastructure in place and some AI technologies in production. The concept of IDC has been built into regional goals, accepted by the political leadership in the region and resulted in the IDC work being currently concentrated within CIDD.

5.3 Organizational buy-in and change

This third findings section contains clustered data that has to do with how change is accepted in the organizations and how buy-in is approached for AI technologies. The data make out four sub-categories related to this, all presented below.

5.3.1 Push from above

Management has a role to play when it comes to communicating ambitions and direction of work. One interviewee in a high-ranking position at SUH states that management can help with pronouncing ambitions out loud as this has symbolic value. SUH top management highlights that AI is something that "really needs to be pushed from above to motivate employees to believe in it", as tangible results are distant. At the same time, top management mentions that everyone needs to take part in communicating and pushing this development, adding that this is each manager's responsibility in SUH.

Top management understanding, buy-in and strong vision is very important to achieve traction. To start a transformation, one needs to make sure that the executive board is onboard with the change, since no traction will be achieved without a strong and clear vision from management, says AI Sweden. GOSH states that "until the board understands the very thing we are trying to do, it is a very hard sell", continuing by saying that management buy-in is both important and difficult. Many (10+) data points from Halland converge toward the sentiment that it is important that top management sanctions the work with AI and is actively engaged; a foundation has to be built within the management structure before doing any data warehousing work. Ericsson clearly states that without top management support, things like AI work will not be successful or financed, saying that champions cannot drive systemic work alone. One Ericsson manager summarizes the thoughts about top management support, vision and buy-in by saying that "when it comes from top management then you [swearword] listen".

SUH management encourages AI interests. At SUH, several high-ranking interviewees state that top management supports AI usage "one hundred percent" through extra emphasis and push for this, as it is thought to be moving too slow. One interviewee in particular mentions that AI feels like a supported initiative from all directions.

5.3.2 Top management focus

The CEO needs to take bigger responsibility and clarify business cases and mandates. AI Sweden says that AI work cannot be a separate part of the organization as this weakens mandates. Instead, AI initiatives must be driven close to the decision-making, where the CEO level understanding of AI's potential and business cases is emphasized as crucial. AI Sweden goes on, saying that if the AI question in its entirety has been delegated away from top management, that in itself is a sign that one is on the wrong track. The CEO must be involved, even though it might be difficult to step up in the consensus-driven environment that exists in Sweden and even though it might be difficult to bring up the fact that "you have not gotten anywhere with AI", says AI Sweden. One interviewee from SUH points out that, ultimately, it is top management that is responsible for AI at SUH.

A leadership that dares to make long-term investments is important. Halland emphasizes that a trust-based leadership is important, saying "leaders must be trustworthy". Leaders cannot be driven by the press, Halland continues. AI Sweden also means that "new cool treatments" have high media value, but that more real value lies in pursuing proactive work. Likewise, GOSH adds that leaders are not always in it for the long haul and that management politics play a part in incentivizing focus on short-term strategies and quick return on investments, as this looks better for leaders and managers. In line with this, one SUH manager also means that large innovation projects can be scary as the press can spread negative views on how the hospital spends its funding or "how it is wasting money".

5.3.3 Resistance to change

Change and transformation is hard since it invites resistance. AI Sweden ties together resistance to change with legacy and routines that are hard to overcome. The same thought is brought up by Ericsson, as one manager says that AI threatens established ways of working, thereby inviting resistance for change. "Of course there is resistance to change in general", but Ericsson has a history of needing to change and most people realize things change, says the same manager. In healthcare, Halland says it takes time for individual parts of an organization to realize that change (in their department) is part of something bigger, while SUH mentions that AI has been met with skepticism such as "AI is just the newest thing" but that the attitude is getting more and more positive.

The unique culture in healthcare can yield resistance due to decentralization and conservatism. LTHT points to the healthcare setting being unique as it is about "life and death decisions". SUH adds that the conservative healthcare professions contribute to slowing down the development as they are cautious about accepting AI, while highlighting that this is for good reasons as well. The physicians shoulder big responsibilities by training and law, so you cannot blame everything on them, reads one data point from SUH. Innovation means risk in the life and death environment of healthcare, and has no strong tradition, SUH continues. Instead, SUH means that IT and technology is overshadowed by the strong traditions of specialization, decentralization and caring about people. In addition, IT systems have previously been pushed from above, prompting SUH to use the less stigmatized term "digitalization" instead of "IT". With this background, Halland means that one has to be ready for disputes and different logics when trying to navigate all the different stakeholders.

5.3.4 Inertia and buy-in

It is not an easy path towards management buy-in and vision around AI and data. Ericsson says it was strenuous to reach full management support and that it came with maturity. Halland has had the same experience, stating that it took several years to spread awareness and highlight needs and possibilities of AI to the top leaders. They had to do preparatory work, including a three-year collaboration with a US hospital (which was what originally sparked insights around IDC and AI in Halland). GOSH has managed to concretize and formalize the strategic work into a five-year plan where AI and data is intertwined so that the board cannot push it aside, whilst Halland has managed to formalize the work around AI in CIDD through the political approval process.

Volvo's size and silos makes scaling and accelerating AI hard. There are a lot of people involved in AI work throughout the organization, which makes matters difficult. Due to the size of the organization, different needs and different stakeholders need to be aligned, scaling AI solutions means interacting with many different units. Volvo says the silo culture, which stems from their preferred way of decentralized governance, will have to be tackled, as this will otherwise hinder them in accelerating and learning about AI. They add that this challenge is nothing new, as Volvo is accustomed to approaching and incorporating new technologies.

SUH is a complex and large organization, part of the even larger RVG. As part of their responsibility as a university hospital, SUH needs to deliver many different things. One part of their mission, aside from providing care, is to put money towards innovation, education, research and development. An additional aspect is that the hospital is part of the bigger RVG, which has its own data and initiatives outside of the hospital. With this in mind, Halland points out that there are many hierarchical layers a strategy has to pass through in publicly financed healthcare. Halland also suggests that their solution (with CIDD at a regional level) might not work in a bigger organization such as SUH/RVG. One SUH interviewee expresses that the SUH-RVG connection is not clearly defined around AI.

Widespread AI awareness and competence in the organization is important and needs to increase. SUH top management says that everyone, including top management, needs to learn and understand what data and AI development means as well as push for it. SUH thinks that they need to educate the existing workforce in addition to recruiting new competences within AI. Clinical personnel, managers and procurement would all be educated if the funding was available. AI Sweden adds that the procurement competence is important as to know what one is ordering or buying. Similarly, Halland mentions that the first step is knowing what AI should be used for. SUH highlights that they should not become experts at coding, because that competence exists somewhere else. Multiple data points from the NHS manager and NHSX also emphasize that upskilling of the workforce is key to facilitate AI deployment in the healthcare environment. Competence is also something private industry focuses on; at Ericsson, GAIA has created an online education package and they are trying to establish a metric for measuring their AI competence across the firm. Volvo says competence is vital for AI and that there is a need for greater awareness across the organization, which their AI network and dedicated training providers is there to help develop.

5.4 External knowledge and collaboration

The fourth grouping consists of findings related to collaboration outside the organizational boundaries. This comes in different forms, as will be detailed in this section. Initially, the role of industry and academia will be presented.

5.4.1 Collaboration with industry and academia

Hubs are an important channel for collaboration throughout the whole AI ecosystem. The Halland strategist asserts that due to sparse AI competence, cross-fertilization through collaborative and stable networks is "extremely valuable", where AI Sweden is explicitly highlighted. In addition, AI Sweden recently launched an initiative "Information-driven care", where the purpose is to move towards a holistic view on health powered by AI, in collaboration with hospitals, pharma and other actors. SUH also cooperates with external partners through other hubs such as AI Sweden and Chalmers AI Research Center[26] (henceforth CHAIR). Ericsson and Volvo similarly value the collaboration opportunities offered by AI hubs and participate in different ways.

Important but difficult to ”sense” and keep track of AI activity. The interviewed NHS manager articulates that due to the novel nature of AI and its applications, wide collaboration is needed. Volvo agrees that continuous learning is needed and adds that due to current hype around AI and digitalization, there is much public money to draw from the increasing number of "fashionable ecosystems". For Ericsson, GAIA has the responsibility to be cutting-edge around AI technology implementation and innovation. Hence, GAIA takes the lead together with R&D around sensing and collaboration. A key AI individual at SUH recognizes the need to be tuned in with the environment, but argues it is difficult: "you have to learn to navigate the strange network of actors that all want to have a say, [...] I cannot quite do it".

Wide recognition of academic involvement and collaboration being important. Multiple data points elucidate the specific importance of academia for the different actors' AI work. LTHT highlights the possible synergies with creating a data platform and hopes for collaboration with academia around this, both intellectually and financially. GOSH participates in a large collaboration program driven by the Computer Science department at University College London, which has proved highly useful as some students who conducted projects with them through the program stayed for permanent employment within the DRIVE unit. Halland has close collaboration with a department at Halmstad University focusing on applied AI (equivalent to CHAIR at Chalmers University of Technology); this university is also the home of Halland's Leap for Life center. SUH similarly argues that collaboration with academia is essential, and top management believes that it

[26] AI hub driven by Chalmers University of Technology and several partner organizations.

needs to increase. Chalmers University of Technology is a key partner in this due to their technical competence; besides being a core partner within CHAIR, a wider collaboration between SUH and the university is being initiated, as well as a joint effort in establishing courses to adapt education to the changing nature of healthcare. However, it was also evident with one SUH executive that all of these collaborative agreements are quite undefined and early stage.

Industry collaboration deemed important for financial and knowledge synergies, especially for healthcare. An SUH executive highlights that larger investments can be done through collaborative projects with industry and/or academia than could be done independently. The same executive also adds that healthcare could benefit from the extensive technical development happening in large organizations such as Volvo. In Halland, close industry connections have yielded large amounts of funding and rich networks; "that (in industry collaborations) is where the best solutions will be generated", a leading figure in Halland argues. One top management interviewee at SUH corroborates that AI products and their implementation will have to be heavily driven by external actors, as healthcare lacks a tradition or system for these efforts.

5.4.2 Commercial products in healthcare

Commercial products are thought to be important (for healthcare) for legal and practical reasons. Interviewed SUH executives agree that procuring finished and validated AI products is preferable, and perhaps even necessary, instead of developing internally. This can be derived partly from a competence gap, as one interviewee states: "Out of our 17000 [employees], there are very few with competence in this area when you look at the percentages". The complexity and intricacy of internally developing AI solutions further incentivizes procurement, as it is highlighted that regulation might actually prevent SUH from developing in-house AI; by law, healthcare should spend time on providing healthcare, not conducting product development (AI or otherwise). This statement mainly regarded clinical AI, and when asked about internal AI, the interviewee says that it is yet unclear. The interviewed GOSH manager states: "it is completely stupid for healthcare to think that they will do it on their own as they always do" about developing AI, why the DRIVE unit explores commercial product collaborations.

Commercial AI products are at an early stage and involve a complex dynamic. Despite the importance of commercial products, SUH and Halland both state that implementation of commercial AI products is still rare and that often, external solutions do not meet the complete set of demands that healthcare poses. Through an interview with a SUH executive, it appears that the internal process of matching a need to an external product is not clear at SUH, as there is no standardized way of identifying viable solutions; as with most clinical products, the process is highly decentralized, and clinicians have to go through a complex process using regional procurement. SUH top management acknowledges that integration of such commercial AI products is troublesome, where compatibility against IT systems is one big hurdle (if they make it past public procurement, that is). Healthcare being publicly funded presents another complexity, where both the interviewed NHS manager and an SUH executive highlights that regulation exists against healthcare favoring one technology.

The Innovation Platform acts as an interface between commercial AI products and internal use/need. Even though there is no apparent standardized way of matching commercial AI products with internal needs, SUH executives do point out that they believe the Innovation Platform has a role to play with regards to external companies and products and the complex process and regulation attached to it. As one interviewee explains, the Innovation Platform does in fact operate an external interface in both directions: clarifying internal needs to then match with external solutions on the one hand and taking suggestions from external companies to match with internal needs on the other. Due to their involvement, one seat in the RVG AI council is reserved for the Innovation Platform.

5.4.4 National collaboration

National collaboration between regions around healthcare AI argued to be needed. AI Sweden puts forth that a joint effort across all regions would be preferable to each attempting something themselves, something both Halland and SUH agrees with. AI Sweden further expresses that the decentralized regional structure in Sweden slows down AI transformation as collaboration is scarce, something AI Sweden is currently trying to enable, along with tackling large issues with synergies across sectors, such as infrastructure and cultural questions.

5.5 Organizational structure around AI

In this final findings section, discoveries from the different organizations regarding specific structural considerations for AI are detailed. The groupings regard informal structures, AI networks, central AI teams, whether this AI team should focus on supportive or enabling work, how this team could enable overcoming operative focus and how placing the AI team higher in the regional structure could prove beneficial. First off, informal structure as one way of driving AI will be detailed.

5.5.1 Less mature organizations tend to drive AI without a formal structure

AI at SUH has initially been driven informally by sporadic formation. So far, the work around AI at SUH has been driven through an organic grouping of people, with a core of three: one executive, one strategist and one manager. This group allegedly began driving the AI initiative on their own prerogative less than 2 years ago, where they have since then pushed discussions internally and established some collaborations externally. One core member suggests that top management has been duly involved in the dialogue, but that no formal responsibility or mandate has been involved. Another top manager at SUH, who has also been involved to a degree, believes it has worked well: “when knowledgeable people meet it usually works out”.

Volvo is not relying on a central organizational structure to coordinate work with AI or Analytics. Volvo thinks of AI as permeating the entire organization, where quotes like “it is a method, a tool, to help us with our business” and “AI is not a business end point” from a high-level manager in the organization exemplifies. As a result of this reasoning, AI capabilities and responsibility are decentralized; about 80% of AI roles can be found outside of the central technology organization (GTT). In addition, responsibility is also dispersed out into the business units, where their AI network (more on this below) is argued to create responsibility with the members who participate. Data from an interview with such a business unit, although specialized in analytics, points toward that they indeed feel responsible to accelerate AI within and around their unit, as they have a clear strategy that breaks down into different roles and missions. Analytics at Volvo is owned by the business units, and the goal appears to be that AI should be as well.

