A Master's Thesis

Exploring Colorectal Cancer Surgeons Experience of Their Interactions with an Artificial Intelligence based Clinical Decision Support System

Evaluating the Integration of AIS-1 in the Clinical Context of Colorectal Cancer Surgery at Zealand University Hospital, Køge

Martin Clinch (20211630)
Laura Damsgaard Ebbesen (20174002)

Supervisor: Mette Dalgaard Ebbesen

Number of characters: 154707

Number of standard pages: 64,5

Number of actual pages: 71

M.Sc. in Techno-Anthropology
Aalborg University, Department of Development and Planning,
Rendsburggade 14, 9000 Aalborg, Denmark

Abstract

Colorectal Cancer (CRC) with 935,000 annual deaths makes it the third most malignant disease in the world. To tackle this issue, the Department of Surgery at Zealand University Hospital, Køge has established the *AI-based tailored perioperative care in colorectal cancer surgery* or AID-SURG project containing pre-, peri-, and postoperative as well as post-discharge interventions for the enhanced recovery of CRC Patients. The AID-SURG project is supported by AIS-1, a Clinical Decision Support System (CDSS) operated and used locally at the Department of Surgery. The purpose of AIS-1 is to support the CRC surgeons, through a one-year mortality prediction, in their decisions regarding the best treatment option and increased survivability of CRC patients undergoing curative elective cancer surgery. In this master’s thesis we explore the experiences of CRC surgeons in their interaction with AIS-1 through the use of ethnographic methods. Through our literature we have established a lack of research on the implication of integrating CDSSs within a clinical context. Through the attained insights we have explored the surgeons’ experiences of interaction with AIS-1, and found that further training and information is required for a successful adoption of CDSS in the clinical practice. Furthermore, we conclude that the surgeons’ attitudes towards and visions for AIS-1 has an impact on the sustainability of AIS-1 within their practice.

Keywords: Artificial Intelligence, Clinical Decision Support System, Machine Learning, Colorectal Cancer, Surgery, Enhanced Recovery

Table of contents

Table of figures

Abbreviations

AI	Artificial Intelligence
AID-SURG	AI-baseD tailored periopeative care in colorectal cancer SURGery
AIS-1	In-house AI decision support and prediction model for colorectal cancer surgeons, version 1
CDSS	Clinical Decision Support System
CRC	Colorectal Cancer
CSS	Center for Surgical Science
DCCG	Danish Clinical Cancer Group’s database
ERAS	Enhanced Recovery After Surgery
MDT	Multidisciplinary Team conference
ML	Machine Learning
NDA	Non-Disclosure Agreement
OMOP	Observational Medical Outcomes Partnership
SP	Sundhedsplatformen (The e-Health Platform)
ZUH	Zealand University Hospital, Køge

1. Introduction

Over the last few years, a growing interest has arisen in the application of artificial intelligence (AI) particularly within the area of healthcare. AI has the potential to reshape the field by improving access to healthcare for patients. Moreover, improving diagnostic capabilities as well as helping to allocate and optimise how resources are used, and thereby improving the effectiveness and efficiency of healthcare systems (Esmaeilzadeh, Mirzaei, & Dharanikota, 2021; Lekadir, Quaglio, Garmendia, & Gallin, 2022). Furthermore, AI can contribute to the field of healthcare by helping in the analysis of big data and making sense of large datasets (Grote & Berens, 2021; Lynn, 2019; Rundo, Pirrone, Vitabile, Sala, & Gambino, 2020; Wagner et al., 2022), improvement of workflow (Grote & Berens, 2021; Rundo et al., 2020) and patient care (Esmaeilzadeh et al., 2021).

With the growing interest of AI in healthcare it is no wonder that companies are investing increasingly in the global market of AI and healthcare. According to Global Market Insights in 2020 that AI in the healthcare market will exceed US $4 billion with an annual growth rate of 33.7% between 2021 and 2027 (Emani et al., 2022). The global market increase in AI in healthcare is also represented in the increase in published literature. As noted by the *Journal of Medical Internet Research,* seeing a growth rate of 45.15% of papers published between 2014 and 2019 surrounding this field (Emani et al., 2022). However, despite the growing interest in both market value, published literature and the numerous potential benefits that AI may bring, there are also specific challenges associated with the introduction of AI in healthcare.

To elucidate the current pressure on the Danish healthcare sector we draw on the current issue of Aarhus University Hospitals (AUH) cancer case. During the Spring of 2023, major problems in the Department of Gastrointestinal Surgery at AUH Skejby, were uncovered, as 293 cases of extended delays in elective cancer surgeries had come forward (Steenberger, 2023). This was a result of reduction of beds as well as a lack of professional personnel to care for the patients, post-surgery. These factors directly affected the number of patients the surgeons would be able to operate, as the patients required a highly specified care for their best recovery, and instead provided a continuously growing waiting list. Prioritising patients was deemed necessary by the Chief Surgeon at AUH, as they had to elect patients with the highest possibility for curative surgery, to counteract the growing pressure of patients (Steenberger, 2023).

In March 2019, the Danish Government published the *National Strategy for Artificial Intelligence*. They hereby underlined the importance of exploiting the opportunities of AI to support the competitiveness of Danish businesses, and to support the public sector by improving services, such as quicker diagnosis of illnesses. They emphasised that AI aids in analysis, understanding, and making improved decisions. Highlighting that the technology should not replace people and make decisions for us, but AI should instead be used as a supplement to human decision-making without compromising social values (Ministry of Finance & Ministry of Industry, Business and Financial Affairs, 2019).

A more recent report by the European Parliament published in June 2022 called *Artificial intelligence in healthcare - Applications, risks, and ethical and societal impacts* identifies seven main risks of AI in medicine and healthcare;

1) *"Patient harm due to AI errors,*
2) *The misuse of medical AI tools,*
3) *Risk of bias in AI and the perpetuation of existing inequities,*
4) *Lack of transparency,*
5) *Privacy and security issues,*
6) *Gaps in AI accountability* and
7) *Obstacles in implementation in real-world healthcare."*

(Lekadir et al., 2022, p.15).

Additional challenges to AI in healthcare include those of black box, communication, and collaboration between AI and clinicians (Denecke & Baudoin, 2022; Esmaeilzadeh et al., 2021; Grote & Berens, 2021; Lynn, 2019; Wang et al., 2021), implementation (Esmaeilzadeh et al., 2021; Wang et al., 2021), technical (Denecke & Baudoin, 2022; Esmaeilzadeh et al., 2021; Grote & Berens, 2021; Wagner et al., 2022) and regulatory (Denecke & Baudoin, 2022; Esmaeilzadeh et al., 2021; Papadopoulou & Exarchos, 2022).

Despite the perceived risks and challenges, local departments are implementing AI for the benefits of patients and patient outcomes. In this thesis we present AIS-1, an in-house Clinical Decision Support System (CDSS) and prediction model developed and used locally by the Center of Surgical Science (CSS) in the Department of Surgery at Zealand University Hospital (ZUH). AIS-1 is aimed at providing decision support for Colorectal Cancer (CRC) surgeons in the management of patients in curative elective surgery for CRC.

2. Problem analysis

Following the above introduction, we present our problem analysis. As AI becomes more prevalent in healthcare, we, as Techno-Anthropologists, understand the role of technologies as entities of themselves capable of carrying meaning through their presence in the world. With AI's implementation into healthcare, we express the need for considering the impact this integration has on the relation between clinicians and AI, to understand how they can collaborate for a sustainable future within healthcare. The purpose of our problem analysis is to provide an overview of the field of research, by situating AI in healthcare in a local context, by investigating AIS-1 in the clinical setting of CRC surgery. This section provides an overview of our field of research, through the presentation of our collaboration and positioning in the AID-SURG project.

In the first section of the problem analysis, AIS-1 is presented through internal documents, a semi-structured interview with the Lead Data Scientist as well as published papers on the development of such a prediction model. Furthermore, we present our literature review and process of finding and selecting literature, and our results of the review. This was done to clarify existing literature concerning AI in healthcare and to create a knowledge base for the entrance to our field.

2.1 Presentation of the AID-SURG project and AIS-1

Firstly, we present the overall project AID-SURG and how AIS-1 assists in said project. Furthermore, we present a more in-depth look at AIS-1. Here we cover the prediction model's purpose, its development and intended use as well as the end users of AIS-1. Information referenced (Internal Documents, n.d.) in this section originates from acquired internal documents provided by our gatekeeper and the Lead Data Scientist from CSS. These documents have been paraphrased in accordance with a signed Non-Disclosure Agreement (NDA) and have subsequently been approved for use in this thesis. In addition, supplementary semi-structured interviews with the Lead Data Scientist have been used to provide more clarity and additional information not found within the internal documents.

CSS is a research department at ZUH, concerned with four research areas through a cross-disciplinary approach. These four areas are: Translational, Clinical Outcome, Big Data and Personalised Medicine, and Nurse Research (Center for Surgical Science, n.d.). AID-SURG and AIS-1 are positioned within the area of Big Data and Personalised Medicine.

2.1.1 The AID-SURG project

The ***AI**-base**D** tailored perioperative care in colorectal cancer **SURG**ery* or **AID-SURG** is a project concerned with the implementation of personalised treatments assisted by AIS-1 within the clinical setting at ZUH. CRC is the third most common malignant disease with over 935,000 deaths per year (Vogelsang & Gögenur, 2018). The purpose and objective of the AID-SURG project therefore is to help reduce the risks of complications, readmissions into hospital, and mortality of patients by applying evidence-based treatment interventions based on the patient’s individual risk profile. Based on predictions, the project is estimated to include around 600 patients over a 30-month period, with a total project time of four years (Internal Documents, n.d.). An overview of the AID-SURG project can be found in *Figure 1*. Starting from the left the fig shows patients referred to the Multidisciplinary Team conference (MDT) where AIS-1 (AI-based stratification model) and the multidisciplinary experts are a part of. The risk prediction score is used to stratify the patients into different groups from low to high risk. Based on the group, Enhanced Recovery After Surgery principles are applied offering different interventions for improvement of surgical outcomes (Internal Documents, n.d.).

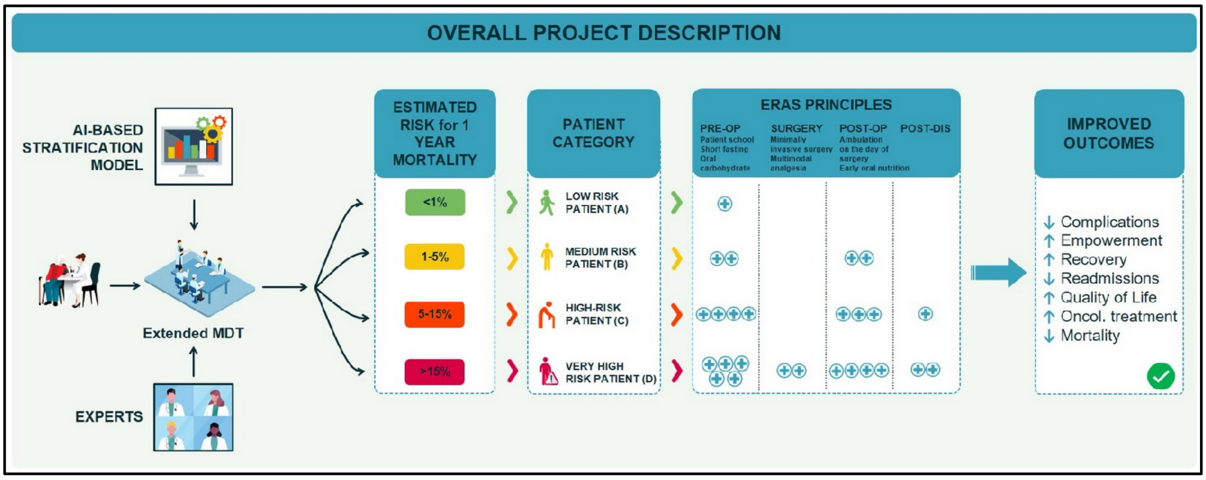


Figure 1: AID-SURG project description.

2.1.2 AIS-1

The goal of AIS-1 is to aid in identifying high risk CRC patients and improve surgical outcomes associated with CRC surgery. Correctly identifying patients with high-risk surgery-related factors may lead to a potential decrease in perioperative morbidity and mortality, as well as provide a more optimised individual treatment plan through interventions before surgery (Bräuner et al., 2022). Due to machine learning (ML) algorithms' abilities to capture complex relationships between multiple variables, they are increasingly being utilised in medical research as well as in surgical risk predictions (Lin et al., 2022). However, a good prediction model identifying patients with low risk of complications may also lead to accelerated treatment strategies (Bräuner et al., 2022). Few prediction models are used within a clinical setting and even fewer include preoperative information, something that is a prerequisite in the MDT (Bräuner et al., 2022).

> *"[…] (what) we did is centred a lot around what, you see, being called machine learning or AI, or all these fancy titles. We call it prediction-model because it is a machine learning model, basically, that predicts an outcome on a specific patient group that you are selecting, and we have selected a patient group with colorectal cancer patients."*
>
> (Interview Lead Data Scientist, 9/2/23)

As previously stated in the introduction, AIS-1 is developed and operated locally at the Department of Surgery at ZUH. Classified as a Class IIa medical device, its purpose is to meet the needs of the targeted patient group which cannot be met by other similar CE-marked devices (Internal Documents, n.d.). The targeted patient group of AIS-1 are CRC patients undergoing intended curative elective surgery. With CRC having an incidence of 1.8 million patients and 935,000 deaths per year makes it the third most common malignant disease in the world. In Denmark, CRC accounts for 12% of all newly diagnosed cancer incidents, which corresponds to roughly 5,000 new cases each year (Vogelsang & Gögenur, 2018). The only definitive cure for CRC is surgery (Bräuner et al., 2022) and each year 80% of all Danish patients with CRC undergo surgery (Vogelsang & Gögenur, 2018). However, surgery is not without risks as postoperative complications such as anastomotic leakage are associated with an increase in morbidity and mortality (Lin et al., 2022) with a 20-25% risk of relapse after surgery within a period of five years (Vogelsang & Gögenur, 2018). The intended use of AIS-1 is therefore to provide surgeons with a tool to support the decision process regarding treatment options and strategies at the MDT conferences, subsequent surgical consultations, and at the pre-examinations. AIS-1 is not intended for non-surgical, non-curative, and non-elective surgeries as well as deciding whether a surgery should be performed or not. The final decision made regarding treatment and surgery always rests with the surgeon. Furthermore, AIS-1 is only intended for patients of 18 years and above at the time of diagnosis (Internal Documents, n.d.).