5.5.2 Structure around AI at SUH is unclear and is being discussed

Responsibilities around AI at SUH and RVG dispersed, undefined and deemed unclear for many. There are several data points (15+) converging on the theme that the responsibilities around AI at SUH are dispersed and unclear. This is something explicitly mentioned by different interviewees, with "it is not totally clear who is responsible" as an exemplary statement. However, the strategist (from the informal grouping mentioned above) has statedly gotten formal and large responsibility for driving AI from top management. Meanwhile, another executive (also from the informal grouping) has no other responsibility than the divisional responsibility top management has given the role. Instead, through self-interpretation, it is thought that responsibility and mandate for driving AI within the division is included in the divisional responsibility. Yet another top manager at SUH does not have formal responsibility for AI either, but is told to support AI usage and "see to that we use it". Likewise, how a fourth manager answers to top management is not clear regarding AI; the position answers to top management "in some way" and "some kind of responsibility" arguably lies in the managers division. SUH top management argues that its role is to push and contribute with resources, whilst the details around the plan and next steps are known further down. However, there is one data point indicating ambiguity regarding responsibility for these next steps. As the AICC is under construction, its responsibility and role in the AI initiative is not official yet. It is also unclear how SUH's responsibilities interface with RVG. In particular, uncertainties surround the newly established AI council in RVG, with one SUH manager saying that "it is not clear to me what they do" and another pointing out that the AI council has no official mandate, unclear assignment and that it "serves as a counselling function to... I do not know really".

Organizational AI structure and center at SUH currently under development and discussion. The organizational structure around AI feels "messy" at SUH, one source claims, and it is under development another interviewee adds, referring to the AI competence center that is to be set up. The competence center is thought to support the AI work around the hospital, such as AI research projects and implementation of commercial AI products. The core team to reside in this center will preferably have different roles within it, such as infrastructure competence, clinicians, analytics roles that can apply AI and legal competence, says another SUH interviewee. Moreover, more than five data points state that it is unclear where this center should be located and that there are different opinions on this. One interviewee says it will be set up under Area 4 where it will be close to most AI research and another says it probably will be located near the top due to its priority.

Prevalent opinion is to keep much AI work decentralized, especially dominant at SUH. Again, multiple data points from different interviews illustrate this sentiment at SUH. "As much clinical proximity as possible is important", says SUH top management, and another interviewee states that things must happen out in the organizational structure and that management and support functions can stimulate, but that building a central AI unit will not result in much progress. Moreover, it is essential to be in touch with reality and patients, meaning focus should be on solving actual concrete problems out in the divisions, SUH continues. The need for digitalization (and AI) should stem from the operations, not be pushed from above, which goes hand in hand with the strong traditions of business development close to the specialties. The same thoughts circulate at Volvo, where the responsibility for AI is put on each business unit and it is up to them to decide if and how to approach AI, instead of relying on a separate central structure.

5.5.3 AI networks have been established to accelerate AI

SUH has established an AI network, which exemplifies the bottom-up structure of AI work. SUH recently formed an AI network, where researchers engaged with AI projects regularly meet to share work and experiences. SUH top management highlights that this forum was partly established to facilitate the important role of researchers and clinical champions to drive and communicate around AI and its advantages.

The AI network at Volvo is driven centrally and creates space for sharing knowledge. As described above, Volvo has decided not to establish a centralized structure for AI; instead, they established an AI network to connect the internal units' AI work. The network has a core team, mainly from the central GTT organization, who all have it as a formal responsibility to develop the network. Furthermore, the network is still argued to be under development, with focus on finding synergies and stimulating learning, competence and research. According to one business unit manager participant in the network, it has so far been about different units sharing work around AI. The same manager highlights that communities and networks of this kind are used on different levels throughout Volvo to bridge the commonly occurring silo culture that otherwise acts against "high-value AI".

5.5.4 Central AI teams have been seen

There are some good arguments and examples of centralized teams. Halland has set up CIDD, a center for information-driven care, whose mission is threefold: system analysis to identify potential for change; maintain and develop the holistic analytical platform and its methods; support research that finds value in the data platform. A central hub was deemed practical, much due to the risk of system sub-optimization if each decentralized unit optimizes individually. The next example of a centralized team is found at Ericsson, where GAIA has been operational for a few years, helping spread AI across the organization. A manager at Ericsson believes that realizing the need for this separate centralized structure was key as it "proved a strength and prerequisite"; heavy recruitment and roll-out of common AI strategy benefited from this. The same manager continues saying that "centralizing the build-up was an incredibly important component" and that without it, some business areas might have matured in AI, but that Ericsson would not have achieved the unified strength that they now possess. Another advantage of GAIA is argued to be the short distance to the executive level, something that will be detailed further in the next paragraph. GOSH established the DRIVE unit, which is described further under *5.5.9*. SUH is not there yet, but one AI employee at SUH believes that a core AI team that networks and collaborates with the rest of the organization is the way to go.

Some actors have established AI teams with close proximity to the top. All of the centralized AI teams mentioned in the previous paragraph are located close to top management of their respective organizations. In Halland, the political healthcare leadership is ultimately responsible for CIDD, where one political leader's management team is utilized as the CIDD "priority group", responsible for prioritizing the work therein. GAIA similarly sits in close proximity to top management; the steering committee that meets every quarter consists of the Chief Technology Officer (CTO) and the business area heads. Most decisions are taken autonomously within GAIA, but if bigger decisions or investments are required, this is brought up to this committee. The board of the DRIVE unit, in turn, includes two hospital executives.

Ericsson's strategy is to centralize first, then dismantle and disperse knowledge back out into organization. "In the long term, GAIA should not really exist, the competence should return to the product development organizations", states an Ericsson manager. The interviewee also recognizes that during these initial years, where GAIA started out solely driving larger strategic projects, and for some years to come, the extensive centralized GAIA structure has been important. Furthermore, rolling competence back out is evidently some years away, as Ericsson still see an uneven AI maturity across the organization, and they have yet to solve the problem of how to carry out the dismantling and competence redistribution of GAIA. Finally, the manager does believe a skeleton of the current GAIA structure will remain long-term, but instead of the current 300 employees, only a handful of experts along with maintenance of the common assets will remain.

5.5.5 Supportive work is important

Healthcare deems that the focal purpose of central structure ought to be supportive work. Even though clinical researchers are autonomous, they are argued to need support with AI work at SUH. One way of supporting AI would be to support research and another to support the implementation, both of which are thought to be important aspects in supporting AI. In Halland, part of CIDD's work is to help clinicians and researchers navigate data, as well as to spread awareness and knowledge to enable better collaboration. CIDD also extracts data for researchers, as does a dedicated unit at LTHT.

The role of the Innovation Platform is to finance and support projects and guide people through the complex process of innovation in RVG, which includes AI. The Innovation Platform deals with all types of innovation, thereby AI technologies as well, but it can just as well be plastic objects or surgical robots. Through 20 MSEK a year in earmarked capital, they finance innovation throughout the region. Another key mission is to clarify and support the innovation process in the region, all the way from an idea and a need for an innovation being seen to seeing real-world value. Innovation Platform work is mainly directed toward financing internal projects and individuals looking to innovate, but can also include "procurement matchmaking", guiding external parties to the right party within SUH to take product evaluation further.

GAIA spends most man-hours supporting and teaching the business areas. Around 75% of GAIA's man-hours are spent on projects in the business areas, help that business areas have applied for. AI use cases or projects come from business areas themselves and they have to request help from GAIA, which screens and approves projects accordingly. Then, when GAIA sees a wider company need or a common need between multiple projects, they develop common and enabling assets for Ericsson. It is also the business areas that finance these projects, using GAIA as an internal consultancy unit. Similarly, it appears that Halland has also created a model where CIDD gets reimbursed for work they do for others, but this data is incomplete.

5.5.6 Enabling actions emphasized and practiced by some

Some actors argue for the value of enabling actions. NHSX are especially clear on this point, as the entire purpose of the organization is just that, to enable. More specifically, they highlight the importance of "system-level enablers" such as data quality, analytically capable workforce, standards and sandbox solutions. As another example, NHSX has mapped out a generic roadmap for driving AI initiatives, identified the pain points and set up a plan to remedy these.[27] Halland is on the same track, as the interviewed strategist there argues that the system needs to be proactively set up in order for AI to be brought in. This is partly the mission of CIDD. LTHT aims to enable clinical AI work through a common data platform, while one Volvo analytics team focuses on enabling through working on data quality and cataloguing, indicating a decentralized form of enabling work at Volvo. Ericsson also values enabling work highly, as will be evident in the next paragraph.

GAIA doing some enabling work, where developing common assets in one part. On top of supporting the business areas with AI projects, GAIA also undertakes Ericsson-wide foundational work. This was especially true in the first few years of GAIA, where it is now down to around 25% of total work, says an Ericsson manager. These 25% are spent on strategic projects such as developing common assets (data models, gathering reusable data into a database and developing a platform), for which an "internal budget" formed by top management resource allocation is utilized. This enabling work is driven by issues with data and data access as the data is officially owned by the business areas, where GAIA is working to achieve common data streams. This, along with other common assets developed by GAIA (and others) are then supplied to the organization through an internal software marketplace.

5.5.7 Virtual or physical AI organization is not an obvious choice

Halland sees value in keeping the IDC team partly cross-functional. The team in CIDD is cross-functional and horizontal, meaning the team does not share the same boss and act as peers. Halland thinks it might be beneficial to report to different bosses outside the CIDD team, to continue developing professionally within one's functional area, for example economics or legal. Under a joint boss, one's specialty is harder to develop further, Halland reasons. This means CIDD is not a box on the organizational chart, but instead a network of people from different functions, where they define eight functions to be filled rather than full-time positions. Depending on the

[27] To read more about NHSX and their work, see NHSX (2019).

assignment, an agile addition to the CIDD team is then put together through established pathways, where legal competence, HR and clinical personnel are examples of such agile roles brought in.

People in the same space and with clear affiliation is important for centers. Halland means that it is important that necessary competences work closely together, physically as well as intellectually. Although CIDD does not have a physical space yet, they have "talked about wanting to do something like that". It is more important that team members sit in the same space and spend time together, rather than reporting to the same boss. Moreover, a modern and creative workspace might help, Halland adds. Ericsson believes that it is important that GAIA is a separate structure, since this enables explicit recruitment in a way not possible for a virtual unit. In addition, GAIA is situated in four physical spaces (spread across the globe) with a common boss. GOSH mentions that DRIVE is a physical space, which means it is both a place for the team to come together and it sends a clear message to the rest of the organization. "Everyone commented that it felt different to a normal hospital" GOSH continues, saying it was a differentiation advantage important for creating cohesiveness and an affiliation for the team, in addition to making it an attractive place for people to work.

5.5.8 Overcoming operative focus

Some healthcare organizations create teams and roles focusing on major change and overcoming operative dominance. This is especially explicit with the GOSH DRIVE unit, as the GOSH interviewee states the unit to be GOSH's way of doing strategic work, their role being mainly to visualize what different strategic investments could accomplish (creating business cases in a sense). The unit also "drives innovation", which means working on big issues such as how to evaluate, implement, train and work with new technologies such as AI. The interviewee further argues that in order to work with such strategic issues in healthcare, "there has to be a thing, something tangible" that is designed to do something explicitly different than the remaining organization (see paragraph six in *5.1.5* for more background on this issue). Establishing a physical unit and space as done with DRIVE is believed to send a clear message, as well as creating affiliation for the team assigned to the unit. In Halland, the CIDD organization is similar to DRIVE in this way; they also have a stated long-term view, where the focus is on "change" with a horizon of up to five years into the future. Halland highlights that the political healthcare management in the region says that improvement work cannot be done marginally, on the side of the day-to-day operations, as it is very hard.

5.5.9 Regional-level center enables wider analysis

Regional responsibility of centers enables wider encompassing care chain analysis. Halland has seen that when each part in the healthcare chain tries to optimize their own organization, it leads to sub-optimization. Healthcare services are interconnected, where for example primary care, somatic care and psychiatry connect to each other, Halland suggests. With CIDD they changed perspective, looking at the patient throughout the healthcare value chain instead of looking at organizational processes, Halland says. They continue by drawing implications for an AI competence center at SUH: if the SUH competence center's influence stops at the hospital boundaries, this is a limitation. Instead, it would be of much value if such a center has regional sanction and can connect with and access other organizations such as primary care, says the strategist in Halland. The placement of the center is not that important, as long as it has sanctioned holistic access to other organizations' data and has an accordingly holistic mandate, the interviewee claims. The Halland strategist continues by stating that if the SUH AI competence center is placed at the hospital level, it needs clear interfaces toward the world, where regional connections to primary care, ambulance services and remote patient monitoring are highlighted as examples.

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6

Discussion

In this section, findings and the theoretical framework will be synthesized in order to predominantly answer the second research question:

What key considerations and learnings for the AICC can be derived from other actors' AI work?

The discussion consists of three themes: enabling work, administrative AI, and characteristics of an AI center. In line with O'Connor (2008) and Assink (2006), these are interconnected, and can only be fully realized in combination. Though, they are discussed in order for the sake of clarity. Within each theme, the implications regarding the third research question (recommendations for SUH) will be hinted towards, to be explicitly addressed in the subsequent section *7*, together with the key arguments behind them. This discussion section will be more elaborative and yield a more detailed perspective behind the recommendations.

6.1 Enabling work needed to gain traction

In this initial discussion section, the importance of enabling work will be discussed. Firstly, the need for enabling work to accelerate AI will be detailed, and its connection to exploration and big innovation elucidated. Subsequently, the three groups of enablers most emphasized in findings and literature will be discussed: data infrastructure, vision and internal AI process.

6.1.1 Enabling and exploratory work needs its own structure and team

One consistent finding is that there exists a clear distinction between efforts that are *supportive* and *enabling* in nature. Using Mintzberg's (1989) terminology for parts of an organization, supportive efforts can be classified as done on request from the operative core. In contrast, enabling efforts are done more top-down, driven on the prerogative of the strategic apex or support staff to proactively enable the operative core in different ways. In the studied organizations, both these activities are highlighted, with the clear preference at both LTHT and SUH being towards supportive work. SUH is very attached to the idea of "clear demand needed", where either patients or professionals must benefit to justify any efforts with AI. The autonomous nature of healthcare professionals and the *professional bureaucracy* they constitute (Mintzberg, 1989) likely play a part, as top-down initiatives are not the tradition in healthcare. In line with the reasoning from Harris (1977), the two separate worlds of administration and clinical are clearly seen at SUH and LTHT, where the clinical side's asserted power that Harris (1977) describes likely contributes to the pull towards supportive focus with AI. But perhaps this is just the nature of healthcare? However, by all other organizations interviewed, including healthcare organizations Halland and GOSH, enabling actions were emphasized and enacted in different ways, as especially shown through the work done by DRIVE (GOSH) and GAIA (Ericsson). So, it seems that expanding the view from solely support is possible, even for healthcare. Additionally, enabling actions that become routine and normal as time goes on, transition into being supportive in nature. This means that in a way, even enabling actions become supportive with time.

Multiple findings as well as literature sections demonstrate why enabling is probably needed to accelerate AI. Firstly, findings suggest that the great complexity of implementing and using AI becomes evident with time, as it inevitably expands into the responsibility of other functions. As detailed in *3.1.3*, widely adopting AI and leveraging it for big innovation entails major organizational change where many complementary assets become crucial to consider and develop. In fact, following the technology-innovation-impact conceptualization in this thesis, the AI technology in itself has both technical (such as data quality and infrastructure) and non-technical (such as culture and legislation) peripherals that need to be considered to fully actualize the value of AI. Such peripheral dimensions naturally span functional boundaries and interfere with the status quo. Hence, these dimensions cannot be dealt with by using a pure ad-hoc bottom-up approach, as the operative structure does not demand such complex change, as highlighted by both Pisano (2015) as well as Bower and Christensen (1995). This means that no matter what innovation one hopes to leverage AI for, certain coordinated enabling efforts will be needed. Ericsson credits the enabling work of GAIA for their current level of organization-wide AI maturity, and that without it, islands of maturity would have been the result. This latter state is precisely where SUH currently finds itself, as AI value and interest so far has grown in areas where convenient conditions and demand presented themselves, as detailed further in section *6.2* below. Likewise, Volvo drives AI in a decentralized manner, but states that AI maturity does differ throughout the firm.

The findings further suggest that in order to achieve systemic effects with AI, systematic and structured work is needed, and the intricacies of implementation need to be considered early on. In particular, GOSH emphasizes that responsibility for foundational work has to be explicitly dealt with, as a bottom-up approach driven by short-term value gains will not be enough, much due to the complexity of AI as discussed above. A centralized effort is especially relevant in healthcare, as Ferlie et al. (2005) highlight the difficulty of spreading innovation within the multiprofessional environment a hospital organization constitutes. For SUH, this means that the responsibility for this type of foundational work is appropriately appointed to the AICC. Though it sounds simple, there is a trade-off at play as well. If AI is to be leveraged for systemic effects, altering the business model and achieving major improvements in performance, which is what Lee et al. (2019) argue as the most powerful use of AI, the conversation is essentially about organizational innovativeness and renewal. This brings the discussion towards the trade-off between exploitation and exploration detailed in the theoretical framework, and how a balance between the two can be achieved.

Exploiting the current mode of business is currently dominating at SUH as findings clearly suggest, exemplified by groupings such as (taken from the findings):

- "AI is not considered valuable if no real problem can be solved through it."
- "No clear AI vision or plan for next steps at SUH, except for establishing the AICC."
- "AI impact is not quantified at SUH."
- "Prevalent opinion is to keep AI work decentralized, especially dominant at SUH."
- "SUH has established an AI network, which exemplifies the bottom-up structure of AI work."
- "Healthcare deems that the focal purpose of central structure ought to be supportive work."

This is not exclusively a bad thing, as will be described further in a later paragraph; all other studied organizations also support business areas in some way, but they do however maintain a *dual* focus. The problem with solely pursuing what the operative departments demand is that the large-scale impacts that AI can catalyst are easily missed. Decentralized ownership of AI is in line with how healthcare generally operates, but only works if AI is ready to be implemented, which due to prerequisites currently being unfulfilled, it is *not*. Quite naturally, the long-term nature of the work of laying the foundation for AI does not harmonize well with the clinical departments and their pressured environment. Patients in the built-up care queue instinctively pose highly short-term demands as they require care *now* and do not see the direct value of increased administrative efficiency or proactive care schemes; this value would instead be seen by future patients and generations. Findings indicate that fear of bad press contributes to this hesitancy towards making long-term investments into things not directly related to patients.

Literature corroborates, as both Varkey et al. (2008) and Berwick (2003) describe the difficult trade-off healthcare faces when trying to prioritize innovation, pointing out that there is a lack of financial leeway in the strict budgets. In line with this, GOSH suggests that there is in general no time or money allocated in healthcare for strategic change projects, such as building a foundation for AI. The same problem with allocation of resources does not seem to be as severe in private business, as Ericsson and Volvo are very business case driven, even for strategic investments. The situation in healthcare is rather troubling, as literature (e.g., March, 1991; Assink, 2006) unambiguously proposes that a balance between exploiting the status quo and exploring big innovation is needed for long-term success of any organization. What the literature suggests in these cases, although not specific to healthcare, is to develop an organizational ambidexterity, which is most easily done through establishing a separate unit explicitly focused on exploring future opportunities (O'Reilly & Tushman, 2004; Bower & Christensen, 1995; O'Connor, 2008; Grant, 2018; Leifer et al., 2001). In fact, Lee et al. (2019) discuss this in the case of AI, where they argue for an AI team to facilitate business model innovation, one type of big innovation. The SUH AICC holds potential to fill this strategic and exploratory role, but tough resource allocation decisions will still have to be made to realize the potential long-term impact of AI, see Figure 18 on the next page.

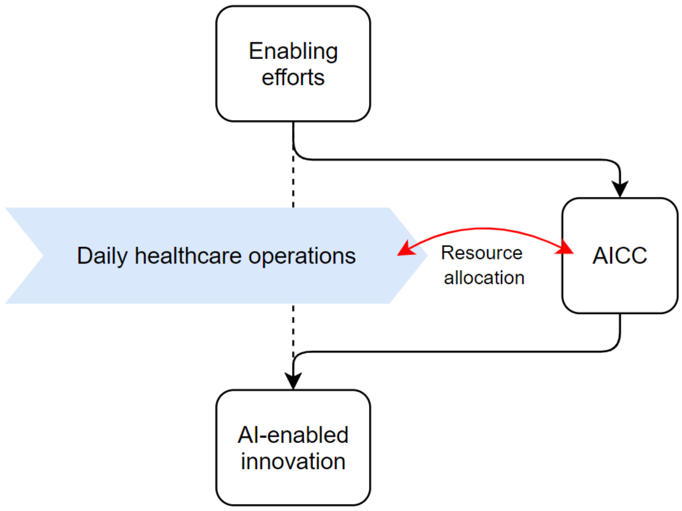

Figure 18: How the AICC can circumvent the operative dominance through structural separation and clear resource allocation.

Some healthcare organizations have done just that, created teams and roles focused on major change and overcoming operative dominance; DRIVE and CIDD both have mainly a strategic focus, looking into things that do not fit in the normal business procedures. This further aligns with theory regarding that room for business model experimentation is needed in general (Chesbrough, 2010), but also with the clear finding that exploration and experimentation is argued necessary for driving AI. Exploratory activities require a different mindset and are indeed needed at SUH, as the vision of where AI could lead and how to get there is yet to be discovered. Varkey et al. (2008) similarly propose that innovations in healthcare ought to mature in a parallel structure, further motivated for AI by the interventionist bias in healthcare as described by Glouberman and Mintzberg's (2001b); most applications of AI and much of the potential value likely does not fit in with this dominant logic (detailed further in *6.2.1*), hence calling for a more top-down initiative in order to move it forward. The enabling actions argued necessary in the case of AI in healthcare will be detailed in section *6.1.2-6.1.4* below.

So far it has been established that a shift towards enabling, in place of mainly supporting, is required to realize the higher-level potential of AI. However, this by no means implies that the AICC should not shoulder any supportive responsibility at all, as the indicatively valuable decentralized research at SUH might need support. Findings from all organizations engaging in the act of enabling AI show that they combine this with supporting the operative business units. Backing in literature for this middle-ground can be seen, as O'Connor (2008), Börjesson and Elmquist (2011), as well as Grant (2018) argue for a clear connection between the exploratory (and as established above, enabling) organizational unit and the mainstream organization if the innovative work aims to be diffused widely. With the AICC supporting clinical departments and their research, the role the center plays in the organization would likely become more widely understood, something O'Connor (2008) emphasizes as a success factor to succeed with big innovation. Something O'Connor (2008) further highlights is the clear integration of the innovative work with the strategic intent, where the middle-ground argued for in this paragraph aligns well with the dual mission SUH holds as a university hospital.

6.1.2 Data and infrastructure serves as the core of AI and needs a dedicated effort

As established above, there is much value in putting emphasis and effort into enabling actions in order to enhance the impact of AI. Within this, the single most important aspect is developing a foundation with data and its infrastructure. This becomes a bottleneck regardless of what type of AI application SUH aims to establish (what type of AI to focus on will be the topic of *6.2*), as Russell and Norvig (2020) accentuate data as the necessary input for AI systems. Lee et al. (2019, p. 8) similarly argue that data quality, quantity and infrastructure ought to be the primary action taken in the quest toward AI, as to not build a "palace on quicksand". Sculley et al. (2015) as well as Lee et al. (2019) further motivate prioritizing data infrastructure highly as they argue that making sure data is available and of proper quality is actually the majority of the actual work with AI. Findings are in line with this reasoning, where data access, quality and corresponding infrastructure are highlighted across the studied organizations, displaying the cross-sectoral nature of this difficulty. However, healthcare appears to face particular hardships in this area, with a multitude of IT systems and poor data quality and reliability highlighted by both SUH and LTHT. Literature similarly suggests that siloed data and outdated IT infrastructure must be dealt with before AI technologies can be implemented in healthcare (Kelly et al., 2019; Arora, 2020). The technical infrastructure is argued by both Halland, GOSH and Ericsson as the very first step towards truly leveraging AI, and this realization has inspired actions among these actors. GAIA does work on common technical assets, DRIVE is taking the lead on installing data gathering infrastructure around the hospital, and Halland has put great effort into gathering data from multiple systems into a central data warehouse. Within SUH and the wider RVG, the large CIF project holds promise to aid in this work.

On that topic, what data should actually be gathered? This thesis does not aim to provide a comprehensive list, however there are some suggestions to be found from the studied healthcare organizations. Returning to Halland, they have found great value in aggregating multiple systems and databases, where the salary system is especially emphasized; this data enables more comprehensive economic analysis as the patient encounter cost can be calculated. Another inspiration can be seen with GOSH, as the DRIVE unit is taking the lead in establishing RFID infrastructure for gathering novel (for the hospital) types of data. Finally, the CIDD's regional position has enabled region-wide data from different providers, which enables analysis across the care chain, with the patient in focus. This regional connection, as well as the preferred hierarchical position of the AICC will be discussed further in *6.3.2*.

Halland's holistic data actually provides a spillover effect in terms of the value it provides, where external interest from companies has been highlighted as one such effect. Furthermore, Halland emphasizes that establishing the CIDD and the data warehouse made it possible to grasp what was actually going on, simply by having more objective data to refer to. Through examining the raw data that was made available, widely accepted correlations and assumptions were proven incorrect. Generating new actionable knowledge through data and insights in this way is what Halland argues IDC is all about, with AI being a tool to enhance these capabilities. Similarly, Volvo accentuates the value of data through their focus on becoming data-driven, where AI is merely a valuable tool within this. Literature corroborates this value, as utilizing data to find new patterns can combat an organization's inability to unlearn cemented mental models, one big obstacle to renewal efforts found by Assink (2006). This highlights that becoming more data-driven through gathering and examining organizational data to a higher degree, argued in this section as the first step in moving towards leveraging AI, can in itself help enable innovativeness in general. It is hard to argue against pure data, and it could be a valuable first step in order to facilitate building awareness and desire, the two initial change factors in the ADKAR-model (Hiatt, 2006).

The essentiality of data is highlighted in findings from SUH interviews as well, and even though there is one large CIF project that seemingly deals with the problem of data infrastructure, it is seldom mentioned by SUH and when it is referred to, its importance is not elaborated on. The way CIF is mentioned solely in passing, indicates that its connection and inclusion into the AI initiative has not been defined yet. One plausible reason for this is the current embeddedness of AI work in the operational structure, which as detailed in *6.1.1* above hinders such strategic issues from being undertaken, or in this case seemingly hinder the strategic projects that *are* being done elsewhere from being incorporated into the AI agenda. In fact, Arora (2020) predicts that investments in technical infrastructure in healthcare may be hard to prioritize over those directly impacting short-term patient care. For private industry, the findings indicate that such investments, although big, are not as hard to initiate if there is a well-founded business case for it. Alas, AI infrastructure requires more work to be prioritized in healthcare. Therefore, long-term infrastructure work is suitable, and necessary, for the AICC to incorporate as one of their main missions, as the separate structure helps facilitate resource allocation. There are however other relevant entities within the large SUH and even larger RVG structure that could, and should, help with this. In particular, the CIF project is very important for AI and the CIF teams ought to be highly integrated into this work. The outdata teams could advantageously be utilized and drawn upon as well.