The development of AIS-1 started back in 2018 with the harmonisation and standardisation of healthcare data and, as of 1st of February 2023, considered to be a static model within its first year of integration.

> *"The model is not trained any more, from the moment that it is released the model is maintained static."*
>
> (Interview Lead Data Scientist, 9/2/23)

AIS-1's algorithm is trained on historical data from Danish National Registry databases. AIS-1 takes known risk-factors to provide an estimated outcome of the mortality risk within one year following CRC surgery. It also provides a suggestion for a risk strata based on the predicted risk outcome (Internal Documents, n.d.). The data used to train AIS-1 derives from the Danish Clinical Cancer Group's database (DCCG) and contains data from over 76,000 patients diagnosed with CRC as well as patients that have had contact with a Danish surgical department since May 2001 (Bräuner et al., 2022). The data includes demographics and detailed information on comorbidities, tumour stages, localisations, and procedure types such as resections, chemotherapy and intra- and postoperative complications with an overall completeness of over 96%. It was last validated in 2020 with an accuracy of 95% (Lin et al., 2022). The data used from DCCG from May 1st 2001 to December 31st 2019, was transformed into the Observational Medical Outcomes Partnership (OMOP) (Bräuner et al., 2022). According to the Lead Data Scientist, the purpose of OMOP is to help standardise and harmonise healthcare data as well as vocabularies to be able to share study data with other institutions.

In addition to DCCG used in the training of AIS-1 other databases such as List of national health registers (Landspatientregistret), The Danish Health Data Authority (Sundhedsdatastyrelsen) and the Danish Microbiological Database (Den Danske Mikrobiologidatabase) were also used in the collection of historical patient data. Databases such as the List of national health registers have patient data going back to the 1980s and so can provide additional information regarding the patients and by extension provide the means for a more accurate prediction model (Internal Documents, n.d.). In addition to this, it is also important to note that the data from the databases does not include specifics regarding socio-economic status such as ethnicity or economic background. It was assumed, according to the Lead Data Scientist, that because the data were gathered on a national level, the underlying characteristics of the population were represented.

> *"So the more you know about the patient in general the better because you have a longer look back on the trajectory data of the patient"*

Interview Lead Data Scientist 9/2/23)

Internal validation of AIS-1 was done by splitting the data into two parts; one was a training set consisting of 75% of patient data while the remaining 25% was used for internal validation (Bräuner et al., 2022; Lin et al., 2022). The second part of internal validation involved withholding 10% of all the historical data from the training of the prediction model. The reason for this, was according to the Lead Data Scientist, due to the performance of the model. Here the prediction model was tested against the unseen historical data to avoid the problem of the algorithm learning to recognise specific things from the data it was trained with and hereby make predictions based on these.

> *"So this is where these 10% comes in, so when the training is finishing the model is tested on these unseen data so, you're thinking that, OK this is data that the model has not seen and has not learned from for this specific (patient) and patients that the model has not seen before, and then you're trying to see how it's going to perform."*

(Interview Lead Data Scientist, 9/2/23)

AIS-1 is accessed through a virtual desktop hosted on a Secure Private Cloud by VMWare Horizon, this provides additional security as AIS-1 deals with patient sensitive data. Users can either download and install the VMWare Horizon client on their local workstations or access it through a web interface. Users, in this case surgeons, need to be added in advance and verification of the users' credentials is done through a multifactor authentication protocol. Once logged into the virtual desktop the surgeons can then enter the relevant data into the interface and predict the one-year mortality outcome of the patient (Internal Documents, n.d.). The data entry into the AIS-1 interface consists of four steps:

Steps	Patient information / Covariates
Step 1	Patient Information: Patient ID (name or CPR number); Sex (male or female); Age.
Step 2	ASA score; Body Mass Index; Clinical M Category; Clinical T Category; Smoking status; Weekly alcohol consumption; WHO performance status; Procedures (e.g. rectal resection etc.); Medication; History; Comorbidities (e.g. dementia, diabetes etc.).
Step 3 (Blood work)	Alanine aminotransferase; Albumin; Bilirubin; Carcinoembryonic Ag; Creatinine; Haemoglobin; INR - Coagulation; Platelets; Potassium; Sodium.
Step 4 (Prediction results)	Predicted risk score in percentage, strata group and summary of entered data.

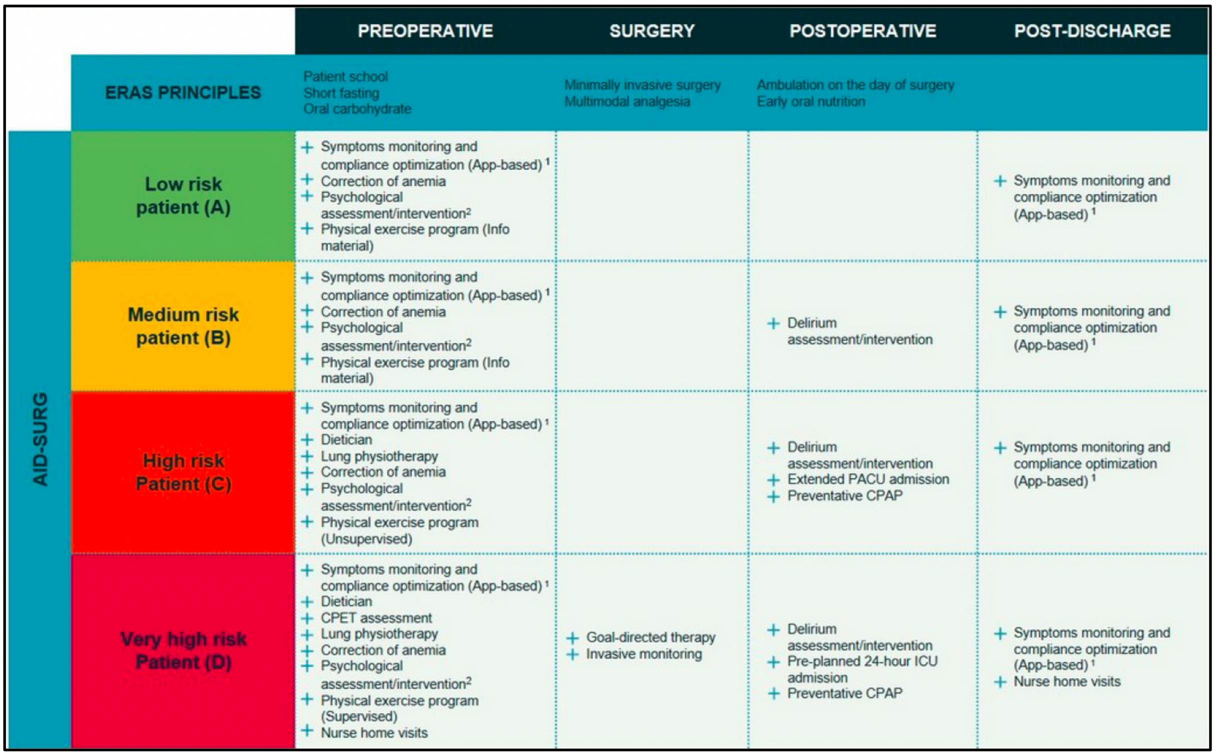
Figure 2: The four steps within the AIS-1 interface.

The surgeon is expected to fill out as much of the above information as possible, but if information is unknown then no value is inputted. The data to be inserted into the prediction model stems from the patient's data that can be found in the e-Health Platform (Sundhedsplatformen (SP)). According to the Lead Data Scientist, some surgeons as well as the Head of Research at CSS were involved in the initial development stage of AIS-1. They contributed with selection of the included covariates along with covariates identified in the historical data as important for the prediction.

> *"[...] so that's important, as someone who is not familiar with medical terminology and what is actually applicable in a clinical setting, you can't really say what is best to select, from all these variables [...]."*
>
> (Interview Lead Data Scientist, 9/2/23)

A significant thing to note is that in step 3, the surgeon is required to tick the box *"I understand that the final decision rests with the healthcare professional"* underlining AIS-1 as a CDSS. The prediction outcome takes the form of a report, which is then exported to the Data Science Unit, and as a local file on the surgeon's computer. Once the report has been exported, it cannot be reopened again, therefore if a new prediction outcome is needed on the same patient, the surgeon must re-enter all information in AIS-1. The prediction is used by the surgeons during the MDT conferences to support the treatment options and strategies for patients intended to undergo curative and elective CRC surgery (Internal Documents, n.d.).

In addition to the predicted risk for one year mortality, AIS-1 also suggests risk strata for the patient to better personalise pre- and postoperative surgical interventions. The prediction outcome score determines the strata group and interventions are based on Enhanced Recovery After Surgery (ERAS) principles, which is a standardised evidence based perioperative guideline for reducing complications. Patients with a prediction score of below 1% are assigned to strata A, moderate patients scoring 1-5% are in strata B, high patients scoring 5-15 % are in strata C and very high-risk patients with over 15% are in Strata D. Depending on the individual risk profile of the patient, post- and pre-operative interventions are put in place to help reduce the risks associated with CRC surgery (see *Figure 3*) (Internal Documents, n.d.).



		PREOPERATIVE	SURGERY	POSTOPERATIVE	POST-DISCHARGE
	ERAS PRINCIPLES	Patient school Short fasting Oral carbohydrate	Minimally invasive surgery Multimodal analgesia	Ambulation on the day of surgery Early oral nutrition	
AID-SURG	Low risk patient (A)	+ Symptoms monitoring and compliance optimization (App-based) [1] + Correction of anemia + Psychological assessment/intervention[2] + Physical exercise program (Info material)			+ Symptoms monitoring and compliance optimization (App-based) [1]
AID-SURG	Medium risk patient (B)	+ Symptoms monitoring and compliance optimization (App-based) [1] + Correction of anemia + Psychological assessment/intervention[2] + Physical exercise program (Info material)		+ Delirium assessment/intervention	+ Symptoms monitoring and compliance optimization (App-based) [1]
AID-SURG	High risk Patient (C)	+ Symptoms monitoring and compliance optimization (App-based) [1] + Dietician + Lung physiotherapy + Correction of anemia + Psychological assessment/intervention[2] + Physical exercise program (Unsupervised)		+ Delirium assessment/intervention + Extended PACU admission + Preventative CPAP	+ Symptoms monitoring and compliance optimization (App-based) [1]
AID-SURG	Very high risk Patient (D)	+ Symptoms monitoring and compliance optimization (App-based) [1] + Dietician + CPET assessment + Lung physiotherapy + Correction of anemia + Psychological assessment/intervention[2] + Physical exercise program (Supervised) + Nurse home visits	+ Goal-directed therapy + Invasive monitoring	+ Delirium assessment/intervention + Pre-planned 24-hour ICU admission + Preventative CPAP	+ Symptoms monitoring and compliance optimization (App-based) [1] + Nurse home visits

Figure 3: AID-SURG interventions.

With the presentation of the AID-SURG project and AIS-1, we now understand the clinical context and development of AIS-1. From this acquired knowledge, we were in a better position to explore the meaning of AIS-1 and its relation to the surgeons. From here we move on to our literature review, which serves as a further extension of our knowledge on AI in healthcare.

2.2 Literature review

In the following section, we describe the approach for our literature review where we elaborate our search protocol, as well as present our findings. This process lasted from January 9th to February 23rd, 2023. The literature review provided knowledge on topics of technicalities of AI, implementation in healthcare context and regulatory background. The purpose of the literature review was to provide a knowledge base and to provide knowledge of AI in healthcare.

Our literature search was initiated through a meeting with an Aalborg University Library librarian on January 9th, 2023. This was done to secure an accurate entrance to our literature search, as she assisted us in navigating the different databases as well as advising us on our search blocks. Our chosen databases ended up being ACM (Association of Computing Machinery), Embase and PubMed. These three were selected considering their individual area of research. ACM is *"the world's largest computing society" (acm.org, n.d.)* with a focus on technology and technical aspects. Embase declares to be *"The comprehensive biomedical research database"* (elsevier.com, n.d.) and has a specific medical perspective. Lastly, PubMed provides knowledge on general healthcare by providing citations from the National Library of Medicine including relevant topics in the field of health, and life and behavioural sciences (National Library of Medicine, n.d.). This provided us with a broad and still curated spectrum of databases to operate our literature searches within. Access to the three databases was admitted through Aalborg University Library Primo and Aalborg University subscriptions of the databases. The access was profoundly relevant for entering Embase and ACM, whereas PubMed is an open access database. Commencing our literature search, we defined our research subject as follows:

AI-based prediction model used in treatment assessment of colorectal cancer patients.

From this, we formed five aspects, or blocks, which contained our search terms in relation to the above subject specification, this is displayed in *Figure 4* below:

Aspect 1	Aspect 2	Aspect 3	Aspect 4	Aspect 5
AI	HCI	Prediction	Healthcare	Clinicians
"ai" OR "artificial intelligence" OR "machine learning" OR "deep learning"	"hci" OR "human-computer interaction" OR "user experience" OR "ux"	predict* OR interpret* OR probab*	healthcare OR cancer OR oncology OR "colon cancer" OR "colorectal cancer" OR mortality OR surgery	surgeon* OR clinician* OR physician*

Figure 4: Our five blocks of search aspects.

For our aspects we used Boolean search query, to connect the terms to a collected query, this is done by using the Boolean operators "OR", "AND" and "NOT". In each of the aspects, the boolean operator "OR" was used between terms, and underlying an "AND" is between the aspects (e.g., 'aspect 1' AND 'aspect 2'). Depending on which operator you use, you either expand ("OR"), narrow ("AND") or exclude ("NOT") terms of your search (Hansen, Shneiderman, Smith, & Himelboim, 2019). Furthermore, we used MeSH terms, as a way to specify the aspects to each database, e.g., in aspect 2 "hci" and "human-computer interaction" meaning the same thing, but ensuring we get hits from literature using abbreviations and the full term. We also used it in aspect 4 with 'cancer' and 'oncology' - again to expand the possible results. Using the asterisk (*) at the end of a word, enables any possible ending of it, and thereby evading figuring out the correct endings (-ability, -abilities, -ed, -s etc.) (Columbia University, 2022).