6.1.3 Clear vision and communication creates both symbolic and practical value

Cosgriff et al. (2020, p. 1) argues that "the lack of clinical results [of AI] is the byproduct of a lack of coherence, leadership and vision". This is troubling, but surmountable. In the studied organizations, the degree of clarity and explicitness of AI visions differ quite widely, with SUH on the lower end of the spectrum. Findings suggest the AICC to be the only clear element regarding a vision or plan for next steps at SUH, where uncertainty also exists whether healthcare should be early adopters of AI or not. The difference between this situation and the one seen at either Ericsson, Halland or GOSH is rather substantial; all of these organizations have incorporated AI within some long-term plan. Ericsson has explicit AI strategies, Halland has IDC as a main focus on a regional level, and GOSH has constructed a five-year plan with AI and technology explicitly interwoven into each component. Comparatively, AI and technology is argued to be an implicit part of Volvo's strategy. The causality between the strategic thinking and AI progress of these organizations is not obvious, but literature points to there being a connection; a clear and tangible vision accompanied by goals and a strategy is widely regarded as a powerful catalyst to drive change, as organizational inertia can be combated, individual projects aligned, and an organizational sense of purpose instilled (Grant, 2018; Kotter, 1995; Pisano, 2015; McAfee & Brynjolfsson, 2012). Wirtz and Müller (2019) specify this in the case of AI, arguing that a sophisticated strategy is needed to realize the potential benefits.

Findings display that many believe that the work with AI and data requires a long time frame due to the large change it brings. This is exactly where a vision becomes crucial to set the direction of this long journey, something also emphasized by AI Sweden. SUH understands the long-term nature of this initiative and hence the symbolic value found in pronouncing the ambition out loud to instill motivation across the organization. These realizations are promising but need to be followed by tangible and reachable visions and goals. Change and transformation is argued hard since it invites resistance, but Kotter (1995) and Grant (2018) point to the power of a strong vision in overcoming this. The findings point to top management playing a big part in this work, as the vision must be anchored there.

Visions of where you want to go are evidently important, but how do you avoid visions just turning into fluffy and wishful thinking that is never realized? Establishing a sense of urgency at the top of an organization widely emphasized in literature as key to get a change going, something that requires a large effort to accomplish (Kotter, 1995; Leonard-Barton & Kraus, 1985; Hiatt, 2006). One way organizational inertia such as dominant logic and cemented routines can be counteracted is through creating perceptions of crisis and hence a clear urgency for change (Grant, 2018; Greenhalgh, 2004). This is highlighted by some of the studied organizations with regards to AI acceleration as well, as a sense of urgency is one of the common denominators behind the formation of all the central AI teams of the study: CIDD, DRIVE and GAIA. As seen in the findings, Volvo has also explicitly stated that "we must do it" to maintain competitiveness. SUH is through its AI initiative displaying their inclination toward working with AI, but a sense of urgency appears relatively lacking. It is not that healthcare has to fake this urgency either, as highlighted in the thesis' opening pages: healthcare as a whole is up against big challenges with an aging population and an increasing prevalence of multi-sick patients. Halland utilized this to instill a sense of urgency towards long-term work with information-driven care, indicating that a sense of urgency can aid in overcoming the operative focus in healthcare[28], a topic explored in the previous section *6.1.1*. It is recommended that SUH and the AICC try to do the same.

Crafting a transparent and clear vision and a considerable sense of urgency is tightly coupled to the need for effective communication; without persistent communication efforts, the vision and the urgency of reaching it will never be diffused through the organization (Kotter, 1995). The importance and current lack of widespread AI awareness and competence is a consistent finding from the study, where Hiatt (2006) as well as Gustafson et al. (2003) accentuate the need for this if a change and an innovation is to accelerate. Lee et al. (2019) believe broad AI training is needed, and literature further points to formal knowledge-spreading activities such as workshops as being effective tools to increase competence and innovation diffusion in general (Meyers et al., 1999; Hottenstein et al., 1999). This task is suitable for the AICC, through being the core of the organization's AI quest, to lead, where AI Sweden and their educational efforts could be drawn upon for collaboration. The very existence and role of the center needs to be widely communicated as well, in line with O'Connor (2008).

[28] The dramatic digitalization leaps taken in healthcare to cope with the COVID-19 pandemic exemplifies what a sense of urgency can do to accelerate change.

In order to communicate effectively, both literature and findings suggest that utilizing champions and boundary-spanners are beneficial. Champions should be utilized to drive change and diffusion (Grant, 2018; Meyers et al., 1999), while boundary-spanners contribute with knowledge and ideas from the outside that can add to an organization's *sensing* capability and innovativeness (Rogers, 1995; Zahra & George, 2002; Takey & Carvalho, 2016). One key individual in Halland is deemed by the interviewees to embody both of these roles and is argued to have played a major part in Halland's IDC success so far. SUH ought to ransack the organization for potential champions and boundary-spanners, as their commitment to the AICC and the AI initiative in general could prove pivotal. It seems natural that some individuals have more influence, power and prerequisites for communication, so finding and promoting boundary-spanners and champions does not go against what the top management says about everyone needing to take part in communicating around AI per se. It is also reasonable that the AICC in itself can function as a boundary-spanning unit, detailed in *6.3.4*, as well as championing AI work at SUH.

However, findings suggest that developing a clear and aligned top-down vision, strategy and buy-in is a difficult journey. While Volvo implicitly speaks of AI in their strategy and rely upon the business divisions to do much of the AI work, Ericsson drives AI very explicitly and centrally. After its conception, the centralized GAIA structure took the lead on the strategic work around AI at Ericsson. Due to the complexity and size of SUH, part of the even larger RVG, the formalized AICC is deemed most the appropriate structure to drive the strategic work, as a coordinated and dedicated effort is believed necessary to get the large organization moving.

6.1.4 Internal AI innovation process is relevant

One final act of enablement is mapping, clarifying and formalizing the *internal AI innovation process*. Pisano (2015) puts forth that an innovation process has to be constructed systematically, with coherence ranging from search to funding. In healthcare, clinicians and researchers are autonomous but do require guidance for certain things, the very reason for the large support structure in hospitals as highlighted by Mintzberg (1989). At SUH, the general innovation process already has a facilitator, the Innovation Platform. However, due to the distinctiveness of the requirements for AI, the ethical concerns (Topol, 2019), the lack of implementation to learn from (Sun & Medaglia, 2019), and the great uncertainties that follow an "era of ferment" technology (Afuah, 2003), this study proposes a specialized procedure dedicated AI to enable the acceleration of AI diffusion. This follows the recommendation given by Arora (2020) to proactively construct organizational procedures in order to prepare the organization for AI and its future impact. Speaking of impact: the internal innovation process proposed in this section could help clarify how SUH actors can navigate from the pure technology into valuable hospital impact, a conceptualization proposed early on in *3.1.1*, and seen again on the next page in Figure 19.

Figure 19: How this thesis conceptualizes the different stages of AI value-creation. Slightly adapted from Figure 8 in 3.1.1.

Through clarifying and documenting this internal AI process, the innovative and enabling AICC could be integrated to the mainstream organization in a clear way, as emphasized as beneficial for such an innovation unit by O'Connor (2008). As there are multiple stakeholders (other than the AICC) involved in the internal innovation process, by further clarifying how all these units can support AI innovation, uncertainties in navigating this process can be reduced. In particular, there are four aspects that this thesis has identified as essential to clarify and incorporate into this internal AI innovation system: legal barriers, data access, commercial product interface, and testbed availability. Responsibility for this endeavor is suitably given to the AICC, as the competence and experience accumulated from other AI-related work provides synergies, although competence from the Innovation Platform could advantageously be drawn upon. Figure 20 below visualizes the stages and highlights the stakeholders whose potential contributions need to be clarified.

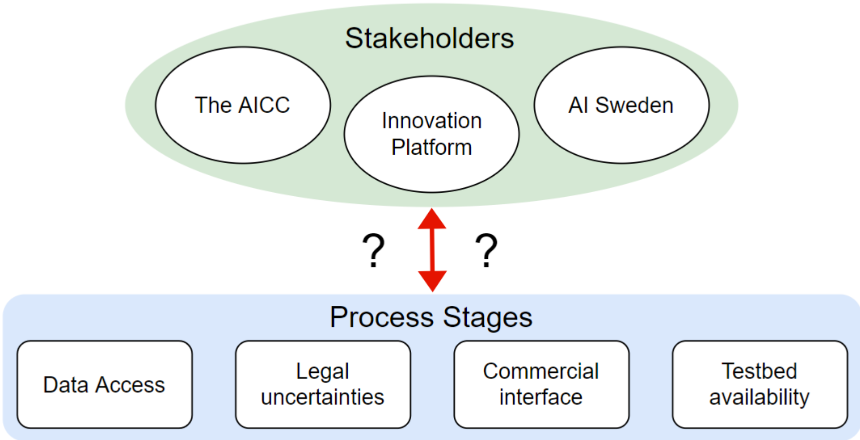

Figure 20: Stages in the internal AI innovation process, the relevant stakeholders and the yet unclear connection between them.

Findings display that legal and regulation makes AI hard and is often blamed for slow progress, especially intricate in healthcare due to the data sensitivity. Herzlinger (2006) does point out the importance for innovators to properly understand the legislative landscape as legislation does pose a threat to innovation otherwise. Although the legislative barrier can largely be avoided through shifting AI application focus, discussed in great detail in *6.2* below, a comprehensive mapping using knowledgeable legal staff could remedy some of the headaches and fears currently experienced. NHSX and Halland argue that without displaying great knowledge of legal aspects such as confidentiality and integrity, resistance will be strong, as they argue legal competence as highly valuable in AI work. At SUH, the Innovation Platform houses some relevant legal competence, which could be drawn upon in the work with this legal aspect of the internal AI innovation process. The AICC could here find inspiration from the NHSX and the regulatory mapping done in their report (NHSX, 2019).

Although one considerable part of the regulative mapping recommended above, data access still deserves its own consideration. Data access is highlighted as complex across the studied organizations, not only due to national policies lagging behind the development, but also due to technical system complexity within large organizations. As a result, LTHT assembled a research data team to aid with navigating and collecting data across the hospital's systems. CIDD in Halland similarly devotes part of their work towards guiding and consulting researchers looking for data. Extrapolating to the AICC's work on the internal AI innovation process: drawing upon the work with data quality and infrastructure detailed in *6.1.2* above, a protocol for supplying researchers and others with usable data could be established.

Also, likely to be interested in the data gathered by the AICC is external product suppliers. Commercial products are deemed important for healthcare by the studied organizations, both for legal and practical reasons; regulation prohibits publicly funded healthcare to conduct product development, instead forcing them to clarify the need to then source externally. It also simply falls outside of a hospital's core capabilities which invites commercial products as a more effective option. However, Russell and Norvig (2020) detail that AI applications for healthcare with formal approval are currently few, although rising in numbers exponentially. Commercial AI products are indeed found to yet be scarcely seen in the studied healthcare organizations and involve a complex dynamic as they do not always match the need and are not always compatible with existing IT systems. At SUH, the Innovation Platform statedly acts as an interface between internal need and commercial products in general, which includes AI. This interface ought to be included and further investigated in the internal AI innovation process mapping done by the AICC.

Relevant for AI applications regardless of origin, is a dedicated testing environment, as SUH points out the required evaluation and testing as a main source of difficulty with commercial AI products. The findings propose that AI requires rigorous testing, where real-world evaluation in the later stages of an algorithm or product is especially important. Cosgriff et al. (2020) highlight that too few algorithms have been evaluated on patients. NHSX and GOSH have realized that this is the real bottleneck in moving AI through the innovation process, where the DRIVE unit at GOSH is pioneering a "future ward" that will act as a staging post for AI and other technologies. Halland also offers a testing environment for commercial products looking to enter the healthcare sphere. Something pointed out by one SUH interviewee however, is that AI Sweden houses a testing environment, one which SUH could be the beneficiary of instead of developing their own. Again, much of these difficulties could be avoided through a displacement of AI focus, which will be detailed in the subsequent section *6.2*. Still, the process and guidance towards a testbed should be incorporated into the internal AI innovation process, where AI Sweden can be utilized.

6.2 Administrative AI is valuable

The second major discussion point concerns which type of AI applications are appropriate for SUH and why. The subheadings divide the very interwoven discussion into more digestible parts, where only the last subheading contains a recommendation building on everything discussed herein under.

6.2.1 Clinical focus on AI is currently dominating

Following the reasoning above, it seems natural that organizations focus on their core business when talking about AI, such as Ericsson speaking about customer-oriented AI in their products to make them better. In healthcare, this translates to making the delivery of care better with AI. Throughout the findings when SUH refers to AI in healthcare, there is a subtle but important undertone of *healthcare AI* being equivalent to *clinical AI*. While clinical AI is a promising use case of AI technologies as put forth by Topol (2019) and Liu et al. (2019), it is not the only one. This can be seen in the empirical data, as Halland clearly and explicitly proposes that AI can be used for precision management. More concrete examples of administrative usage of administrative AI from the findings are to make healthcare logistics more efficient, predict staffing and influx of acute care patients, predict health care damages, and find complex casualties in admin data undetectable by humans. What the NHS says about using AI for system efficiency and knowledge generation touches upon the same idea of using AI for non-clinical applications. Even private organizations, Ericsson and Volvo can give examples of non-customer focused AI, such as using it to catalog data or predict failure reports. Repeating what Arora (2020) mentions about there being usages of AI that are not immediately affecting patients medically, such as predictive staffing, shows literature supports this notion as well. Interestingly, this distinction between different applications of technology can also be seen in more general definitions of innovations as put forth by Damanpour (1996) as well as Kimberley and Evanisko (2017), who speak of administrative innovation and technical innovation. See Figure 21 below for an illustration of these two distinct uses of AI in healthcare.