Figure 5 shows our performed searches as well as search queries copied from the databases, to replicate the search. We experienced, due to the different composition of the database's search builder, that by directly inserting the search string, would provide a misrepresented result. As an example, doing so in ACM and PubMed provided respectively 360.038 and 6.991.091 results. Boolean operators are highlighted as blue (OR), green (AND) and red (NOT), to visually separate terms from each other as well as operators. Not all aspects were utilised in all three databases, hence their individual research areas:

ACM	Embase	PubMed
"ai" OR "artificial intelligence" OR "deep learning" OR "machine learning" AND "hci" OR "human-computer interaction" AND predict* OR interpret* OR probab* AND healthcare OR cancer OR surgery OR Oncology AND "observational medical outcomes partnership common data model" OR "OMOP CDM" OR "LASSO" OR "LASSO regression"	"ai" OR "artificial intelligence" OR "machine learning" OR "deep learning" AND "hci" OR "human-computer interaction" OR "user experience" AND "healthcare" OR healthcare OR "cancer" OR cancer* OR "colon cancer" OR "colorectal cancer" or "mortality" or mortality OR surgery AND clinician* OR physician* NOT "electronic health record" OR "ehr" OR "robotic surgery"	"ai" OR "artificial intelligence" OR "deep learning" OR "machine learning" AND "hci" OR "human-computer interaction" AND surgeon* OR clinician* OR physician* OR surgery OR operat* NOT "robotic surgery"
<u>Query box:</u> AllField:("ai" OR "artificial intelligence" OR "deep learning" OR "machine learning") AND AllField:("hci" OR "human-computer interaction") AND AllField:(predict* OR interpret* OR probab*) AND AllField:(healthcare OR cancer OR surgery) AND AllField:("observational medical outcomes partnership common data model" OR "OMOP CDM" OR "LASSO" OR "LASSO regression")	<u>Query box:</u> ('ai' OR 'artificial intelligence'/exp OR 'artificial intelligence' OR 'machine learning'/exp OR 'machine learning' OR 'deep learning'/exp OR 'deep learning') AND ('hci' OR 'human-computer interaction'/exp OR 'human-computer interaction' OR 'user experience'/exp OR 'user experience') AND ('healthcare' OR 'healthcare'/exp OR healthcare OR 'cancer'/exp OR 'cancer' OR cancer* OR 'colon cancer'/exp OR 'colon cancer' OR 'colorectal cancer'/exp OR 'colorectal cancer' OR 'mortality' OR 'mortality'/exp OR mortality OR 'surgery' OR 'surgery'/exp) AND (surgeon* OR clinician* OR physician*) NOT ('electronic health record'/exp OR 'electronic health record' OR 'ehr' OR 'robotic surgery'/exp OR 'robotic surgery')	<u>Query Box:</u> ((("ai" OR "artificial intelligence" OR "deep learning" OR "machine learning") AND ("hci" OR "human-computer interaction")) AND (surgeon* OR clinician* OR physician* OR surgery OR operat*)) NOT ("robotic surgery")
67 results	**59 results**	**65 results**

Figure 5: Our performed search strings and queries.

All three searches were executed on January 10th, 2023. The following days, we tested if our search strings were replicable to validate our searches. As mentioned above, this was not feasible for two out of three of the databases, we therefore entered our search aspects once again, and copied the queries directly from the query boxes into our search protocol. The results of our search were as follows: ACM = 67[1], Embase = 59 and PubMed = 65. As our chosen databases only include Peer-reviewed articles, we had made a natural limitation on that note. From our search in PubMed, we set a delimitation in "Year" from 2006-2023, as this was the default year limitation in ACM as well as Embase. We did not encounter

[1] 67 of which 29 were conference proceedings, and 38 articles.

articles in languages other than English. For ACM, we had 67 results, of which 38 were articles and 29 were conference proceedings, the latter consisting of 0 up to 746 articles each. In the process of retrieving the articles, we experienced being unable to find some articles, and as a means used a normal Google search in hope of retrieving it that way. This led us to the finding of 7 more interesting articles, which were included in the literature body. *Figure 6* visualises our process of including and excluding the articles. As visible in the first box "ACM", there are n = 2277 articles, this being the 38 articles from our search in the database, as well as articles within the 29 conference proceedings.

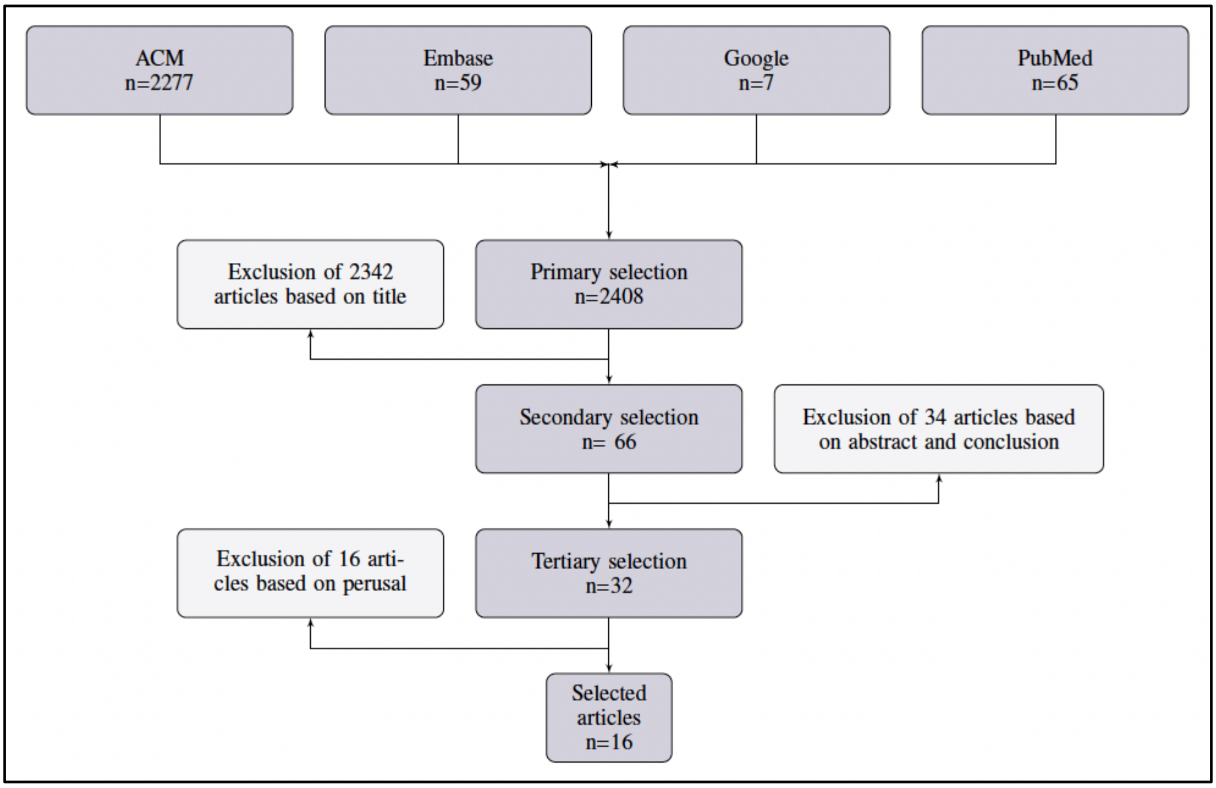


Figure 6: Visualisation of our search strategy.

The combined number of articles were 2408, from these 2342 articles were excluded based on the title, continuing 66 articles to the secondary selection. Based on reading abstracts and conclusions, a further 34 articles were excluded. 32 articles were then thoroughly read, excluding 16 and 16 articles as the final selection. These 16 articles are apportioned as follows: ACM n = 5, Embase n = 5, Google n = 3 and PubMed n = 3.

The literature search happened in parallel while also doing field visits, our initial thought, as seen in search aspect 2, of researching HCI/UX, was therefore not found as relevant for our case. As our literature search had provided a wide range of papers and articles surrounding other more relevant topics, we saw a natural exclusion of potential HCI/UX papers, and decided not to redo the search.

2.2.1 Literature findings

The following processing of our literature findings was inspired by Thematic Analysis (Braun & Clarke, 2006). We divided the articles equally between us in the thorough reading process, and by that disclosed some recurring topics across the literature. We then began a joint read through of the articles, to make a more systematic account of the topics. This was accommodated through a coding process, where we used our familiarity with the articles' contents to make general codes, under which we gathered relevant paragraphs and quotes. This provided eight general codes, which were titled as follows: ***Definitions, advantages of AI, concerns of AI, recommendations for use of AI, ethical reflections, background, facts,*** and ***methodology***. Afterwards, we read through our selected text extracts, and coded these into more specific sub-codes. Through this process, we renounced some paragraphs either due to being beside the point or due to misplacement in the general code. In terms of the latter, it was moved to the general code, which we deemed more appropriate for it. In the following section, we elaborate our literature findings, through presentation of the general codes, amplified by the content of our sub-codes.

Definitions

Although there is no clear definition of ***Machine Learning (ML)*** (Wagner et al., 2022) it was originally described as a program that learns to perform tasks or decisions automatically from data rather than from the behaviour being explicitly programmed (Beam & Kohane, 2018). ML can also be said to utilise computational algorithms involving large inputs of data sets to recognise or learn patterns (Gupta et al., 2022). According to Grote & Berens (2021) an analogy of "*the ML algorithm resembles a student who excels in a test by memorizing the textbook overnight, whereas the clinical expert tries to pass the test through a combination of theoretical understanding and repeated exercise"* (Grote & Berens, 2021, p. 138)

Artificial intelligence (***AI)*** can be described as a computer system (Esmaeilzadeh et al., 2021; Papadopoulou & Exarchos, 2022) that incorporates the fields of ML, natural language processing, expert systems and signal processing (Denecke & Baudoin, 2022; Papadopoulou & Exarchos, 2022). However, AI can also be said to be a set of theories and techniques that aim to increase the performance of computers by imitating the cognitive abilities of humans (Esmaeilzadeh et al., 2021; Papadopoulou & Exarchos, 2022) or giving machines the ability to reason and perform tasks such as decision-making or problem-solving (Esmaeilzadeh et al., 2021; Gupta et al., 2022). These computerised systems can be distinguished into physical hardware such as robots or virtual software systems such as electronic healthcare records (Denecke & Baudoin, 2022; Esmaeilzadeh et al., 2021). Although difficult to discern a definition that incorporates the complexity of AI, a definition suitable for this thesis we find to be "*a computer application that integrates ML into the clinical workflow to support surgical decision making*" (Wagner et al., 2022, p. 3).

Clinical Decision Support System (CDSS) can be described as a tool, based on large data sets of literature or register data from Electronic Health Records (Gupta et al., 2022). It is based on Big Data, with the goal of providing clinicians with faster and more accurate diagnostic decisions (Esmaeilzadeh et al., 2021). With this definition, we classify AIS-1 as a CDSS.

Advantages of AI in Healthcare

We now proceed to our second code, advantages of AI in healthcare, and begin with the sub-code ***Analysis of Big Data***. An AI’s performance of analysing larger and more complex datasets is an advantage (Lynn, 2019), as Big Data is deemed ineffectual without interpretation (Wagner et al., 2022). In another article, it was described how AI was benchmarked against clinicians, and when doing so, they found the algorithm exceeding the diagnostic abilities of the clinician (Grote & Berens, 2021). In terms of advances in AI, it is proven to contribute with cognitive support for the clinicians, as well as improving the workflow by adding a systematic approach to electronic health data, and thereby support the decision-making process (Rundo et al., 2020).

This leads us to our next sub-code ***Improvement of workflow,*** where Grote & Berens (2021) point to ML as a way to provide assistance rather than take over the clinicians work, with a specific focus on decision-support in diagnosis processes.

AI was seen as a contributor in ***Patient care*** as it can improve the overall patient care, diagnostics as well as aid in interpretation of medical data and patient management (Esmaeilzadeh et al., 2021).

Concerns of AI in Healthcare

We now move on to concerns of AI in healthcare, and start with ***Black Box AI***. The heed of black box comes from the complexity, interpretability of data, and transparency of AIs (Wang et al., 2021). Here the generated predictions and the inner workings of the algorithms must remain transparent to clinicians (Denecke & Baudoin, 2022; Lynn, 2019) but due to the complexity of these models clinicians may struggle to understand the diagnostic decisions of AI (Grote & Berens, 2021). According to Lynn (2019) a definition of black box involves how the *“complex analytics may be provided by AI without disclosure of the data used to make the decision or the analytic processes applied”* (Lynn, 2019, p.3).

Black Box AI is focussed on interpretation of the data and processes from AI to clinicians, and therefore we extend the above with ***Collaboration between clinicians and AI/ML***. Literature has found that AIs can, in decision-making cases, improve accuracy of diagnosis, where the potential harm is clinicians' sensitivity to rely on the AIs decision-making process (Grote & Berens, 2021). As the field of utilising AI and ML in healthcare settings is newly emerged, it *“[...] is certainly exacerbated by the public hype around ML-based AI and the lack of targeted advanced training for clinicians in AI/ML-related aspects”* (Grote & Berens, 2021, p. 138). Another point of AI’s position in healthcare, is the perceived threat from clinicians, that the AI will replace them (Denecke & Baudoin, 2022; Wang et al., 2021). In a study clinicians mentioned the concept of professional autonomy, where *"the clinicians need guarantee to freely operate their professional judgement and decision-making in patient care without any interference"* (Wang et al., 2021, p. 3).

Enhancing the above concerns is ***Communication***, and being a primary function of healthcare, this is equally important from AI to human as with human to human communication (Lynn, 2019). Trustworthiness and detection of reasoning errors are what constitutes human to human communication, where these errors can be misinterpreted if an AI is to provide a diagnostic decision (Grote & Berens, 2021). Furthermore, it is worth noting that in healthcare, not all processes can be taken over by AIs, as some patients will demand social contact with clinicians (Esmaeilzadeh et al., 2021). In terms of the patient-clinician relation, AIs, though capable of high performances and logical thinking, are lacking empathy skills, and thereby demand human surveillance when engaging with patients. Patients' trust in AI supported treatment must be obtained through appropriate use of the AI by the clinicians, providing high accuracy of diagnosis as well as beneficial treatment (Denecke & Baudoin, 2022).