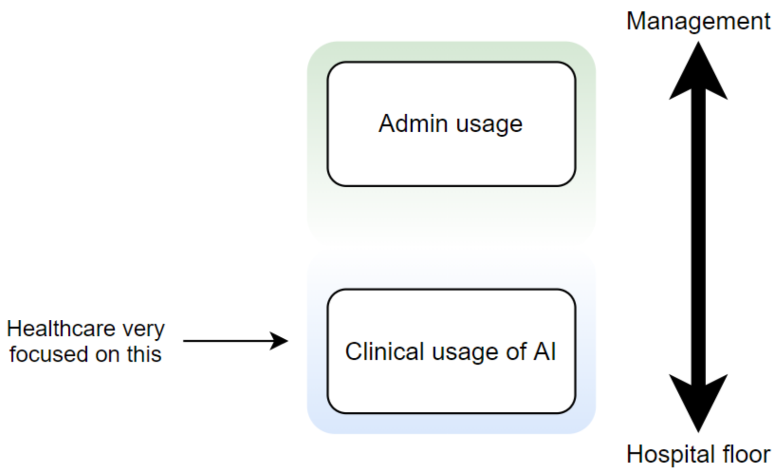

Figure 21: Illustration of the two distinct uses of AI in healthcare and on what organizational level they are used.

So, with this prominent distinction of clinical and non-clinical use of AI, why is it that when SUH speaks of AI it is always with a focus on clinical AI? The discussion in the previous Section 6.1 has already hinted towards an answer that is detailed hereafter. Tying back to what Afuah (2003) and Chesbrough (2010) labels dominant logic, the special healthcare culture impacts how AI technology is approached, in which Glouberman and Mintzberg (2001a) suggests that technological change is focused on by physicians. If administrative change is instead driven by administrative managers and physicians have a tradition of strong influence (Glouberman & Mintzberg, 2001a), it is not all that surprising that administrative uses of AI have been overshadowed by the clinical uses that are tightly connected to the work of physicians. Findings from SUH explicitly state that there is a strong tradition of business development happening close to the specialties.

The unique life and death situation of healthcare as described by LTHT is evidently hard to ignore at SUH as the findings point to. It is not unreasonable that this creates a strong pull to make clinical AI the most prioritized application of AI. The same reason operational investments are prioritized over strategic ones in healthcare, as detailed in section *6.1*, sensibly applies to clinical AI being pursued before administrative AI. "When people are dying right next to you", as SUH puts it, there is an understandable focus on fixing this immediate situation.

Focusing on fixing the immediate situation and not on administrative AI at SUH connects to what Glouberman and Mintzberg (2001a) say about physicians being interventionistic in their approach to healthcare. By preferring to rely on medicine or incursions over manipulation such as touch or talking, care that might actually help prevent the need for cure entirely is often overlooked (Glouberman & Mintzberg, 2001b). For AI technologies this possibly means that clinical applications with focus on diagnostics or medicine personalization fit the preferences of physicians better, resulting in the collective devaluation of administrative AI as its effects are more indirect in nature. When looking at the data, a parallel can be drawn to the fact that SUH, Ericsson and Volvo emphasize that AI must be applied to solve a problem or need. For SUH, this evidently means AI applied in a clinical setting.

It is also interesting to view this from the perspective of the different innovation characteristics described by the literature. Particularly how the definition of *sustaining innovation*, as described by Christensen (1997), fits in with clinical AI being the primary application of AI technologies at SUH. It can be argued that sustaining innovation, meaning innovation that improves existing processes and products, describes what is happening with clinical AI at SUH as the findings suggest AI's main purpose is to improve the capabilities *in* diagnostics or radiology workflows. An extension of this is that workflows can largely remain the same and still allow for this type of AI technology to be implemented, which is indicative of a sustaining innovation as well. As such, the current way of focusing on clinical AI does not challenge the status quo and dominant logic to a great extent, which provokes the thought: what if that is the very reason AI is currently approached with mainly clinical applications in mind at SUH? Is clinical AI in focus because it is the easiest acceptable AI application by the majority of personnel?

Explicitly pointing out that there is value in administrative and management applications to SUH is met with enthusiasm, alas this quickly transitions into an eagerness to talk about something else. This is in line with what GOSH and Halland both state about the difficulty of getting to the point where administrative AI is seen as valuable in their organizations. This tells us that the forces making clinical AI so attractive are indeed strong, indicating a separate structure further removed from these forces could be needed to focus on administrative AI, something the AICC shows great promise to facilitate. While it is understood both why and how clinical AI is important, the attractiveness of clinical AI as the first step towards an AI acceleration at SUH is questionable. Through initial focus on administrative AI, the approach to accelerating AI implementation is deemed adherent to the guidelines Arora (2020) presents: introduction of AI has to be gradual and well thought-out.

6.2.2 Shifting focus entails more implicit but holistic value

As has been alluded to throughout this and the last section, there is a more holistic way of approaching the implementation of AI technologies. Again, Halland and NHSX see value in applying AI for administrative and managerial benefit and data from Halland even tell us that AI technologies can have a more paradigm-shifting clinical value and impact, with the example being predicting mental illness. Value realized at that level would correspond to what the definition of *big innovation* entails; proactively providing healthcare through direct means as the case with mental illness prediction, or indirectly enabling better healthcare by making logistics or staffing more accurate, means that one cannot rely on the same workflows or processes that are used for reactive healthcare today. This connects to what Arora (2020) says about AI having the potential to redefine healthcare capabilities and can be referred to as a step towards establishing a data-driven culture and business model through big innovation. Inherently, this would also involve structural and organizational changes which are not easy to overcome, as stated by Davenport and Bean (2018) and Lee et al. (2019). The findings converge with the literature, as all actors mention cultural challenges. Even SUH mentions that AI has the potential to change how things are done, but that it will be difficult.

Yet, the main focus is still on clinical AI applications at SUH at large. Again, other studied healthcare actors are starting to become self-aware and realizing that there is value in administrative uses of AI that ultimately help the mission of healthcare delivery. What the data displays is that these organizations are making an effort to think about administrative AI to a greater extent, the more they realize its potential. This goes for private actors as well, as both Volvo and Ericsson see value in administrative uses of AI. With that said, the findings also show that there are still limitations to how much concrete work is done with administrative AI among actors. Still, the important step other actors have taken is that they have started to *think about* and *realize* that there are other applications than clinical or customer-facing AI. The hope is that this very thesis contributes to such a realization at SUH as well. Just as the AICC is an opportunity to focus on enablers, it is also an opportunity for SUH to start thinking about administrative AI.

Now, why is that an important realization? There are several reasons why thinking about administrative AI can be important. Seemingly, the most obvious one is that the statedly enormous administrative workload can be tackled by the use of AI to make smarter observations and take more efficient actions, which according to Halland is "incredibly value-generating". As mentioned in *6.1.2* above, simply examining administrative data before applying AI is of great benefit on its own. Even though Glouberman and Mintzberg (2001a) classify care and management as two separate worlds in healthcare, the fact that better and more efficient administration ultimately enables better healthcare delivery cannot be overstated. The data showcases that Halland and GOSH have both come to the same conclusion. That is the first reason why the realization about non-clinical uses of AI is important. Though, should not clinical AI enable better and faster healthcare and in a more direct way as well?

The problem is not that clinical AI is inherently bad and will not lead to major improvements for healthcare, but rather that it is very difficult to actually productionalize at this stage. The most apparent metric for measuring this would be the number of clinical AI applications in use today. The findings point to virtually no usage of clinical AI in day-to-day operations of any actors, including SUH. In fact, it is apparent from the findings that there are few AI technologies in use in healthcare *overall*, supporting what Sun and Medaglia (2019) says about AI in healthcare being in the early stages in terms of *implementation* despite the hype. Drawing upon the discussion in Section *6.1.1* about a lack of enablers for operationalizing AI, this is not surprising. Though, yet another question: perhaps there are few operational AI applications at SUH, precisely because they are stuck with a narrow clinical AI focus? Findings indicate a similarity between SUH and Volvo in this regard. Namely, Volvo started their AI journey by focusing on self-driving vehicles, which they in hindsight realized was the hardest AI application. Even though it was the most obvious use case of AI for Volvo, they say they could have started with focusing on less sensitive areas of AI implementation to get to market and mature quicker. For healthcare, clinical AI could be thought of as autonomous vehicles in that it is the hardest application of AI to productionalize. Instead, administrative AI is easier and more convenient for SUH to move forward with AI. That is the second reason why the realization about non-clinical uses of AI is important, the details of which follows below.

6.2.3 Administrative AI is further from the complex clinical culture

What might appear like the most sustaining, relevant and low-hanging fruit, clinical AI, ends up becoming complex quickly and very hard to implement. In the findings, the way AI implementation expands into others' responsibility and becomes a cultural problem is described. This means all AI implementation is complex, but the clinical setting is particularly complex as described by literature: clinical practices are specialized and physicians are autonomous (Glouberman & Mintzberg, 2001a; Mannion & Davies, 2018). Data from SUH says conservative healthcare professions are cautious about accepting new technology, slowing down the development of AI. This is not the ideal arena for deploying AI, where multidisciplinary work and cooperation is required to operationalize, and where the value of the technology is not as clear as the value of medicine. Even more so, for clinical AI that is more holistic and proactive (such as mental illness prediction) and not just about helping make diagnostics faster and better (sustaining in nature), the challenges with culture are even bigger, as literature around big innovation suggests as well.

For administrative uses of AI, the silo structure of healthcare is still a factor, as are cultural difficulties. Notedly, the healthcare administration is still connected to the world of clinical culture and practice. For example, the data highlights that several managers in healthcare have a medical background. There are even investment and prioritization difficulties due to the very fact that administrative AI does not directly affect clinical operations, which connects to the discussion in *6.1.1*. Though, that is the very reason administrative AI is advantageous to focus on as well, it is *further* removed from the complexities of clinical operations and its culture.

6.2.4 Less uncertainties around legislation of administrative AI

One clear finding is that using clinical data for AI is difficult due to legalities and regulation meant to protect patient's data, as every healthcare actor mentions this. Hwang and Christensen (2008) also point out policy as a showstopper for healthcare innovation in large. Moreover, in the findings it is clear that approval for clinical AI applications is required, meaning they must be CE marked. Again, this regulation is there to ultimately protect the patient. Importantly, as mentioned in *6.1.4*, SUH states that they are not allowed by law to operationalize in-house clinical AI, as the hospital's main mission is to provide healthcare and not develop and maintain new healthcare technologies fully. Thus, the clinical AI applications that are currently being worked on at SUH are done within the university and research mandate of SUH, in a sandbox shielded from culture and the reality of operationalizing AI. As discussed in *6.1*, the legal landscape in healthcare is complex, which according to Herzlinger (2006) means that one must understand the legal landscape for innovating in healthcare. Now, by understanding these legal factors blocking clinical AI, one can try to find another way towards AI acceleration. Is there something subject to fewer legal challenges? Yes, administrative use of AI. Reasonably, administrative AI is more of a process development, while clinical AI is often product-oriented. This is backed up by the findings, as Halland says no CE marking is required for analyzing patterns that do not affect individuals. Moreover, Halland states that administrative AI applications work perfectly fine to develop internally, especially at SUH due to their size. *Every* healthcare actor hypothesizes that it is easier to implement administrative AI than clinical AI, even SUH themselves, stating that there are fewer ethical considerations to take into account for administrative AI. So, the threshold evidently seems lower for administrative AI and by virtue of not being subject to as many laws, administrative AI can be productionalized within a shorter time frame as it can circumvent the legal barriers and make its way into healthcare production in a way clinical AI cannot, see Figure 22.

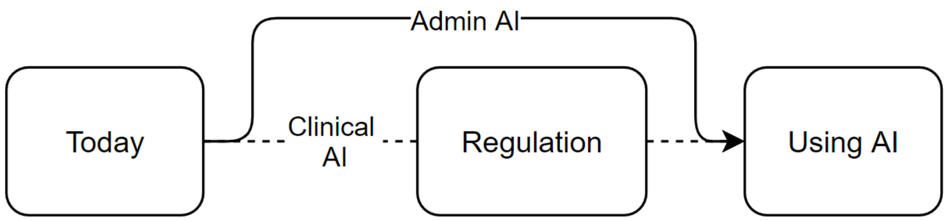

Figure 22: Visualization of how administrative AI can side-step regulatory difficulties to allow for starting to use AI.

As suggested by SUH and GOSH, one way of productionalizing AI in healthcare while still abiding to regulation is to rely on externally sourced solutions. Though, the data from Halland and SUH also suggests that there are many uncertainties when it comes to commercial AI products. Due to these uncertainties and as described in *6.1.4*, this process requires clarification and formalization, before it being a viable option. This means, by process of elimination, internal focus on administrative AI is a good starting point, see Figure 23 below.

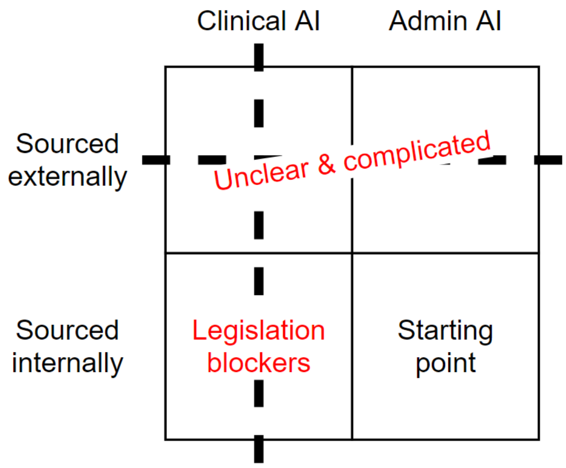

Figure 23: Depiction of the process of elimination that suggests internally developed administrative AI to be a good starting point with AI.