Big Data was mentioned as an advantage in the above paragraph, but it can just as well be recognised as a ***Technical*** concern. Medical datasets are incomplete in the sense of errors in documentation and absence of information on the patient (Denecke & Baudoin, 2022). Furthermore, bias in AI appears if data sets are discriminating in terms of representing population, gender, race or stereotypes, as well as societal discrimination. Even with training, AI models have a potential to produce biassed outcomes unnoticed, if the algorithm is not transparent for clinicians to detect these biases (Denecke & Baudoin, 2022; Esmaeilzadeh et al., 2021). A way to accommodate and disclose bias is through external validation. An external validation can prove an AIs generalisability as a clinical decision-support tool, through testing with a dataset, from outside the clinical environment wherein the AI has been trained (Wagner et al., 2022). Lastly, another technical concern, is the AIs overconfidence in uncertainty cases, e.g., if data was ambiguous or inconclusive, this was found to be avoided with calibration of the AI with clinicians uncertainty levels (Grote & Berens, 2021).

Willingness to adopt and use AI, is one of the most important concerns in the ***Implementation*** of AI in any context. Many resources are allocated to the implementation of AI in healthcare systems, and thus it has the potential to aid the clinicians, it likewise has the potential to cause harm for both clinicians and patients (Esmaeilzadeh et al., 2021). Additionally, we found in the literature, that a lack of deployment of CDSS in practice, withholds the CDSS in the development stage, as challenges and barriers of use cannot be investigated (Wang et al., 2021).

Regulatory concerns include that of security implications of the implementation of AI, as well as stolen or misused patient data sets. This is being accommodated through a legal framework by the EU

Commission, underlining the potential risks when implementing and using AI (Denecke & Baudoin, 2022). Furthermore, responsibility of the AI is another concern, as the clinicians cannot be held accountable for software malfunctions, neither can developers be held liable for misdiagnosis (Esmaeilzadeh et al., 2021). This is something the European Parliament addressed in their Resolution on AI from 2017 (Denecke & Baudoin, 2022).

Recommendations for use of AI in Healthcare

The literature further provided recommendations in terms of utilising AI in a healthcare context. First up, ***Successful implementation*** was pointed out to consist of a multidisciplinary, participatory, and collaborative approach with developers and clinical staff, as well as technical, regulatory, and public stakeholders (Emani et al., 2022; Lynn, 2019; Papadopoulou & Exarchos, 2022; Wang et al., 2021). A successful implementation encloses detailed research into users' perceptions and attitudes toward AI (Esmaeilzadeh et al., 2021). As the AIs are socially situated in a complex field, with varying cultural workflows subservient to the clinical setting, knowledge from clinical stakeholders is imperative for a successful implementation. Furthermore, this approach for implementation is recommended to avoid profound ethical risks, as well as potential misuse of the technology (Lynn, 2019; Papadopoulou & Exarchos, 2022; Upol Ehsan, Q Vera Liao, Muller, Riedl, & Weisz, 2021). Moreover, was the view of understanding the sociotechnical context in which the AI is being implemented (Grote & Berens, 2021), a strengthening position for a Techno-Anthropological research.

Users ***Attitudes*** towards new technologies like AI and acceptance hereof, is, as mentioned, inevitable for a successful implementation. Users' attitudes and levels of trust towards the AI is elementary for user-acceptance and willingness to adopt the new technologies properly to avoid misuse or mistreatment (Cheng, Li, & Xu, 2022; Rundo et al., 2020).

Training of clinical staff was also found relevant, as their current clinical knowledge does not extend to interpretation of AI outputs (Cheng et al., 2022; Lynn, 2019). It also enables a faster implementation, as well-informed and educated staff are more attentive to technical bias or outcome errors (Lynn, 2019).

In continuation hereof comes the ***Technical*** recommendations, with points equivalent to those of black box AI, as transparency is the key factor for successful implementation, and willingness to adopt the new technology (Esmaeilzadeh et al., 2021). A recommendation for AI to make a simple explanation of the rationale of the diagnosis rather than a refined statistical model, could improve interpretability of the communication from AI to clinician (Grote & Berens, 2021). User-friendliness, as well as applicability of the AI into the users' practice, must be insured to improve service quality and work efficiency of healthcare workers. With a focus on performance and effort expectancy, users can become an active, rather than a passive receiver of AI-assisted recommendations (Cheng et al., 2022; Esmaeilzadeh et al., 2021)

With AIs recent entry in the field of healthcare, ***Regulatory*** stakeholders have yet to provide clear guidelines and recommendations for use in clinical practice (Esmaeilzadeh et al., 2021). Such guidelines are proposed to be upheld through strict protocols, which concern both ethical and legal regulations, to integrate AIs in a routinised clinical practice (Gupta et al., 2022).

Ethical Reflections

Dividing the literature's ethical reflections on the use of AI in healthcare into sub-codes was more troublesome, in the sense of separating their basic meaning - exactly those of being ethical reflections. We, nonetheless, identified the sub-code ***Clinicians VS. AI***. Here literature elucidated, how an intellectual dependency on AI systems, would surplus the need for clinicians with competence and knowledge, and cause diagnosis errors (Grote & Berens, 2021). Rather than providing decision support, the AI would take up the primary role of acute care in hospitals, and instead demand for clinicians to withdraw and take on a more emphatic and comforting role. From Lynn (2019) this was assumed for AIs, which lacked potentiality in detailed communication. Further, it was found that a possibility for inhibition of novice clinicians potential for becoming experts, if they become overly reliant on the AI (Grote & Berens, 2021). We expand the ethical reflections on clinicians vs AI, with the following quote:

> *"The use of AI is a two-edged sword – on the one hand, it can significantly alter the way surgeons work for the better, but on the other hand, it has the potential to be dangerous. The power of intuition and experience matters – no matter how much ML or deep learning a robot does, it is still not capable of full independent thinking – what it does is a mimicry of what humans can do, albeit faster and more logic based. Surgeons often work by intuition and that human touch cannot be replaced by AI – at least not yet."*
>
> (Gupta et al., 2022, p. 5)

As described in the above quote, AI and ML are not yet capable of standing alone in diagnosis and treatment, as much of the knowledge used by clinicians has been attained through experience and some of it from intuition. We see logic conforming to an inferior function rather than the *"human touch"* (Gupta et al., 2022).

Elaborating on ethical reflections of AI use, ***Trust*** is emphasised in the literature as the key issue in the ideal clinician-patient relation. As mentioned above, the human touch is exclusive to the clinician, and the main concern is therefore about the non-human character of AI. Trust is seen in the benevolent motives of a clinician in relation to treatment, and the authors point out that by renouncing this trust in exchange for AIs, the personalised care provided by the clinician disappears (Gupta et al., 2022).

The last sub-code included is the ***Technical*** aspect of an AI only being as good as its developer, and thereby underlines the AIs actual purpose in the healthcare domain. The notion that AIs are going to improve healthcare, may be proven wrong by the aforementioned statement, as it, instead of contributing to better treatment, can end up enhancing the worst aspects of the current systems. It further possesses legal liability issues, in terms of the purpose of use, as well as conflicts with human actors in relation to AIs (Papadopoulou & Exarchos, 2022).

Background, Facts & Methodology

The last three codes were used mostly as inspiration, along with background knowledge concerning AI, healthcare, and literature reviews.

The code background was utilised as a way for us to emphasise our field through the literature findings. It was intended as inspiration for our thesis framework. These findings have been utilised throughout the project, with a main focus of use within the problem analysis.

Under the code facts, we noted information about ***Economic incentives*** in the field of AI, which is used in our thesis introduction. Furthermore, the literature helped us identify the ***knowledge gap*** of AI research. Studies found a lack of research on AIs in real-world settings (Emani et al., 2022), as well as attitudes towards AI as being definitive in implementation in clinical settings (Esmaeilzadeh et al., 2021). The latter being a study on medical students, where 67% said that AI could reduce medicine demand, but at the same time, 47% of the students were concerned about clinicians future association with AIs (Esmaeilzadeh et al., 2021). Though referring to real-time collaboration of clinicians and AIs, there was still seen a lack of research on this relation (Daronnat, Azzopardi, Halvey, & Dubiel, 2021)

Methodology refers mostly to inspiration for conducting and conveying a literature review, as our literature corpus consists of five very different approaches to doing this (Bertrand, Belloum, Eagan, & Maxwell, 2022; Denecke & Baudoin, 2022; Lynn, 2019; Thieme, Belgrave, & Doherty, 2020; Wagner et al., 2022).

Extended literature

In cooperation with our supervisor, we found further literature to support our above literature review and thesis aim. We therefore present the following texts in this section: *The right to a second opinion on Artificial Intelligence diagnosis—Remedying the inadequacy of a risk-based regulation* by Thomas Ploug and Søren Holm (2022). Furthermore, we present *Artificial intelligence and the doctor-patient relationship expanding the paradigm of shared decision making* by Giorgia Lorenzini, Laura Arbelaez Ossa, David Martin Shaw and Bernice Simone Elger (2023). In addition, a report published by the European Parliament called *Artificial intelligence in healthcare - Applications, risks, and ethical and societal impacts* (Lekadir et al., 2022) as used in the introduction, will be extended upon to provide more clarity on the seven main risks. These articles are introduced as extended literature to provide additional perspectives on AI in healthcare.

The first article, by Thomas Ploug and Søren Holm, is titled *The right to a second opinion on Artificial Intelligence diagnosis—Remedying the inadequacy of a risk-based regulation* (2022). This article discusses how receiving AI assisted treatment should have a rights-based rather than risk-based approach to a second opinion. It is further discussed how the second opinion does not necessarily have to come from a physician but might as well be from another AI system. We draw on the article's exposition of the automation bias in AI diagnostics and treatment in healthcare systems. Automation bias is defined as *“the surrendering of independent physician diagnostics”* (Ploug & Holm, 2022, p. 6), which is executed through the abandonment of a physician’s skills, and an overreliance on the AI. The difference between physician and AI diagnostics is explainability and transparency. On one hand, the physician's explanations are rooted in cognitive interference of hypotheses, and the perception of symptoms and signs of the patient. On the other hand, an AI diagnostic is based on an algorithmic weighted system of numbers that can be difficult to replicate, making it an unexplainable black box. As of this, the authors present that AIs must only be considered as a CDSS, and physicians must be able to explain the steps of decisions from the AI (Ploug & Holm, 2022).

We further expand the extended literature by introducing the article *Artificial intelligence and the doctor-patient relationship expanding the paradigm of shared decision making* by Giorgia Lorenzini, Laura Arbelaez Ossa, David Martin Shaw and Bernice Simone Elger (2023). The article investigates the implementation of AI into the doctor-patient relationship, in terms of diagnostics. Patients' autonomy in diagnostic and treatment is specifically highlighted throughout the article, regarding the paradigm shift of implementing AI into shared decision-making. The article enhances how a paradigm that promotes patient autonomy is considered a more ethical one, than a suppressing paradigm, as autonomy is deemed as a right, not a duty for the patients. AI has the potential to enhance the shared decision-making paradigm, but should be carefully implemented, as the lack of attention could result in a situation where AI is the decision maker and so takes on a paternalistic role. Paternalism can be understood as a doctor steering the patient towards a specific treatment that they consider to be in the patient's best interest. Autonomy, within a shared decision-making paradigm, enables the involvement and empowerment of patients in their treatment, enabling them to become experts of their values. With doctors taking the role of experts in medicine, this encounter constitutes a respectful relationship, where both parties have a shared understanding of sharing information within their expert knowledge (Lorenzini et al., 2023).

Lastly, we present the European Parliaments report *Artificial intelligence in health care - Applications, risks, and ethical and societal impacts* (Lekadir et al., 2022) which presents seven risks of AI in healthcare. The report states that these risks could result in both harm for patients and citizens, while also reducing trust levels in AI algorithms from both clinicians and society. The seven risks will be further elaborated below.

Patient harm due to AI errors. Major sources of AI errors in clinical practice include those of noise in the input of data when using an AI, shifts in data sets between AI-training data and real-world data, and difficulty in AIs ability to adapt to unexpected changes in environment and context. These errors can lead to safety concerns such as false negatives in the form of missed diagnosis of a life-threatening disease, false positives leading to unnecessary treatments, and unsuitable or incorrect prioritisation of interventions. Through evaluations and regulatory approval, designing and implementing AI as an assistive tool means that clinicians remain part of the processing of data workflow and can report potential errors. Lastly, AI should have solutions embedded to promote a dynamic ability to learn from mistakes detected in clinical practice. This requires a degree of human surveillance and control to identify problems.

Misuse of medical AI tools. Health technologies are dependent on how end-users, such as clinicians, use these in clinical practice and, as such, incorrect usage may lead to incorrect medical assessment and decision-making processes. It is not enough for clinicians to simply have access to AI medical tools, but also necessary that they understand how and when to use said technologies. Multiple factors exist which may lead to incorrect use. Firstly, the design and development of AI technologies without involving clinicians and end-users, can lead to clinicians experiencing complex interactions. Second, clinicians may experience difficulties in applying and understanding the AI technology, which may limit their perception of informed decision-making, increasing the chances of human errors.

Risk of bias in medical AI and perpetuation of inequities. Concerns have arisen recently of AI technologies being embedded with human biases. Main factors of contribution to inequities and inequalities in healthcare include those of sex, age, ethnicity, income, education, and geography. The most common cause of inequity in medical AI stems from the bias within the data used for the training of machine learning models. Addressing medical AI inequity involves the collaboration of AI developers and clinical experts, paying close attention to the selection and labelling of both the data and variables used within the model training.

Lack of transparency. The concepts of traceability and explainability correspond to two levels required within transparency. Traceability being the transparency of AI development and usage, and explainability being the transparency of AI decisions. The lack of transparency within the development and use of AI in healthcare could result in a lack of trustworthiness, which then could impact the adoption of AI by clinicians. Furthermore, the lack of transparency can make it difficult for clinicians to incorporate the AI into real-world settings as clinicians need to understand the principles behind the decision even when AI has the potential to improve their productivity.