6.2.5 Administrative AI is an opportunity for experimentation

Multiple findings showcase that it is not clear exactly how all this (data access, infrastructure, culture, value, regulation and external sourcing) should come together. SUH, Volvo, Halland and AI Sweden all state that experimentation is an important part of tackling the many unclarities with implementing AI in healthcare, as to start small and test your way forward. This is connected to the field of healthcare AI being in an era of ferment characterized by high uncertainty (Afuah, 2003) and what Lorica and Loukides (2018) says about the path toward AI being unclear for many organizations. Tying back to healthcare regulation, experimenting and "trying things out" with patient data hardly seems realistic outside very controlled research settings at this stage, meanwhile real-world testing is an important part according to GOSH and NHSX. On the other hand, for experimentation and learning purposes, administrative AI presents more opportunities, as data regulation is more lenient, and the experimentation happens further from life-and death situations. Through doing this, key learnings and takeaways can possibly help the process of implementing and operationalizing clinical AI as well. This process summarized in Figure 24 on the next page.

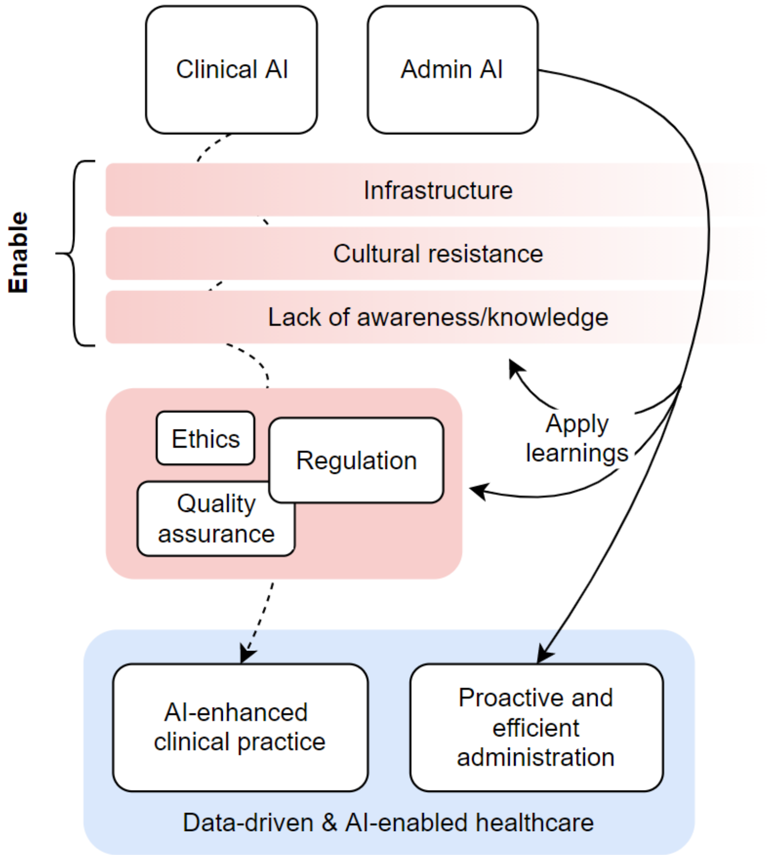

Figure 24: Obstacles are easier to overcome for administrative AI. Learnings can be applied towards clinical AI, which together with AI-enabled administration eventually moves towards data-driven and AI-enabled healthcare on the whole.

6.2.6 Communicating success becomes easier with administrative AI

Administrative AI is an opportunity to showcase quicker successes, which in turn can be used to combat cultural resistance among the large majority of personnel not yet familiar with AI, as the Figure 24 above also suggests. This is corroborated by Lee et al. (2019) who suggest that taking on feasible smaller projects can be used to increase familiarity and enthusiasm toward AI. Likewise, the findings propose that the value of AI needs to be clearly demonstrated for more adoption, especially for acceptance by clinicians. Moreover, there exists the notion that AI is not considered valuable if no real problem can be solved through it. Although administrative AI is not clinically anchored in itself, it can still be used to demonstrate the holistic value of AI-enabled problem-solving and mindset. It seems reasonable that some key learnings are actually directly transferable to clinical AI implementation, such as technical infrastructure configuration. Other learnings, i.e., about culture management and the AI development process, should also be useful knowledge for clinical AI deployment. The important thing is that clear small steps and progress could gradually chip away at the "AI is only the newest thing" attitude at SUH. As put by Kotter (1995; 2012), tangible effects make the progress unambiguous, anchoring changes into organizational culture. Assink (2006) and Gustafson et al. (2003) suggest that the mindset barrier can be gradually broken down by clearly communicating signs of progress. This should not be an alien suggestion to SUH, as the data points to both GOSH and SUH believing in using good examples to spread enthusiasm, trust and awareness. The latter deserves to be underlined as well, namely spreading awareness.

SUH believes the awareness and competence needs to increase in the organization, something that is indeed important as described in *6.1.3*. Grant (2018) and data from Halland suggest political acceptance and understanding is hard to achieve, so communicating with good examples and having something to show can be helpful for SUH to gain political acceptance for AI initiatives as well. By focusing more on administrative AI, this process of communicating with good examples can be started sooner than if clinical AI was the only focus. As detailed in *6.1.3*, the AICC could preferably take charge on communicating the AI vision and help spread awareness, which ties in well with the reasoning in this paragraph, as administrative AI can be added to their communication portfolio.

6.3 Location and composition of center can be impactful

The third and final discussion session regards the location and composition of central formation SUH is planning, the AICC. As discussed in the previous two sections, the separation of the AICC from the operative structure is motivated as it allows for pursuing enabling efforts as well as embracing the opportunities administrative AI offers. By interpolating Figure 8 from *3.1.1* with Figure 12 from *3.2.2*, an interesting congruence can be seen that supports the formalization of the AICC further, visualized in Figure 25 below.

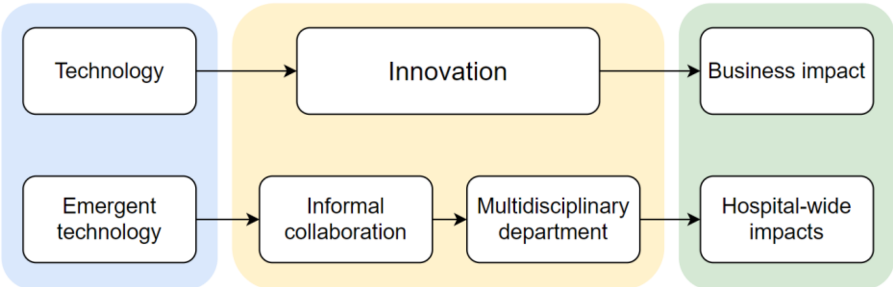

Figure 25: Combining the two figures gives an implication of what is needed in order to realize innovation in a hospital setting. The top row is Figure 8 from 3.1.1 and the bottom row is Figure 12 from 3.2.2.

The top row in Figure 25 displays the general conceptualization of how AI can move from a technology via an innovation to reach business impact. The bottom row displays how Cosgriff et al. (2020) argue that new technologies are effectively realized into hospital-wide impacts. Looking at the middle section of Figure 25, innovation can also be seen as distinct two steps: informal collaboration followed by a multidisciplinary department. This implies that in order to realize a technology-based innovation in healthcare for big impacts, informal activity followed by a formalized department is appropriate. This reflects Halland's and GOSH's journey with AI well, as well as the journey of private Ericson. SUH has gone through the informal phase as seen in the data, and the formalization of the AICC appears to align well, especially since responsibilities around AI are currently deemed unclear by many. This provides additional backing for clearly separating the AICC from its surroundings, which aligns well with the reasoning in previous sections and the requirements for ambidexterity put forth in the theoretical framework. In the following subsections, further desirable characteristics of the center will be discussed. The characteristics that will be investigated are *proximity to top management*, *sanction from regional management*, *multidisciplinary team in a physical space*, and lastly *interface in- and outwards*.

6.3.1 Proximity to top management is important

Following the recommendations about enabling work and focus on administrative AI, it seems that one important dimension to consider when placing the AICC within the SUH organization is its proximity to top management. As hinted towards, enabling actions require top management to be involved in AI work and administrative AI is further from the hospital floor than clinical AI. Moreover, viewing AI as a technology that enables big innovation and a cultural shift toward a more data-driven business, this naturally involves top management. Among several data points, there is a clear tendency for centralized structures around AI to be near top management: CIDD in Halland, DRIVE at GOSH and Ericsson's GAIA.

Greenhalgh (2004) suggests that complex innovations might require top management decisions, because of the need for the whole system to assimilate around the innovation. Likewise, Chesbrough (2007) suggests that business model innovation means that the strategic apex of the firm must be involved to achieve authority. Hence, if central structures such as AICC at SUH are thought to help drive AI as a big innovation, top management needs to be involved somehow. Meanwhile, CIDD, DRIVE and GAIA all have a clear *enabling* mission and strategic intent. Interestingly, Volvo does not have a separate central unit focusing on AI, though GTT is still assigned to connect AI to the overall strategy. Instead, Volvo mainly relies upon business areas to work with AI but says that their size and silos makes scaling and accelerating AI hard. At SUH, the work around AI has been driven informally, but by high-ranking individuals and champions, indicating some sort of connection to management still. Much literature says that top management support, commitment and involvement is widely regarded as essential for successfully driving change and implementing big innovation (Meyers et al., 1999; Gustafson et al., 2003; Afuah, 2003; Takey & Carvalho, 2016; Berwick, 2003). Moreover, direct management involvement is a key characteristic of administrative innovation, says Damanpour (1996), while O'Connor (2008) states that if a separate innovation team is created, the team should have full endorsement from top management in order to gain authority. Moreover, findings from AI Sweden indicate that the question of AI has to be driven close to where decisions are being made and involve the CEO. The unfinished discussions at SUH about where to place the AICC are worrisome and perhaps seemingly unmotivated with this background; Why is SUH even considering locating the AICC anywhere other than close to top management?

The reasons for thinking about placing the AICC away from management are strongly founded in the cultural tradition of healthcare at SUH, displayed clearly by data such as "As much clinical proximity as possible is important" from SUH top management. The sentiment continues clearly: digitalization should not be pushed from above and a central AI unit will not result in much progress. Comparatively, Volvo shares the same idea of business development happening out in the business divisions and not centrally. This is especially interesting considering that both SUH and Volvo are the only studied organizations that have AI networks as a primary method for organizing AI work. To further understand why SUH wants to place the AICC near clinical practises, a parallel can be drawn to the skewed power balance of physicians versus management, as described by Glouberman and Mintzberg (2001a).

However, the fact that SUH is now in the process of establishing the AICC suggests there is another driving force at play. SUH mentions that it is time for things to become more organized, indicating that there is a notion that pure diffusion of AI technologies is not enough for appropriate progress. Again, the findings show that such an urgency similarly led to the establishment of CIDD, DRIVE and GAIA, as detailed in *6.1.3.* Instead of relying on pure diffusion, the setup of AICC indicates SUH is willing to take a more disseminating approach in Greenhalgh's (2004) terms. This internal battle at SUH of wanting to set up the AICC, but at the same time wanting specializations and areas to drive AI themselves is worth elaborating on. Taking a step back and considering once again that SUH mainly talks about *clinical AI*, the notion of AI being developed in the specialties of the hospital makes sense. SUH's ideas around the AICC mainly being a supportive function also makes sense from this point of view. As proposed above in *6.1* and *6.2,* there are views and arguments that contrast with this. If the AICC is to focus on enablers and administrative AI a close connection to top management is important.

Glouberman and Mintzberg (2001b) mentions that hospitals are better off facilitating self-management within the clinical specialization, seemingly contradicting placing the AICC near top management. However, the level of facilitation must be considered. Could not bigger enabling actions, such as building data infrastructure, support self-management in the clinical units the same way state-sponsored roads make it possible for cars to go wherever they want? While decentralization might be good for AI (especially for clinical applications), AI first needs to be more ready to implement, something not easily facilitated decentrally. Hence, an initial effort coordinated closer to management is seemingly called for. Though, the findings also highlight that a central structure close to management is not a given in the future, as Ericsson's GAIA is not supposed to be around forever. Instead, the ultimate goal is for GAIA to dissolve with time once it has dispersed knowledge and ownership of AI out into the business units. This too validates the need for business areas to ultimately be responsible for AI as proposed by SUH and Volvo, but more importantly it also means that there is an understanding that bigger investments into enabling action are initially needed, which requires a close linkage to top management.

Drawing upon the literature and the locations of other AI centers, it is recommended that SUH follows suit and places the AICC centrally and near top management. This also rhymes well with the discussion regarding the AICC preferably working to enable AI and focusing on administrative AI. There are also other opportunities and advantages that come with this. Reasonably, by placing the AICC on a high level, the unclarity around responsibility and vision at SUH will have to be dealt with; if the AICC becomes a top management concern, a more thoughtful review of the AI responsibilities and AI vision will reasonably follow. This is also in line with what AI Sweden says about the CEO needing to take bigger responsibility. Likewise, Kotter (1995) states that management embodiment in this way is important for change. Moreover, the data says that top management understanding, buy-in and strong vision is very important to achieve traction. Although Ericsson is not in a healthcare setting, the following statement from them also indicates the importance of top management association: "when it comes from top management then you better [swearword] listen".

Reasonably, shorter decision-paths between the AICC and top management also mean financials can be discussed on another scale. This is important as it is necessary for leaders to facilitate "slack for change", translating into time and money, according to Berwick (2003, p. 1974). In line with this, Chesbrough (2010) and Pisano (2015) say that clear resource allocation is strategically important, as big innovation might need an earmarked budget to avoid internal competition. As evident from 6.1, the difficulty of this financial prioritization in healthcare is understood, but its importance cannot be overstated. Lastly, the data suggests "SUH management encourages AI interests" and placing the AICC near top management at SUH would legitimize these words further.

6.3.2 Sanction from regional management means more holistic value

As established through the reasoning above, proximity to SUH top management is recommended for the AICC. However, what remains ambiguous is what role the AICC plays within the larger regional structure of RVG. As pointed out by Halland, there are many hierarchical layers in public healthcare, with RVG being one of the largest regions in Sweden. While arguments for placing the AICC close to top management have been put forth, Halland points out that placing the AICC in RVG might not work the same way CIDD does in Halland, due to the size difference. Moreover, as SUH is the region's only university hospital, meaning it has an ambidextrous mission of not only providing care but also performing much of the research and innovating in RVG, pioneering such a healthcare AI center within SUH appears logical for the region as a whole. In fact, as stated by Halland, the value lies not in the regional placement, but rather in the mandate to access and execute on data. But why does that matter?