Privacy and security issues. AI in healthcare can lead to security data breaches where personal information may be widely available, compromising citizen privacy rights and making them vulnerable to identity theft and other cyberattacks. With the opaqueness of AI and complicated consent forms, it has become harder for patients to understand the decision-making processes and the different ways their data can be reused. In addition, these may also limit the autonomy and shared decision processes between patient and clinician. AIs themselves are also open to cyberattacks, resulting in anything from burdensome to fatal outcomes.

Gaps in AI accountability. The term *algorithmic accountability,* refers to the creation of algorithms through machine learning and human design and that mistakes made by the algorithm stem from humans developing, introducing or using the technology (Lekadir et al., 2022, pp. 25-26). That being said, accountability of AI is significant in healthcare, as this can lead to future adoption and acceptability. If clinicians feel that they are systematically held responsible for AI medical errors, they are less likely to adopt these emerging AIs. Currently, there is a lack of clarity regarding responsibility for AI medical errors, which poses new challenges for regulators in the fast expanding field of AI in healthcare. These new challenges can be seen in the form of the multi-actor problem where identifying responsibility may be difficult due to multiple actors involved in the development, implementation, and use of AI. Accountability is also linked to transparency and explainability, where clinicians are more likely to be held responsible when using AIs where they are unable to explain their medical decision. This is seen with assistive AI, as this may be considered the same as consulting a clinical colleague.

Obstacles to implementation in real-world healthcare. When implementing in practice, real-world factors should be considered, as experience within healthcare shows that the implementation period is paramount in the innovation process. The factors to consider include those such as; limited data quality and structure in existing electronic health systems, alteration of patient-physician relationship, and finally difficulties related to clinical interoperability and integration. Quality of electronic health data is key to the facilitation of implementing AI in a real-world practice. However, health data is often unstructured and noisy. The introduction of AI in healthcare is expected to change the traditional paternalistic relationship between patient and physician to a joint decision-making due to increased transparency and deepening of patient-physician conversation. It is unclear if AIs can be systematically interoperable across clinical sites and health systems, and whether they can easily be integrated into existing workflows without the need for significant alterations to existing clinical practices.

From our problem analysis, we derive an understanding of how AIS-1 is situated in a complex field. Through the presentation of the AID-SURG project, we now understood the need for the establishment of such a project when faced with the extent of CRC. Furthermore, we now understand the interventions and how this provides us with knowledge to better understand AIS-1 as part of the surgeons' practice. We gained further insights into the relation between the AID-SURG project and AIS-1 and the intentions behind how AIS-1 supports the surgeons in the field of CRC surgery. The literature review provided us with an understanding of the complex field of AI in healthcare. Through the interview with the Lead Data Scientist and the literature review we were able to establish AIS-1 as a CDSS. Furthermore, the literature review and extended literature provided us with multiple perspectives on both advantages and concerns in the integration of AI in healthcare, as well as a knowledge base for moving forward into our field work.

3. Problem statement

Through the problem analysis, we discovered how the Department of Surgery at ZUH is hoping to take advantage of the benefits offered by AI and ML algorithms. As part of the AID-SURG project, AIS-1 utilises ML to improve the outcome of patients in relation to risks associated with CRC surgery. The one-year mortality score predicted by the model is used to help support the surgeons during MDT in their decisions regarding treatment options for patients. Despite the increased interest and literature surrounding AI in healthcare, there are notable concerns, such as the fear that AI may replace clinicians and the willingness to adopt AI. Furthermore, ethical reflections include those of the balance between the strength and benefits of AI while maintaining the autonomy of the clinicians. With CRC as the third most malignant disease in the world, AI is expected to have a more impactful role in the optimisation and care of CRC patients. The growing use of AI induces more interactions between developers and users of AI. In this regard understanding the interactions between users such as surgeons and CDSS technologies such as AIS-1 becomes paramount for the future development. Therefore, we find that understanding the sociotechnical context in which AIS-1 is integrated into, is necessary to be able to consider its implications for both surgeons and patients. We see how Techno-Anthropology can contribute to this understanding by being able to uncover the interrelations between humans and technologies. In this thesis, we focus our area of research on the understanding of the relation between surgeons and AIS-1, by exploring the impact of the surgeons' experiences of the current and continued use of AIS-1. We hereby present the following problem statement:

> *How can the experiences of Colorectal Cancer surgeons shape the continued use of AIS-1 in the clinical setting? And how can these experiences translate into knowledge for the sustainability of AIS-1?*

4. Methodology

In the following section, we present our ethnographic methods of conducting field work, with use of participant observations and interview methods for data generation. The ethnographic approach enables us to study the culture of our field, through observing and by learning from surgeons within their natural environment. We further expand how ethnographic methods propose an inductive research approach, as the field of study is seen as an unfamiliar world that is yet to be discovered, by us (Spradley, 1979). With the unfamiliarity, we came to the field with little to no knowledge of what to expect. From our initial field trips, we started to interpret and assess the experiences we had to our area of research. As we understand, the reinterpretation of the experiences and phenomenon of AIS-1 in the surgeons' practice, can be constituted as a hermeneutic phenomenological perspective. Approaching informants and the field with a curiosity, the hermeneutic phenomenological method enabled us to get insights into their lifeworlds, and through continuous interpretation, to be able to make sense of the clinical practice from these understandings (Oerther, 2021). From the phenomenological perspective, we understand that phenomena exist on their own, and it is by approaching them, as they are, without prejudice, that we truly can experience them in their true meaning (Jacobsen, Tanggard, & Brinkmann, 2015). Gaining insights into the surgeons' experiences of the phenomenon and their relation to that subject area, the narrative becomes significant as it conveys these experiences. We found that with a narrative approach to our chosen methods, this allowed for a continuous interpretation of our data, further constituting the hermeneutic phenomenological understanding of the applied ethnographic methods.

In the following section, we will elucidate how we approached our research field, as we through the presentation of the field present our contacts and informants. We then describe our initial visits to the field, as these confined our approach for planning our field work. We further describe our chosen methods, being interview and participant observations, as means for conducting an ethnographic field work. Lastly, this chapter ends with how we addressed our data processing with thematic analysis as inspired by Braun & Clarke (2006).

4.1 Presentation of the Field

The initial contact was established through an external actor from a previous project, here we met a Senior Consultant in December 2022. Due to unforeseen circumstances, the former project, which initially was to be the focus of our master's thesis, was unable to be realised. The gatekeeper expressed an interest and concern on our behalf and thereby extended an invitation to participate in the AID-SURG project, at the CSS. After careful consideration and clearance with our former project coordinator, we accepted this invitation. Our gatekeeper granted us access to CSS, and it was here that we established contact with the Head of Research at CSS. Through this contact, we were able to secure access to relevant information, internal documents, and access to the MDTs.

On the 9th of January 2023, we had our first meeting with the Senior Consultant, the Head of Research, a Ph.D. MD from the Data Science Unit along with an Anthropologist from CSS. At this meeting, we discussed possible research areas for our thesis, matching expectations, and explained what Techno-Anthropology is. At this meeting, we were presented with the timeline of the AID-SURG project's pilot study, as well as where we would be able to do field work, make observations and conduct interviews. The pilot study ran from 1st of February to 1st of May 2023. As part of a first physical introduction to the field, the gatekeeper invited us to participate in a MDT on the 16th of January. In the following sections we describe our first encounter with our field through field observations from three different events; our first MDT, a first introduction to AIS-1, and a training session for AIS-1. The field description is based on field notes made at the respective events, and our observations are supported by digitised versions of field drawings of the physical spaces as well as pictures, to provide a visual aspect to our field descriptions.

4.1.1 Contacts and Informants

The *Figure 7* presents an overview of our field contacts and informants. In the top-left corner is a colour description, showing that green identifies contacts, blue identifies key informants, and boxes with a blue edge is a hybrid role, e.g., our gatekeeper both acting as our contact person in the field, but also as an informant in terms of field-specific questions, and the other surgeons at Department of Surgery, who often pitched in during field work and interviews.

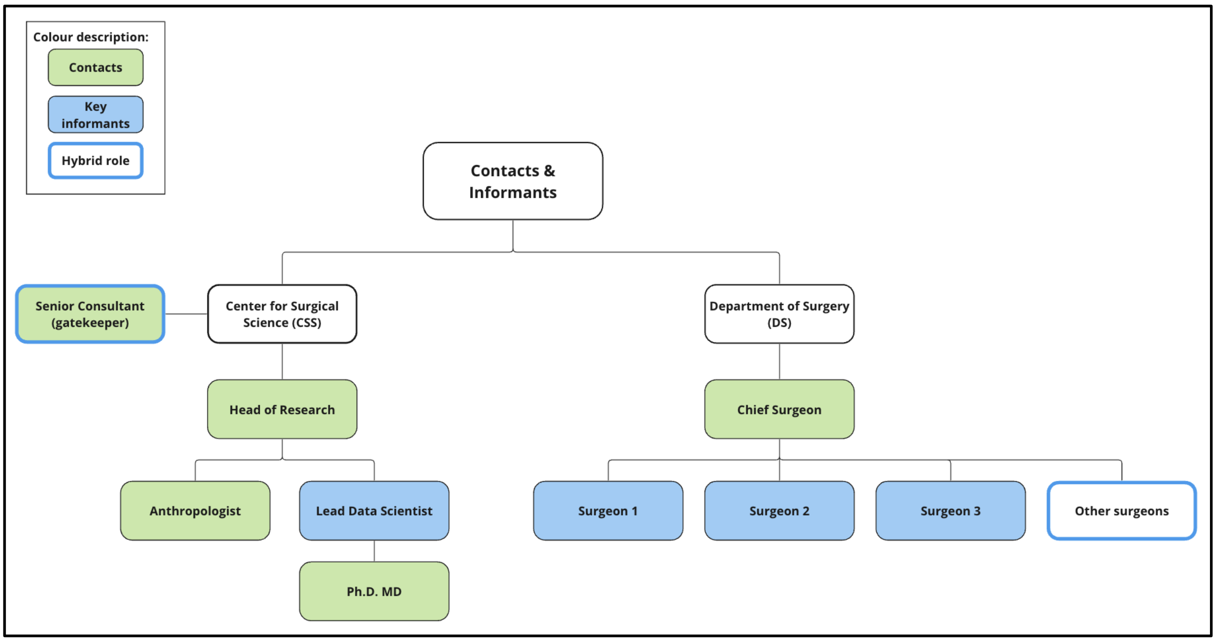


Figure 7: Overview of contacts and informants.

As described above, contact with our gatekeeper was facilitated through a former project. The gatekeeper was a Senior Consultant at CSS in the Senior Clinical Research Department. Our contact with the gatekeeper was initially done through online meetings and later supplemented with physical meetings on field work days.

Through the Head of Research at CSS, we were welcomed into the field both at CSS and the Department of Surgery. Besides being Head of Research, he also practises as a CRC surgeon in the department, and thereby paved the way for our initial interactions with the other surgeons. After the training session on the 26th of January, we had a meeting with the Head of Research and Senior Consultant. Here it became clear that he had a rather deductive approach to research in opposition to our inductive approach. By this statement, we refer to how the Head of Research brought forward his ideas for our project focus and requested us to come up with a problem statement and hypothesis for our project on the spot. He had a rather quantitative take on how to execute his ideas, in opposition to our qualitative methods, here we explained our considered methodological approach for generating data. We elaborated that we are not working from a hypothesis but from an ethnographic perspective, and thereby could not provide him with what he asked for at that time.

An Anthropologist had very recently been employed to conduct qualitative research for the CSS Department. It was therefore suggested that we collaborated to give competent feedback on the AID-SURG project. The project was partitioned into two parts, where the anthropologist would focus on the surgeon-patient relation in the out-patient clinic, and we would focus on the surgeon-AI relation in a clinical setting. Our conversations encompassed field-specific reflections, rooted in deep theoretical and methodological discussions. She often expressed how pleased she was with us being present at CSS to discuss qualitative methods, as she told us that not many at CSS understand the qualitative nature.

To get a technical introduction to AIS-1, we got in contact with the Lead Data Scientist at CSS. The contact was established at the training session on the 26th of January. They helped us understand some of the more technical and algorithmic parts of the model, and explained the databases and the data which the model is built upon. They also provided internal documents, which we have used in Section 2.1 to describe the model. Furthermore, it was due to the access to these internal documents, that we signed a NDA encompassing our whole collaboration with CSS. Whereby we agreed to the terms and conditions listed including that of unpublished and confidential information, which is why certain elements in this thesis cannot be directly referred to. At one point, we were in doubt as to if the information we intended to use would constitute a breach of contract, a copy was then sent to the Lead Data Scientist for approval.

On the 16th of January, the Chief Surgeon at the Department of Surgery, had agreed to meet and follow us to the MDT conference room. The initial plan was to have the Chief Surgeon as an informant, but due to time pressure and his responsibilities, this was not possible. We therefore initiated contact with another surgeon, referred to as Surgeon 1 who, along with the Chief Surgeon, were more involved with the implementation of AIS-1. He later took on the role as our primary contact person by providing us with information on which surgeons would be preparing for the MDT.

Additionally, two other CRC surgeons, referred to as Surgeon 2 and Surgeon 3, granted us access to participate in their MDT preparations and were kind enough to take time out of their busy schedule to answer any follow-up questions that arose during the preparations.