Although not placed in the regional hierarchy per se, regional responsibility of the AICC would enable wider encompassing analysis of the interconnected care chain and overcome the limitations of an isolated SUH analysis, as put forth by Halland. It is for the same reason that CIDD has a regional mandate as well (placed in the actual region hierarchy), as this allows for a more patient-centered approach; holistic data spanning from primary care to post-somatic care puts the patient and the entire care system in focus, avoiding the sub-optimization that Halland as well as Herzlinger (2006) have seen to occur when decentralized analysis is allowed to take place. In addition, the *person-centered* approach made possible by holistic data aligns with Sweden's national healthcare agenda, which came about due to the increased shortcomings of the siloed governance structure of healthcare (Socialdepartementet, 2020). Hence, regionally sanctioned data access becomes the cornerstone of the AICC's potential impact, leaving the position within the regional structure less important. Establishing the center on a SUH top management level, but with sanction and mandate to analyze and affect the entire regional care chain, is deemed a suitable solution. This way the AICC can facilitate big innovation and large impact, while the SUH fear of too much centralization is partly mediated. Furthermore, AICC working with regional data would be one step towards the collaboration between different levels of healthcare providers that Eriksson et al. (2020) argue necessary. The AICC doing work that impacts the whole RVG might be a reason for discussing regional financing, due to the probable increase in workload.

While discussing the RVG-level healthcare AI structures, the way AICC interfaces with the AI Council becomes relevant in order to give a complete picture. The AI Council is quite new, contains representatives from the entire region, and is deemed by most SUH interviewees as highly vague regarding responsibility and mission. However, following the sentiment voiced by both SUH and Halland of utilizing already established structures, the AI council could be utilized as a regional interface as well as priority group for the AICC. Compared to the GAIA committee (where the CTO as well as business area managers participate), the composition of the AI council might require slight reconfiguration to achieve sufficient decisional mandate, but overall appears suitable for the task. The proposed regional relationship of the AICC is visualized in Figure 26 below.

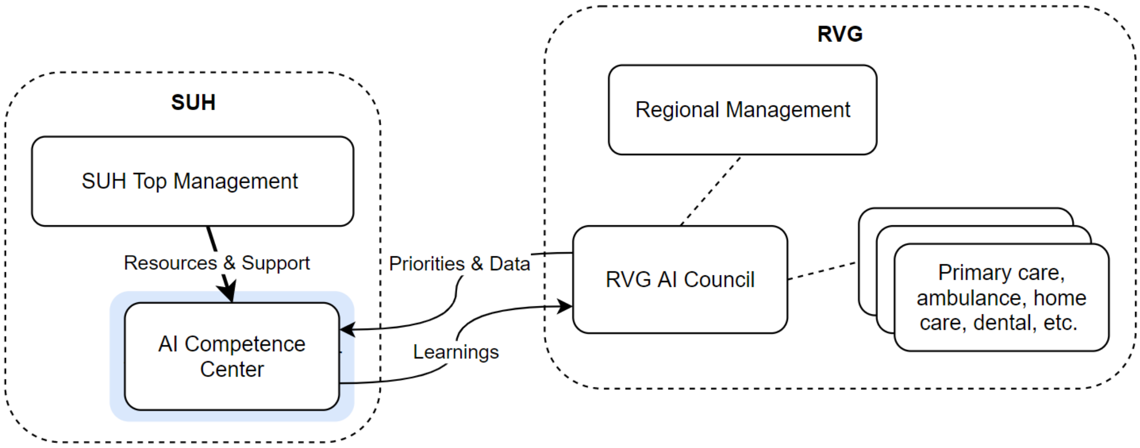

Figure 26: How the placement of the AICC and its interface toward the larger RVG structure could look.

6.3.3 Multidisciplinary team in a physical space provides value

To accelerate novel technology and realize wide impact from big innovation, both literature (Greenhalgh, 2004; Grant, 2018; Kotter, 1995) and findings consistently argue for multidisciplinary teams. This is further called for by the reasoning in Figure 26 above. But what competences are actually needed in the case of healthcare AI? The focus on enabling and administrative AI, as established in the discussion so far, plays a part in what competencies should reside in the AICC. This thesis will not provide an exhaustive list, but the data yields some guidelines. Evident from both Halland's and GOSH's journey is the need for an eclectic mix of expertise, with the core pillars being computer science, medicine, and economics. Due to the recommended focus on enabling efforts, technical infrastructure and database management become important. Availability of legal competence as well as procurement knowledge is also advantageous, as detailed previously in *6.1.4*. Tying back to medicine: incorporating clinical understanding into AI work is particularly emphasized by all healthcare actors, with one reason being to increase organizational acceptance. Bringing clinical expertise into the AICC could further be an attempt to bridge Harris' (1977) two worlds: administration and clinical operations.

When assembling the above competences, keeping the center partly cross-functional (i.e. without a fixed organizational affiliation and joint manager) could reduce the AI initiative's initiation threshold as utilizing current structures relieves the resource-demand. Halland uses this, together with the argument that functional affiliation facilitates professional development better, as motivation for keeping the CIDD mostly cross-functional with agile team compositions. However, looking at the literature, composing the center of part-time (i.e. possibly still operatively active in running the current business) members could possibly hinder big innovation due to their cemented mental models and adherence to the status quo (see *3.2.1* and *3.2.2* for the theoretical background).

In other words, the dedication to the contemporary organization and its processes might impact the willingness to challenge this way of working by pursuing change-bringing innovation within the AICC. This is a trade-off that gets more distinct the bigger the innovation that wants to be pursued; if change is demanded no matter what operational restructuring and revolution might be required, keeping the AICC members more isolated is preferable. GAIA offers a unique organizational affiliation with a common manager for its members, which enables dedicated recruitment and strategic tasks to a degree a cross-functional unit perhaps does not. CIDD does statedly pursue change, indicating that cross-functionality does not rule out attempting big innovation. This trade-off needs to be assessed by SUH, as no clear best practice appears to exist.

But how, and more importantly, *where* should this team operate? On this point, findings are quite clear: people in the same space and with clear affiliation is important for centers. Physical reorganization is highlighted by Glouberman and Mintzberg (2001b) as a more powerful means of coordination than solely rewriting the organizational structure on paper. This implies that no matter if the team is officially employed within the center or not, working closely together is valuable. Both Halland and GOSH argue similarly, where GOSH explicitly states that DRIVE's physical space provided both symbolic value as it sent a message to the organization, as well as affiliation value for the center members.

6.3.4 Interface in- and outwards complements each other

As stated by Grant (2018, p. 241); "the evidence that boundary spanning stimulates innovation is overwhelming". Moreover, the findings point to collaboration being important for driving AI work forward. Collaboration can be categorized into external and internal collaboration, both of which are described below as they are relevant for SUH when setting up the AICC.

The findings propose that Ericsson, Volvo and Halland all believe external hubs such as AI Sweden are important elements in their work with AI. Cross-fertilization through hubs in this way is thought to be "extremely valuable" according to Halland. For healthcare specifically, academic collaboration is highlighted by SUH along with Halland, LTHT and GOSH. Seeing that the field of applied AI technologies is in the early stage of its evolution and is characterized by high uncertainty and speed of development (Afuah, 2003), it makes sense for actors to learn from each other as put forth by SUH as well. However, large uncertainty and fast-paced developments make it difficult to keep track of everything that happens in the ecosystem, as stated by an individual with a key networking position at SUH: "you have to learn to navigate the strange network of actors that all want to have a say, [...] I cannot quite do it". Surveying the ecosystem is important because the first step to building dynamic capabilities is to sense the environment in a systematic way (Teece et al., 1997). In addition, O'Connor (2008) recommends an innovation team to have an external interface to facilitate knowledge generation.

Extrapolating the above reasoning to SUH's situation, the AICC presents a good opportunity to take part in the ecosystem in a systematic way. Following the discussion about the AICC being centrally located and on a high level, this also means that the AICC is a possible representative for SUH in the ecosystem, as opposed to having individuals shouldering that responsibility. To exemplify, the responsibility over the collaborative relationship with AI Sweden. Reasonably, the recommended high-level position of the AICC and proposed connections to RVG means better opportunities for regional and national collaboration as well, which the data highlights as important. Further support for external collaboration can be seen in literature, where mapping and participating in the wider ecosystem is seen by Takey and Carvalho (2016) to facilitate big innovation[29] and by Meyers et al. (1999) to help the implementation of innovation in general. Moreover, Grant (2018) states that organizations are increasingly utilizing *open innovation*, meaning they seek, exploit and apply knowledge from outside the organization.

One way external collaboration can facilitate AI-enabled innovation is via commercial products. Again, the data from SUH and GOSH indicate that commercial products are important for healthcare due to legal and practical reasons. O'Connor (2008) points out that adequate entrepreneurial abilities are not always available internally, supporting what GOSH states about healthcare not being able to do everything themselves and what SUH says about commercial products being a viable way forward with AI due to lack of internal competence. This connects to what is discussed in *6.1.4* about the AICC preferably playing a part in clarifying the process for commercial AI products as well.

Also discussed before, in *6.1.3,* is the proposal that the AICC should be responsible for communicating SUH's AI vision and spreading awareness. This ties into internal collaboration as opposed to external collaboration. Cross-departmental collaboration and multi-professional intraorganizational networks are important for accelerating adoption of innovation and increasing the chances of success (Meyers et al., 1999; Greenhalgh, 2004). Therefore, it is reasonable that the AICC, because of its proposed unique position in driving AI work at SUH, overlooks and interacts with the AI network at SUH, just as GTT does with the AI network at Volvo. With this, the AICC can further enhance its dual focus as described in *6.1.1*, as the core focus can be enabling efforts and administrative AI, while the task of facilitating the AI network can be more about supportive work for clinical AI. Through collaboration and communication with the clinicians and researchers in the AI network, the AICC can (at least partly) cater to the strong traditions of business development and research happening close to the specialties at SUH.

The combination of the AICC as a unit responsible for both external networking and internal networking is deemed especially valuable, as it can collaborate across boundaries and act as a boundary-spanner in itself. Once again, "the evidence that boundary spanning stimulates innovation is overwhelming" as put forth by Grant (2018, p. 241) and being able to sense the external ecosystem and translate this for the internal organization to act upon is what dynamic capability as described by Teece et al. (1997) is all about.

[29] Originally systemic innovation.

7

Recommendations

Here, the reasoning from the discussion above will be synthesized for answering the third and last research question:

What are the recommendations for organizing the AICC?

Hence, the backing and argumentation behind each recommendation can be found in section *6*, as the following section simply details the practical recommendations. Again, keeping with what O'Connor (2008) and Assink (2006) says about interconnectedness of factors for change, the recommendations are to be considered in combination. The structure of this section is similar to that of the discussion for the sake of clarity, with the first recommendation regarding the need for enabling work, the second about initial focus on administrative AI, and where the third concerns the location and composition of the center.

7.1 Enable first

The first recommendation for SUH is to utilize the AICC not only to support the clinical departments and researchers, but also to drive foundational work with AI. Literature and findings suggest that these long-term investments coupled with exploration and experimentation are needed to achieve large benefits, but to not let the constraints of current business and demand obstruct these activities, the separate structure AICC provides is well suited for this type of work. A central responsibility to enhance the innovation spread is deemed especially beneficial within the unique healthcare culture, as the decentralized silo structure otherwise renders the development slow. To fully overcome the operative focus, an earmarked, "untouchable" budget for the AICC to lead enabling work will likely be required.

Within this enabling work, the data infrastructure is the cornerstone. Hence, the recommendation becomes: assign main responsibility for developing an AI-ready technical infrastructure to the AICC. Functional data is the foundation for AI, and this needs to be driven by a separate entity in order for investments to be possible. The AICC could preferably draw upon other knowledgeable units within SUH, such as the Care Informatics of the Future teams and the Outdata teams. Aim to connect multiple databases and systems, preferably from the entire region to facilitate patient-centered analysis with full account of costs and value.

Furthermore, the main responsibility for the foundational work of developing a tangible and reachable AI vision with accompanying strategy and goals could preferably be assigned to the AICC. Establishing a vision becomes crucial due to the long-term nature of AI work and the large change it brings. As a dedicated effort is needed, explicitly assigning responsibility is argued to be beneficial. The vision and the accompanying sense of urgency is closely tied to top management, and the AICC should involve and consult top management in this work. Communicating the vision, urgency, the role of the AICC as well as catalyzing general AI awareness through e.g., workshops is deemed suitable for the AICC to take lead on as well, in collaboration with top management and communication staff at SUH as well as AI Sweden. Utilizing champions and boundary-spanners in this work is recommended, but they have to be identified first.

Lastly, the AICC should, as part of enabling work, investigate and subsequently construct an internal AI innovation process, to clarify and simplify current and future projects related to AI driven outside of the AICC. This would serve as a powerful enabler for AI acceleration, as current uncertainties regarding legislative landscape, data access, commercial product process as well as testbed availability could be individually and cohesively described.

7.2 Focus on administrative AI initially

The outright recommendation is to try to make administrative AI a real consideration at SUH, where the planned AICC is an opportunity to push for this. The value of administrative AI is multi-dimensional: it can provide both direct impact through smarter and optimized administrative work as well as indirectly catalyze overall healthcare AI as its path forward is less obstructed than that for clinical AI. The latter aspect is deemed crucial to accelerate the diffusion and value creation of AI in healthcare. This is because administrative AI is not subject to the same strict regulation as clinical AI, is further from the complex clinical culture, entails more opportunities for experimentation and for quicker early successes to be communicated. An administrative AI focus further motivates AICC as a separate structure to overcome the strong pull for clinical focus, similar to how it is more distant from the operative dominance and focuses on more strategic enabling actions. Enabling and administrative AI therefore appears to go hand-in-hand, as they together bring the hospital closer to becoming more data-driven in general through viewing and acting on holistic organizational data.