4.1.2 Preliminary visit to the field

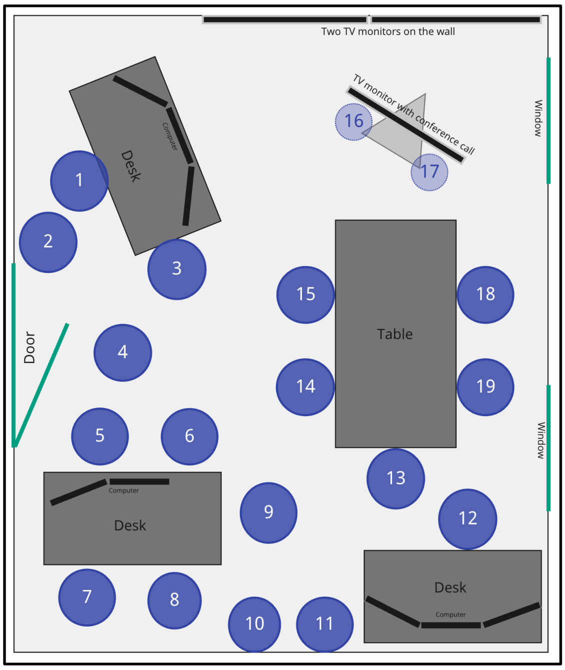


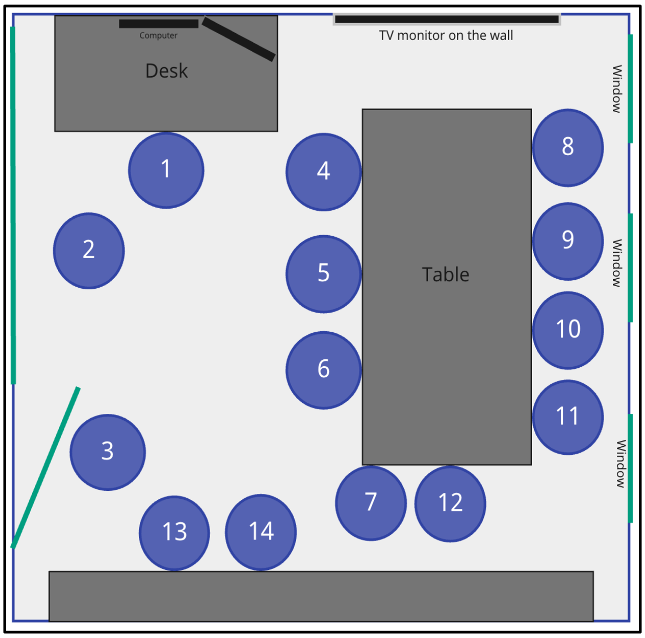
Figure 8: Visualisation of MDT, 16th of January

As presented above, the resolution to one of the first online meetings with our gatekeeper, was us getting to visit ZUH to partake in an MDT. MDT was implemented as part of DCCG guidelines in the deployment of Cancer plan II (Kræftplan II) in 2005. Here, patients should be discussed at least once a week by a panel of experts to ensure an optimal surgical treatment plan. The purpose of Cancer plan II is to help strengthen the prevention of cancer and to improve the conditions of cancer patients by offering early coordinated treatment plans based on a high level of professional quality (Sundhedsstyrelsen, 2005). The Department of Surgery at ZUH is an open surgical unit, with 24-hour shifts, here MDTs are a part of the CRC surgeons' practise and are held on Mondays and Thursdays from 08:00-09:00 every week. MDTs consist of a team of experts composed of CRC surgeons, a radiologist, an oncologist, and a pathologist. The last two attend online, as they are located at ZUH, Roskilde. According to our field observations, there were on average of 15 participants, including the two online, who attended the MDT. Before the MDT one surgeon has prepared conference notes in SP for all the patients listed on the MDT. This surgeon is responsible for starting and guiding the MDT, dictating new information as part of the treatment plan for all the respective patients, via dictaphone. It is their responsibility to ensure that the time schedule is kept within the allotted one-hour timeframe. After the launch of AIS-1, another surgeon prepares the AIS-1 prediction score of the patients included in the AID-SURG project. These prediction scores are then noted and included as part of the treatment plan dictated by the preparing surgeon. AIS-1 patients are the first patients to be discussed at the MDT as they arrive at the out-patient clinic that same day. This means that the AIS-1 preparing surgeon must leave the MDT around 08.20 when the out-patient clinic begins. During these MDTs, the clinical experts discuss the patients’ best possible curative treatment.

Figure 9: Picture of MDT room, 16th of January (Private photo).

The MDTs are located in a rather small meeting room (*Figure 8* and *Figure 9*). The digitised visualisation is a representation of a sketch from our very first MDT, which we attended on Monday, the 16th of January. The circles represent the placement of the attendants and resembles the tight space for 17 physical attendants in the room. Participating online was the pathologist (16) and oncologist (17). The radiologist (1) was placed by a computer ready to navigate through patients' imagery and provide additional information such as tumour categorisation (T1, T2, T3, etc.). Right by the radiologist was positioned a medical secretary (2), who was dedicated to adding the new decisions and information dictated in the MDT, to the patients’ journal. Number 6 was the anthropologist from CSS. Located on the right side of the room, at the table were ourselves (18 & 19), located right by the Chief Surgeon of Colorectal surgery (13), who followed us to the MDT, this first time. By the door, number 4 was Head of Research. The remaining eight attendants were surgeons from the Department of Surgery. Picture X shows the MDT conference room, focusing the online video setup for the pathologist and oncologist, and the TV monitors used for screen sharing imagery from the radiologist's computer (bottom-left corner).

Later, on the 16th of January, we attended a session of the introduction to the interface with the aim of testing AIS-1, troubleshooting login issues, and general feedback from surgeons’ reactions to typing in patient data. Six surgeons had been selected to attend this session, as they would become key actors in the launch. *Figure 10* is a visualisation of the Head of Research’s office, in which the meeting was held, along with a list of the attendants of the session. The attendants in **bold** represent informants and contacts. This was the first time we directly observed AIS-1. Before this day, the model had only been discussed in various meetings with our gatekeeper.



1. **Head of Research**
2. **Senior Consultant**
3. Project Manager
4. Chief Surgeon
5. Surgeon
6. **Surgeon (1)**
7. Computer Scientist (Data Science Unit)
8. Surgeon
9. **Surgeon (3)**
10. Ph.D. MD (Data Science Unit)
11. Post-Doc Clinical Assistant
12. **Lead Data Scientist (Data Science Unit)**
13. Techno-Anthropologist
14. Techno-Anthropologist

Figure 10: Introduction to AIS-1 session, 16th of January.

On January 26th, AIS-1 was presented by members of the Data Science Unit to surgeons in the Department of Surgery. The meeting took place in a large meeting room, *Figure 11*, and the participants were five members of the Data Science Unit, the Head of Research (14), nine CRC surgeons, a project nurse (12), an anthropologist (5), the Senior Consultant (18) and two techno-anthropologists, being us (8+9).

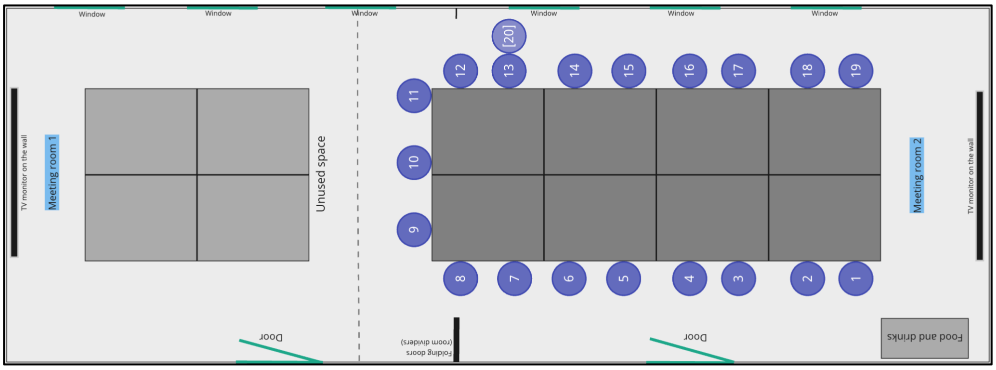


Figure 11: Visualisation of AIS-1 meeting, 26th of January.

The meeting was a more general presentation of how AIS-1 had been built, as well as an introduction to using so-called smart-phrases in SP, to aid in the preparation of AIS-1 notes to MDT. During the meeting, the Head of Research outlined the beginning of the pilot phase by stating:

> Documented at a level as if they were developing a new drug. Clinicians are the patients that will be the test subjects.
>
> (Field note, 26/1/23)

Furthermore, a Chief physician came and shared a new approach for ordering blood work tests, this was within another part of the AID-SURG project. The meeting enabled participants to ask questions throughout, which mostly referred to the issues of log-in and transferability of AIS-1 interface input to other users and computers. From the meeting, we gained insight into the surgeons' initial reactions and concerns with the use and forthcoming launch of AIS-1. We further got to see most of the surgeons in person, as well as had the opportunity to have a casual conversation with the Lead Data Scientist, leading to an inquiry of an interview, to be scheduled later on.

4.1.3 Planning field work

Planning field work and arranging field work were quickly discovered to be two complete opposites.

As described in the above section, our two preliminary visits to the field took place on the 16th and the 26th of January. These two days, consisting of three events, formed a kind of pre-pilot study for us to get familiar with the field we were about to engage with. To coincide within the timeframe of the pilot study, we started planning our field work, running from the 1st of February to the 1st of May. We wanted to take on the role of participant observers as peer-learners to generate data on how the surgeons experienced their interactions with AIS-1. We further had ambitions that this approach would allow us to gain insights into their thoughts and concerns related to AIS-1. As *Figure 12* shows, we had an informal conversation with Surgeon 1 on the 20th of February. Our field work stretched from mid-January 2023 until 1st of May 2023, a timeline of dates and events during the field work can be seen in *Figure 12* (see page 34).

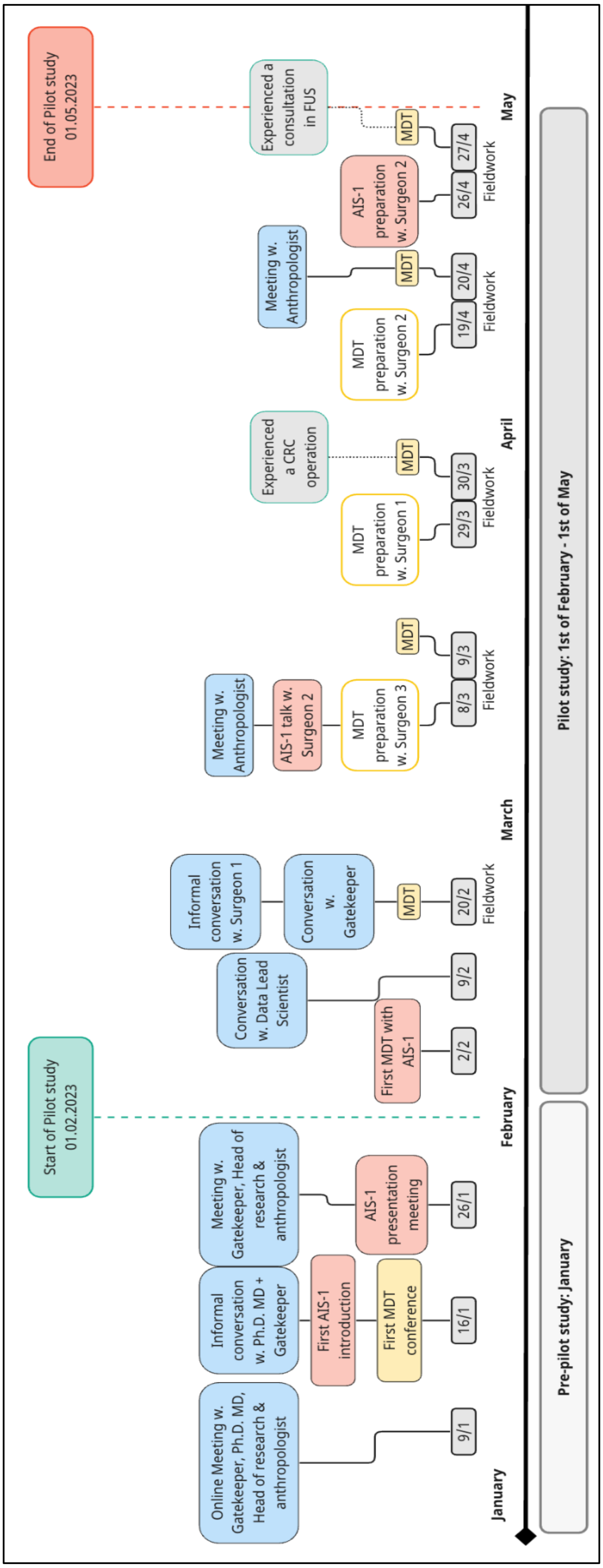


Figure 12: Overview of field work.

From the initial visit to the research site, we planned our prospective field work. In total, 12 days were allocated to field work at the Department of Surgery at ZUH. Seven days (two Mondays and five Thursdays) were used to observe at MDTs. The five Wednesdays served to follow and observe the respective surgeon's preparation for the following Thursday's MDT conference. We therefore aligned our individual schedules and came up with four weeks spread over the three-month period, where we would be able to go to ZUH. In the following, we will briefly go through our process of arranging field work with our field.

Arranging field work

It was made clear to us that each Friday a scheme was sent out, where the MDT and AIS-1 preparing surgeons were assigned. Recommended by our gatekeeper, he said, we should ask to get on the mailing list, to receive this list as well. But this was easier said than done, and after being stand-by for two Fridays in a row, and unable to reach the medical secretary, we decided to change our approach. We therefore decided to initiate conversations with the preparing AIS-1 surgeon just before the MDT started and ask if we could follow them to the out-patient clinic and ask some questions along the way. On the 20th of February, we initiated contact with Surgeon 1 through this approach, asking if he would have time to answer some questions right after the MDT. This was not possible as he was the AIS-1 preparing surgeon and had the out-patient clinic starting at 8.20. We then asked if he had time later that day, which he confirmed. From the later conversation, we learned that he and two others had been the leading surgeons in AIS-1 deployment, and that they probably knew most about the model. After careful consideration and as recommended by our gatekeeper, we emailed the three surgeons, who had been part of the initiating processes of AIS-1's development, as he deemed them to be most willing to let us partake in their works of AIS-1. In the email (see *Figure 13*), we stated our purpose for our approach and asked if any of them would mind if we partook in their MDT preparation, underlining our flexibility with time and dates.

Som i måske ved, er vi de to Teknoantropologi studerende fra Aalborg Universitet, der har deltaget i nogle af jeres MDT-konferencer samt træningssessioner. Vores speciale omhandler implementering og brugen af AIS-1 i den kliniske praksis, samt jeres interaktioner og tanker som kirurger vedrørende det nye værktøj. Efter input fra LP er det blevet forslået, at det giver mest mening at følge netop jer. Vi vil derfor gerne observerer, hvordan i forbereder jer til MDT-konferencen (m/u AIS) - dette forestiller vi som en slags sidemands oplæring, hvor vi vil tage noter og evt. stille opklarende spørgsmål.

Nedenfor er en oversigt over følgende datoer vi har afsat til feltarbejde på SUH:

Uge 10	Uge 13	Uge 16	Uge 17
Onsdag: 8/3	Onsdag: 29/3	Onsdag: 19/4	Onsdag: 26/4
Torsdag: 9/3	Torsdag: 30/3	Torsdag: 20/4	Torsdag: 27/4

Derudover håber vi at i vil have lyst til at deltage i nogle interviews. Disse kan foregå på ovenstående datoer eller evt. online - vi er fleksible med andre tider og datoer. Interviews forventes at tage 30-45 minutter.

Efter ønske, kan vi fremsende samtykke erklæring om vores brug og opbevaring af data. Samtykke kan afgives enten skriftlig eller mundtligt. Til underretning har vi underskrevet en NDA i forbindelse med modtagelse af interne dokumenter fra Data Science enheden.

Med venlig hilsen

Figure 13: Joint email to surgeons.

One of the three surgeons, Surgeon 1, responded to our email, saying that he would gladly include us in his AIS-1 preparation, if he were to prepare on the specific dates sent. The other two surgeons never responded.

Through an email correspondence with Surgeon 1, we arranged to call him on Fridays the week before going to field work, to get a hold on whom the preparing surgeons were for both normal MDT and AIS-1. Planning of the peer-learning was done through individual emails, where we asked the prospective surgeons if we could participate in their preparation.

4.2 Ethnographic Methods

The following section elaborates our chosen methods. As described in the above section of planning field work, we had plans for both doing participant observations within the field and conducting interviews with our informants. As with our field work planning, we were compelled to rethink this approach, when the time pressure of surgeons' work practices, dictated our access to the field. The following sections describe how we adapted our chosen methods to the accessibility and confines of our field work. With the project's aim to research surgeons' experiences interacting with AIS-1, we selected a set of ethnographic methods, to accommodate this approach. The section elaborates on participant observations and interviews as our preferred methods, pertaining to the approach of conducting field work as our main data generating method.

4.2.1 Rapport

Entering a new field can seem overwhelming. However, according to Spradley (1979) this is part of the rapport process which goes through four stages: Apprehension, Exploration, Cooperation, and Participation. Apprehension can be expressed as a sense of uncertainty and unfamiliarity, both from the ethnographer as well as from the informant. We experienced the first stage of apprehension at the start of our field work, as both researchers had never been to ZUH along with new experience of participating in the MDTs. The apprehension soon passed due to the openness and friendliness of the surgeons and their willingness to accept our presence. Apprehension soon gives way to exploration where both informant and ethnographer seek to discover what they want from the relationship. In the cooperation stage, focus is no longer on the worries of offending each other, both parties now know the goal is to discover the culture of the informant. In the final stage, participation, informants may take on more assertive roles and bring new information to the attention of the ethnographer, thereby contributing by discovering patterns in their culture and becoming more participant observers in their cultural scene (Spradley, 1979). This process was helped along by our participation both in the training session hosted by CSS and the MDTs. Here we were able to establish rapport with the department's surgeons by way of informal conversations. This was used to great effect later when asking to participate in the surgeons' preparations of the MDTs, both with and without AIS-1. To respect our new relationship with the surgeons, we made it a point not to impose more than necessary and to respect the surgeons' time by planning and emphasising that they could decline our invitations without the need for giving a reason. We further experienced that our presence in the field and development of rapport with the surgeons, extended an invitation to participate in observing a CRC operation on the 20th of April. Furthermore, we got invited to participate and observe a consultation in the out-patient clinic on the 27th of April.

4.2.2 Interview

The flexibility we found in using interviews, allowed different types of interviews to produce different types of data that can be useful for different types of researchers in different projects (Bernard, 2006).

In our thesis, we decided to go with a combination of informal and semi-structured interviews as our preferred methods of choice. This was due to the flexibility offered by the aforementioned interview forms, allowing our informants to express their concerns while also allowing us as researchers to explore relevant topics in depth. It allowed us to uncover detailed responses to our raised questions, but also enabled us to capture insights that might otherwise have been hard to capture (Lazar, Feng, & Hochheiser, 2017).

Being introduced to the field through the two meetings in January, we were able to meet most of our informants on a more casual level. This prompted informal conversations, which are seen as interviews with a complete lack of structure. Informal interviews are usually reproduced through field notes, which are being taken after the conversation has happened (Bernard, 2006). A result of one of these structure-less conversations led to the arrangement of an interview with the Lead Data Scientist on the 9th of February.

As a further interview form, we used semi-structured interviews. Here, we had a list of questions we wished our informants to answer, but still leaving room for the flexibility in their replies. Semi-structured interviews allow topics to be explored more in depth, this we see in opposition to be harder to achieve in e.g., structured interviews (Lazar et al., 2017). However, the less structure may also mean more challenges in interpretation and require significantly more effort in balancing between the response given by the interviewee and when the interviewer should direct the flow of conversation (Lazar et al., 2017). For the above-mentioned interview with the Lead Data Scientist, we framed an interview guide, divided into different areas of which we wanted clarification. The interview guide helped us to stay within our intended questions, but still allowed us to follow a story from the Lead Data Scientist, as the interview concerned the data scientific and technical compilations of the models structure.

4.2.3 Participant Observation

Elaborating on the above description of our interview approach, we here draw on participant observation as presented by James Spradley (1980). Participant observation requires a social situation to participate and make observations in. In *Figure 14* we see how the social situation is constituted by three elements: actors, activities, and place (Spradley, 1980). As an example, we see MDT as such a social situation as it is in the MDT meeting room (place), with surgeons, radiologist, pathologist and oncologist participating (actors) in discussion of patients (activities). Through our field work, we encountered several social situations in which we participated; Training sessions, MDT preparation, AIS-1 preparation, an operation, and a consultation in the out-patient clinic. As we were located within the field of CRC surgery, our degree of participation was limited to that of being passive participants. This was due to the lack of our practical knowledge of their expertise and with the respect for their time available. For the latter we refer to, e.g., participating in adding SP data to AIS-1. To get most out of our limited degree of participation, we engaged our participant observations at the MDT and AIS-1 preparations, as a form of peer-to-peer sessions. Our entrance was to sit beside the surgeons while they made the preparation and get them to talk about what they did on the computer, and with us having the option of asking questions about their practice. In total, we participated in four peer-learning sessions, whereof the first was not recorded, and thereby only expressed through our field notes from the specific day. The last three were recorded, and further transcribed.

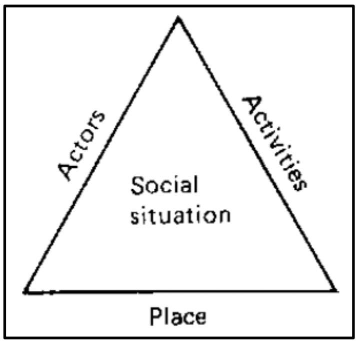


Figure 14: Social situations, (Spradley 1980, p. 40).

We now elaborate on the difference between a normal participant to the participant observer in social situations, as the specific approach is what makes the difference. A normal participant approaches the social situation with the purpose of participating, whereas the participant observers, besides participating, also comes to observe the actors, activities, and the place of the situation (Spradley, 1980). In the MDT conferences, we had, what Spradley refers to as an insider/outsider experience (Spradley, 1980), as we were participating in the MDT, hearing the discussions, seeing the medical imagery, as we were insiders. At the same time, we were studying the MDT situation through an objective, outside view, taking in all new information, trying to get a hold on what it all meant. A last distinction between the normal participant and the participant observer is the point of tracking and keeping note of the social situations they observe, this leads us to the act of taking and making field notes.

Field notes

Over time, each ethnographer will develop their own way of taking field notes and which ones work best for them. However, the way we write field notes also emerges from the field and ethnographic fields each require their own methodological approach (Flora & Andersen, 2018). With this in mind, we chose to use notebooks in an A5 format, and pens to take notes, as we often found ourselves in situations where no table was available for e.g., placing a computer on. Furthermore, we deemed a notebook more suitable, due to fewer obstacles with lack of power or unpredictable technical errors for computers. Notebooks further enabled us to make quick drawings of e.g., the rooms we were in (see *Figure 15*). In terms of field notes, we address this in two ways, jottings and descriptive notes. Jottings were used to make brief notes, in situations where a lot of information had to be noted in a short time, e.g., at MDTs. We further made jottings after informal conversation, as Bernard states that depending on the situation it may not be appropriate to take notes as this can also remove oneself from the situation or conversation (Bernard, 2006). This was the main approach for our notetaking.

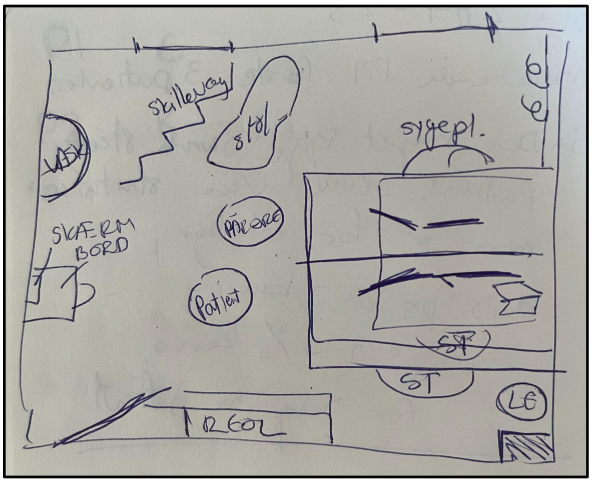


Figure 15: Field drawing of out-patient clinic consultation, social situation.

At the end of each day or sooner, we made descriptive field notes from our jottings. By doing this, we had the day fresh in mind, and could elaborate on the observed events, behaviours, conversations, and questions from the specific day. By writing out in-situ field notes in this manner entailed learning in retrospective, whereby details of the day emerged, which had previously gone unnoticed. Here, field notes can be said to have a meaning beyond the context in which they were written in (Flora & Andersen, 2018).

Besides writing physical field notes, we exploited the down-time available to us during our commutes between Copenhagen and Køge. Here we discussed the day's events, planned a focus or prepared questions. Either placed at ZUH or during the commute back, we had a debriefing of the day, where we talked about our new experiences.

Within the first month of the pilot project timeframe, we had generated a clearer understanding of the cultural aspects of the surgeons. As described in the interview section, we had chosen to make semi-structured interviews with our informants. But as we proceeded, this was not attainable in the classical sense, as the surgeons had a limited amount of time, to both make preparations and for extra tasks during their busy day. Furthermore, we found that the surgeons preparing a normal MDT note, also to some extent had experience with preparing with AIS-1, thus enabling us to include AIS-1 related questions. As a result of our understanding of the field and the surgeons' available time, we therefore decided to make a combination of the semi-structured interviews and the peer-learning sessions.

4.3 Data processing

The following section elaborates on the data generated through the above-mentioned methods. Firstly, we present our data corpus to provide an overview of data sources. Lastly, we present how we have approached our data through Thematic Analysis, inspired by Virginia Braun and Victoria Clarke's article *Using Thematic Analysis in Psychology* (Braun & Clarke, 2006). A visualisation of our data is presented at the end of the chapter. Our reason for using thematic analysis, comes from the flexibility it offers. Its approach to data processing provides a structured, yet creative process when searching for meaning within a data corpus. Before describing our thematic analysis approach, we present the data, from which our analysis is produced.

Data corpus refers to all data that has been collected within a project (Braun & Clarke, 2006). During our 12 days in the field, we produced 20 digital documents from our physical field note write outs. Furthermore, we have four audio recordings: the interview with the Lead Data Scientist, two MDT peer-learning session recordings, and one AIS-1 preparation peer-learning session. All four recordings have been transcribed verbatim, as to maintain the meaning of the informants' utterances. For the project, quotes used from Danish interviews have been translated to English, with utter attention to once again maintain the meaning of the said quote, despite the translation. From the data corpus, a data set is selected, from which we produce our thematic analysis (Braun & Clarke, 2006). Our coded data set consists of the 20 field note documents and transcriptions of the three recorded peer-learning sessions. Data items refer to the individual pieces of collected data (Braun & Clarke, 2006), such as a specific field note document or an interview transcription. As for data extract, this is the specific piece of data, extracted from the data item, which is a part of the data set, and thereby the whole data corpus (Braun & Clarke, 2006). With this presentation of our data corpus, set, item, and extract we proceed to our further data processing, through the Thematic Analysis of our data set.

4.3.1 Thematic Analysis

To initiate our coding process, we familiarised ourselves with our data corpus. This was done through thorough readings of both field note documents, peer-training transcriptions, and listening to the audio recordings while reading the transcriptions.

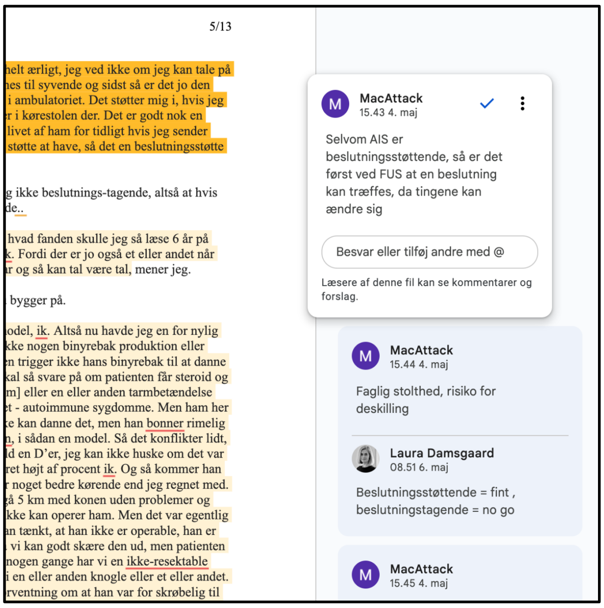


Figure 16: Comment function of shared document, coding extracts

After the familiarisation, we systematically went through our data set, to individually note interesting paths of field notes and interview bites. This was done by using the comment function within the shared documents, as they would directly refer to the coded data extract (see *Figure 16*). This enabled us to always see each other's ideas and codes, as well as respond with further perspectives on the same data extract. When all documents had been coded individually, we went through them all together, and described our thoughts on the specific codes and comments. From this, we built a shared understanding of what our data set could contribute to in the future analysis.