7.3 Location near top and clear interfaces matter

The explicit recommendation is that the AICC will preferably be a clearly separated unit, located centrally and near SUH top management. This is for several reasons; placing the AICC near top management goes well with focus on enabling actions and administrative AI, several prominent actors have placed AI centers near top management and literature says that top management endorsement is needed for full effect of big innovation. Moreover, this placement stimulates vital discussions around the vision and responsibilities.

Although the AICC is preferred to reside within SUH, it is recommended to make SUH and its AICC the beneficiary of a full regional mandate to incorporate and analyze data. One argument for why this is valuable is to avoid sub-optimization by the individual care providers in the region. Another core argument emphasized in findings concerns the value in shifting focus towards the patient, as the full care chain can be analyzed through more holistic regional data. Moreover, the already established RVG AI council could serve as a knowledge-sharing forum as well as a prioritizing function for the AICC, yielding a clear regional interface.

When establishing the AICC, it is recommended to facilitate a physical space where the AICC can operate, as it both sends a message to the organization that the initiative is significant and also provides affiliation for the team within it. The team would preferably be full-time employees, as the literature means the organization's dominant logic could then be circumvented to a larger degree. However, due to the multitude of competencies argued from the findings to be beneficial (technical infrastructure, analytics, economics, clinical and legal being some of the most important), keeping the team cross-functional through utilizing existing resources is a viable option.

Leveraging the AICC for external and internal networking is recommended, as this means it can act in a boundary-spanning way. Literature and findings suggest that partaking in an external network helps with innovation through knowledge generation and cross-fertilization, saying that ultimately healthcare cannot do everything on its own. The AICC is an opportunity to network in the AI ecosystem in a more structured way, not reliant on specific individuals with informal mandate. The AICC is also an opportunity to facilitate internal networking through the AI network at SUH. This allows for a structured cross-departmental communication and collaboration, which also helps innovation succeed according to literature. Moreover, by anchoring the connection between the AICC and the AI network, the AICC can find a middle ground between disseminating AI and catering to the strong traditions of business development near clinical specialties.

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8

Conclusions

AI is emerging as a technology with potential to reshape the healthcare sector. In this thesis, the broad concept of healthcare AI and how it could be organized to accelerate the realization of large-scale impact has been investigated. The study builds upon the premise of an AI Competence Center (AICC) being established at Sahlgrenska University Hospital (SUH), one of the biggest hospitals in Europe, and explores what dimensions are important for accelerating AI usage at the hospital through such an initiative. Ultimately, this study provides concrete recommendations to SUH on this topic.

Concepts around what AI is and what impacts it can have on business through enabling innovation as well as theory around how healthcare culture impacts innovation and AI implementation are foundational in this study. Innovation theory analysis yielded the umbrella concept of *big innovation*, encapsulating the idea of AI technologies enabling large-scale change through innovations. Literature on the diffusion of such big innovation and the accompanying major change further formed the basis for exploring what dimensions become essential for establishing an AICC, where literature regarding the unique healthcare setting gave valuable additions as well.

The findings from six actors working with AI show that there are both differences and similarities between actors and how they approach organizing for AI-enabled innovation. Main dimensions include that actors say AI is complex to implement and that actors have different degrees of direction in their AI work. Moreover, actors state that collaboration as well as external knowledge is important and there is a resistance to AI-driven change where top management support is important. Lastly, the findings show that actors have different organizational structures for working with AI.

Using the theoretical concepts and applying these to the findings, three key considerations and learnings are identified and discussed in the context of accelerating AI-enabled innovation at SUH through the AICC. Namely, enabling work is needed to gain traction, administrative AI is valuable and the location as well as the composition of the AICC can be impactful.

Enabling work is characterized by tackling foundational challenges, subsequently allowing for easier acceleration of AI usage. It needs to be driven by a separate team that can have an explorative approach to overcome the strong operational focus in healthcare. Enabling work entails being responsible for data infrastructure, upholding a clear vision for AI usage, communicating it to the organization and clarifying internal innovation processes. Without tackling these larger challenges, the prerequisites for AI-enabled change are undermined significantly.

Applying AI to administrative tasks is an alternative to clinical uses of AI. While healthcare is very focused on clinical AI, administrative AI is valuable for accelerating AI usage in healthcare. Administrative AI is further from the clinical operations and hence also from the legal and cultural challenges within it. This means it is easier to experiment with administrative data and AI, meaning short-term wins are more easily achievable, which in turn can be used for effective communication around what AI can do for healthcare. Additionally, it is valuable in terms of making smarter administrative decisions that ultimately make healthcare delivery better.

Organizational interfaces of an AI center have an impact on the acceleration of AI usages in healthcare. If AI is thought to bring about large-scale effects, it is important that an AI center is placed near top management to get appropriate levels of authority and management backing. Moreover, this rhymes well with enabling and administrative AI foci. Additional value can be generated through analyzing holistic data from across the care chain, which would require sanction from the regional level. Furthermore, there is value in gathering different competences in an AI center due to the variety of challenges it will work with. A physical space helps cement an AI center, its mission and creates a clear affiliation for different competences. An AI center can also span boundaries by being responsible for networking and communication around AI both externally and internally, thereby increasing the chances of AI acceleration through creating awareness and absorbing external knowledge.

Extrapolating from these key considerations and learnings each yielded one recommendation for how the hospital in question could optimize their center formation. Firstly, enabling work ought to receive increased attention if impactful value is sought. Secondly, it is recommended to shift focus from clinical to administrative AI, for multiple reasons. Lastly, the center would benefit from proximity to top management, regional sanction, multidisciplinary competencies and a boundary-spanning role. These recommendations are interconnected, meaning the potential value of one recommendation can arguably not be realized without the two others. Together however, they provide a comprehensive picture of what role, mission and position the center should embody to enhance the chances of achieving the full potential of healthcare AI in the future.

This means practical value is generated through concrete recommendations of what SUH should take into consideration while setting up the competence center. This can potentially aid the hospital in meeting the pressing healthcare demands of both today and the future. Theoretically, this study contributes to the nascent field of healthcare AI implementation, through exploring the literature white spot of how centralized structures in healthcare can help AI acceleration. In contrast to existing literature that deals with AI in healthcare more abstractly, this study presents tangible guidelines on how to deal with AI technologies at a hospital level. Moreover, this study concretely contributes to the discussion in the AI ecosystem by compiling qualitative data from different actors working with AI.

The contributions are argued relevant, not solely for the target hospital, but for hospitals and healthcare more generally. It is especially applicable for other university hospitals, as they would have the same dual strategic focus as SUH. On top of that, it is plausible that the general essence of the key learnings and recommendations can be extracted and applied to any large organization with the goal of leveraging AI for big innovation and change. The data spans multiple sectors and nations, hence an argument can be made for the discussion points and recommendations possibly doing the same. Naturally, this should be done with caution.

Since the study makes use of a holistic approach through keeping abstraction levels high and including multiple organizations, the level of detail had to be limited. Hence, there are aspects of the study that would benefit from further research. A key difficulty this study has touched upon is the lack of strategic focus in healthcare, much due to the operative focus that comes with a life-or-death environment. It is not hard to understand why redirecting funding from the clinical operations to long-term investments is hard, but do we go about solving this fundamental issue? That is an interesting question further research could answer as this will augment not only AI investments, but also help important and valuable strategic work in healthcare in general. The data from Swedish healthcare indicates that integrating innovative commercial products is crucial as healthcare does not possess the traditions around such processes, nor are they legally allowed to attempt so. How to go about aligning healthcare and the private market around healthcare AI products with their differences in mind, is an important tangent for further research to explore. Legality of AI in healthcare is a subject of much depth that needs to be further explored as well, as this evidently impacts AI efforts in a way that is currently not fully understood.

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Appendix A: Noteworthy undiscussed findings

In this appendix, first order concepts that fell outside of the scope of this thesis are presented. These data groupings were deemed interesting and were hence originally included in findings, but were later deemed to fall outside of the scope of the discussion and recommendations.

The term AI is today used by the studied organizations as a bundling of many technologies and has multiple dimensions to it. GOSH views it as a spectrum of quick (converting current systems or processes into AI-enabled ones) towards complicated (realizing new types of value through e.g. applying neural nets to real-time data), where they believe they have succeeded with the former type but not the latter. Similarly, one interview at SUH partly sees AI as integrated into medical products which follow normal procurement, but mainly as becoming more data-driven and drawing conclusions from data.

General difficulty with placing AI under IT, also present at SUH. Despite the technical requirements such as computing power and data (see 5.1.3), both Halland and AI Sweden argue that IDC and AI is much more than an IT project, and placing it within the IT department will impede on the possible impact. SUH has encountered this issue as well, as they argue that: "it is not at all obvious where AI belongs". However, due to the initiator belonging to the IT-side as well as the technical requirements, AI currently resides within the digitalization organization at SUH.

RPA has been adopted and developed more than more complex AI. Due to being simpler, cheaper and more easily tied to a pressing operational problem, RPA is the AI-type system with most traction in healthcare. Both SUH and LTHT have multiple projects and applications operational, where they are treated much like a typical IT-project.

Ericsson is beginning to mature when it comes to AI and data. Ericsson's products make use of AI, as it is perceived to be a source of competitive advantage for their products. AI is a strategic priority as they are a technically driven company and as such, they are actively researching AI to advance their products, prompting a manager to say that Ericsson are quite far ahead with AI. AI Sweden also supports this latter claim. At the same time, some parts of the organization are more mature than others and the journey toward AI maturity is not finished. Compared to when they started though, there is overall less skepticism and questioning of AI technologies. GAIA has so far financed and completed 300 projects in three years, with 50 running concurrently and 40 projects ending up in production environments internally or in customer-facing offerings

Management can encourage bottom-up experimentation by sanctioning and demanding it. One SUH executive mentions that top management has an important role to play when it comes to the allocation of resources and allowing time for development work. One Volvo interviewee states that "there was a heavy push from above to mature within AI", but that initial value creation actually happens bottom-up. Then, when top management sees the business value, investments are easier. Halland also means that "these things do not start from the top" and that initial work and preparatory ideas commence further down in the organization, while AI Sweden adds that business cases need to be demanded from every division manager for an initiative to gain speed. At Ericsson, the research division led the work with AI in the beginning, until top management decided to start GAIA to accelerate and build more competence.

AI and human work augment each other, which should be emphasized. Staff do not need to worry about their job when AI is introduced, "rather the opposite" SUH claims, saying that this needs to be communicated to the organization. Consensus between AI Sweden and Halland exists regarding AI complementing human thinking and work, meaning personnel needs to be educated and the clinical culture prepared.

Industry interest in healthcare AI acted as a catalyst for formalized collaboration between industry and healthcare for Halland and GOSH. In Halland, this started with a network of medtech companies, who eventually requested a neutral arena to better facilitate collaboration. This arena has developed over the years, the result today being LFL. A similar process lies behind the creation of the DRIVE unit at GOSH, as the initial funding came from a hospital-connected charity. Members of this charity were originally from industry and therefore argued to understand the need for a unit of this kind, and the need for strategic work in general. The interviewee continues to say that the push from the charity was the "only reason we've managed to set up the DRIVE unit and do what we're doing".

International partnerships are emphasized by the NHSX, and benefit Halland. NHSX states that international partnerships are key when it comes to healthcare AI, and points out the organization Global Digital Health Partnership, where both the UK and Sweden are members. Here, the interviewed NHS manager points out the UK's advantage of having a single-payer system (the NHS), as the hierarchy and interface internationally inherently becomes clearer. Halland is benefiting from international collaboration, as they largely credit the success with their data warehouse and CIDD to their early collaboration project with a US hospital and connected universities. During this collaboration, infrastructural issues such as data structuring and database integration were tackled and the joint conference presentation (Vitalis) with Harvard is believed to have brought their work legitimacy and into the spotlight.

Balancing the degree of centralized structures believed to be key by many. One manager at SUH believes that the Innovation Platform's work would not be possible without their close clinical connections; the balance between clinical proximity and central control is delicate. This is exemplified by this statement from a SUH executive: "You need champions out in the units, but still some people who can do certain things". This trade-off is seen in this section's previous paragraphs as well, where SUH both argue for and against creating a central structure. This balancing act seems embodied in GAIA's approach at Ericsson, as the responsibility of applied AI is left to the product owners, but with common assets and support from GAIA one request away. Additionally, as argued by a manager at Ericsson, there is value in GAIA co-locating to share knowledge and optimize holistically, but that being close to the business areas is also important to accumulate domain knowledge; GAIA sometimes deploys a team for a business area project, but through centralization achieves scale and a standardized way-of-working. Such a standardization of AI work is believed possible to a degree in healthcare as well, as the interviewed Halland strategist argues the preconditions in a hospital's different specializations to be quite homogenous, with facilities, labs, medical technology, physicians and nurses being examples of commonalities. The AI network at Volvo, being of facilitatory nature, is so far the only structural aspect of AI at Volvo, and although participation is not mandatory, it is highlighted that in a profit-driven business people take responsibility in these situations. The balance discussed in this paragraph relates to the distinction between diffusion (natural decentralized) and dissemination (planned and managerial), where the interviewed NHS manager believes you cannot do just one or the other: some push is needed but diffusion still must be supported along the way.

No best practice seems to exist regarding structure, and uncertainty about the current way of structuring exists. Even with the great success of GAIA in accelerating the AI usage and maturity at Ericsson, one Ericsson manager means that there is no guarantee that their chosen path is the best one. Halland argues that no one best practice regarding placement and mandate of an AI center exists. They further highlight that the combination of 1) the novelty of AI and IDC and 2) the uniqueness of each organization calls for allowing the AI structure to crystallize over a time of informal development, as it did with them. Both Volvo and SUH display uncertainty in this area, as structural next steps are yet to be figured out.

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