Due to our physical separation between Aalborg and Copenhagen, we approached the third phase of the thematic analysis, by using the online Google-based tool Jamboard, as it provided a great visualisation of using online post-it notes. As we once again went through our data items, we gathered all codes into two separate Jamboards; one for field notes, and one for interview codes. This was done for a better overview of our initial codes. Each Jamboard was then thoroughly went through, pulling forward one note at a time to discuss the possible theme of the code. The following two *Figure 17* & *Figure 18*, visualise the final distribution of post-it notes into themes.

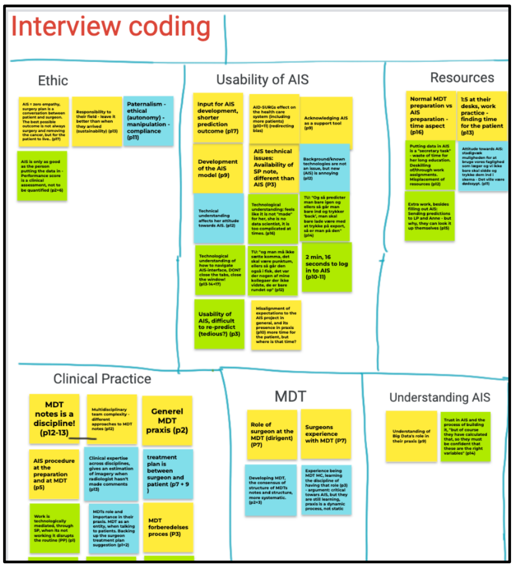


Figure 17: Jamboard excerpt of interview coding.

Figure 18: Jamboard excerpt of field note coding.

These themes were for field notes: AIS in practice, rapport, understanding AIS, usability of AIS, MDT, and surgeons' know-how. For the interview themes, some were similar, like: Usability of AIS, rapport, MDT, understanding AIS, and surgeons' know-how. Additional themes were: ethics, resources, clinical practice, and future AIS.

A pitfall from the Jamboard process was us interpreting the initial codes from the comments, and then forgetting to refer directly to which code belonged to which data extract. To create a better overview of our thematised data, we therefore combined our data extract, initial codes from the comments, and the refined codes into a table, divided into the presented Jamboard themes (see *Figure 19*). The themes were now: AIS in practice, MDT, rapport, surgeons' know-how, ethics, resources, clinical practice, and future AIS. As we had to look through our data sets once again for the correctly assigned extracts, we had the opportunity to review both themes and extracts within each theme and reduced it to eight themes. We

MDT

Data Extract	Coding	Refined code
[Kirurg] pointerer at patient diskussionen bliver for langtrukkent. (LE D p2)	Praksis - MDT	Preparing surgeon's role in MDT - final call
[kirurg 3] siger "Skal vi begynde, kl er sådan set 8" (LE F p1)	MDT	"Skal vi begynde, kl er sådan set 8" - MDT praxis - lead on the MDT is the one who has prepared the normal note
S: Ja, både det, primært det, og så danne sig et hurtigt overblik over hvad planen nok skal være, for selvom at jeg forbereder det her nu, så skal man jo også være sådan en slags dirigent på konferencen i morgen, sådan så jeg ligesom skal - flowet skal være der, og jeg skal ligesom komme	Rolle for den forberedende kirurg	Role of surgeon at the MDT (dirigent)

Figure 19: Excerpt of our table of themes.

hereby both moved some codes to other themes, some were added, and finally some were discarded again, as they suddenly did not seem to fit in with any of our themes. The themes were now: AIS in practice, MDT, rapport, surgeons' know-how, ethics, resources, clinical practice, and future AIS.

For the fifth phase, it was all about defining and refining themes (Braun & Clarke, 2006). We hereby saw how the data almost created a narrative on the use of AIS-1 in practice. We could hereby divide our themes into two: Technical Difficulties in the Initial Phase of AIS-1 and Developing and Understanding AIS-1 within the Clinical Practice.

Approaching the final phase of writing out our analysis, we further divided our themes into subthemes, to create a structure in the narrative. Technical Difficulties were parted into; the surgeons' login process, forming new routines, and more time for the patient and less time for the surgeon? The second theme, Developing and Understanding AIS-1 within the Clinical Practice presents the following subthemes: surgeons' interpretation of patients through quantitative data, making sense through surgeons' visions, and the fruits of AIS-1. *Figure 20* visualises our final themes and subthemes developed from the thematic analysis. This finalises the sixth and last phase of thematic analysis.

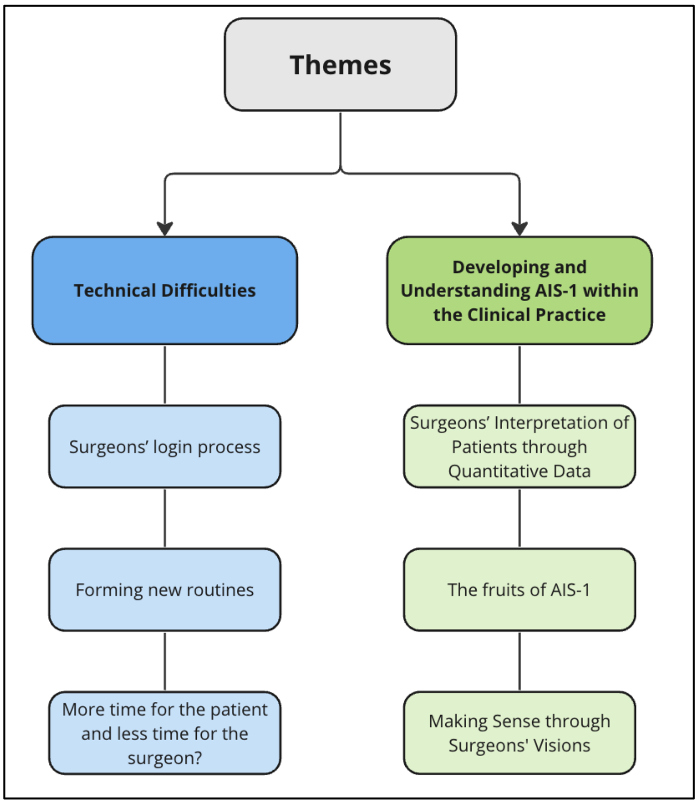


Figure 20: Final themes.

5. Analysis

The following chapter contains this thesis's analysis. The aim of our thesis is to represent how the surgeons' experiences can shape the continued use of AIS-1 in their clinical setting, along with how these experiences can be translated into knowledge for the sustainability of AIS-1. Through our exposition of the project's methodological approach, we now present our field results through quotes and field note excerpts. From our above-mentioned themes, as presented in section 4.3.1, we incorporate postphenomenology to support our analytical insights, which we present in the following sections. At the time of writing this thesis, AIS-1 was still in the developmental phase, but integrated as part of their work practice. Here we acknowledge that our study has been rooted in the pilot phase of the project, with that in mind, a further degree of transparency could develop in the months to follow. This is unfortunately beyond the confines of this research.

Within the sociotechnical context of the surgeons' experiences with AIS-1, we understand the role of technologies in relation to humans as inseparable. We therefore elaborate our thesis with the postphenomenological theory of mediation to elucidate this inseparability of surgeons and AIS-1. As mentioned in the methodological chapter, our approach for our used methods, was with a phenomenological perspective in mind. As described, phenomenology enables the directness in understanding an object, which we see as the patient, to truly experience them (Jacobsen et al., 2015). With the expansion of technologies, the need for postphenomenology was derived from this classical phenomenological approach. Postphenomenology extended the focus by indicating that there is no direct link between subject and object, but the relation is rather mediated through a technology (Rosenberger & Verbeek, 2015; Verbeek, 2016). To relate it to our thesis, we hereby understand how patients as objects are mediated through AIS-1 to the surgeons, the subjects, which constitutes the mediation relation of surgeon and AIS-1. This is to be understood in how we see the clinical practice of surgeons as inseparable from that of technology. As such, the world of surgeons and their interaction between them and the patient is constituted through AIS-1.

5.1 Technical Difficulties in the Initial Phase of AIS-1

The first section of our analysis contains the theme of Technical Difficulties in the Initial Phase of AIS-1. Here we elaborate with our subthemes being surgeons' login process, forming new routines, and more time for the patient and less time for the surgeon? The first subtheme, surgeons' login process concerns itself with the surgeons' initial experiences as part of the login process of AIS-1. In forming new routines as the second theme, we see how the continued use of AIS-1 in the surgeons' practice starts to shape the surgeons' experience from annoyance to acceptance. The last theme, more time for the patient and less time for the surgeon? we look at how the surgeons' time is used for a wide variety of computer-based tasks and the timely aspects of integration AIS-1 in their busy schedules.

5.1.1 Surgeons' login process

At the introduction session to AIS-1, on the 16th of January, we witnessed the surgeons' first encounter with this new, soon-to-be launched CDSS, called AIS-1. The session was built as a try-out, for the project manager and collaborators of the model, to both help surgeons to make their initial login, and also to time them on a prediction. The following field note excerpt is an observation of the surgeons' login process.

> From the beginning, there are problems with logging into the "virtual world". The surgeons have received an email with their username, a manual, and a password to log in with.
>
> The password is a one-time thing, that only has to be put in once to get access to the server. But when they have to put their new password in, for safety reasons, they can't see what they are typing.
>
> There are also issues with typing in too many wrong passwords, which then locks them out of the system.
>
> (Field note, 16/1/23)

Although the surgeons found this initial login session extremely tedious, it provided them with a much smoother access to the virtual desktop called VMWare Horizon, in terms of their next login. The need for an extra security level was because AIS-1 was being tested as a medical device as well as housing patient sensitive data such as the social security numbers (CPR number) of patients. Due to GDPR legislation, the model cannot be linked up to SP yet. There are only a few examples of deploying CDSS in practice, which both Bräuner et al. (2022) and Wang et al. (2021) recognise as an inhibition in terms of development of such systems. We therefore see that AIS-1 is aiding in this lack of development by being tested as a CDSS, giving momentum for further research on both a local level at ZUH and on a larger scale of CDSSs in practice. Returning to the introduction session, one of the surgeons, who we refer to as Surgeon 1, expressed *"This doesn't work, you can't get people to do this"* when dealing with logging into VMWare. As a first encounter with a new technology, such issues with an essential step may cause a rather negative attitude towards using AIS-1 in practice. At the session, there were mixed experiences with the login process; there were many disconnects under the session, this was stated by the Lead Data Scientist to probably be due to *"too many users accessing the same port"*. Furthermore, it took 30 minutes for the first surgeon to login, then the rest followed within minutes after that. The Head of Research and a single surgeon never made it into the interface, as they were locked out due to too many failed login attempts. The surgeons joked about the inconvenience of the login process, something we experienced as being a mood lifter, when engaging with this strange and "*annoying"* new technology.

As described in the above field note excerpt, an issue of the login process was the *“blind”* typing of passwords at the initial login stage, which created a shared frustration among them, sparking memories of a past shared experience. The surgeons agreed that this past experience, luckily, was way more tedious than this, then laughed about it and went back to being unimpressed by AIS-1. These experiences would go on to form their impression of AIS-1, but based on this first session, it was difficult for us to gauge what effects their attitudes would have on their future perception of AIS-1. Their inside jokes changed the mood in the room from being negative towards the CDSS to a positive one due to their previous experiences. By using humour to endure their shared frustrations of logging in, we were a bit confused if their willingness to adopt AIS-1, could be ‘manipulated’ to be a positive experience, due to their relationship and history on a collegial level. As mentioned earlier in this section, studies have pointed to how a lack of user-friendliness can inhibit the willingness to adopt a technology in practice (Esmaeilzadeh et al., 2021). Willingness to adopt and attitudes are two important steps, for a successful use and development in practice. From this we make a distinction between using and adopting a technology, as the use of AIS-1 does not necessarily translate into an adoption. According to the Head of Research, surgeons are required to use the model. This is a unique situation, as it gives AIS-1 a slight advantage in its utilisation, as surgeons cannot oppose its integration. We see a mediation occurring as the surgeons are required to reinterpret the patient, through the predictions provided by AIS-1. It hereby shows that the use of AIS-1, can constitute a mediation without the technology being adopted by the surgeons, as a result of their negative attitude towards the model.

The deployment of AIS-1 further insinuates the divide of surgeons attitudes as we observed how technical difficulties expanded from login issues to more general issues as Surgeon 3 is quoted to say that making AIS-1 predictions was *"damn annoying“*. Despite his apparent annoyance, he further expressed that he was pleased that the model was only to support and how the final decision still was with the surgeons. This agitation was brought forward in the surgeon's consciousness and experience of AIS-1, resulting in resistance with a focus on how AIS-1 does not live up to its intended purpose. Instead, we see that their focus should be on the current position of the model to contemplate on its possibilities in their practice. Surgeons' attitude had an effect early on in AIS-1 deployment and as a result of the initial login in phase affected their willingness to adopt the technology as seen in their hesitant attitude. The attitudes observed on the first AIS-1 session, was our steppingstone, for looking further into attitudes towards the launch and use of AIS-1 within their clinical practice.

5.1.2 Forming new routines

Figure 21: Electronic card reader.

Logging in was an essential part of using AIS-1 and even though the introduction session tried to ease out any initial obstacles, logging in still required a two-factor process. Surgeons have their personal password they type into VMWare and then receive a one-time password in the form of a text-message to login. Passwords and high security levels are not an unfamiliar action when working as a CRC surgeon, but during a conversation with Surgeon 2 she proclaimed the inconvenience of having additional codes to remember. For a quicker access to SP, they use their name tag (physical card) and scan it at a card reader located by the computer (see *Figure 21*). They are then prompted to type in a so-called *"quick code",* consisting of four digits. While Surgeon 2 told us about the fast procedure, another surgeon pitched in from across the room:

> Surgeon: We have everything on here (holds up phone); driving licence, and all kinds of access on an iPhone, and then we have to go into some ancient system
>
> (Field note, 8/3/23)

Through our observations of the surgeons, we found that when talking of AIS-1 the go-to, to describe this relation, was by comparing it with the practice of a normal MDT preparation process. This way, the surgeons could exemplify and counterpoint the 'issues' with AIS-1. From the above notions of the tediousness of logging into AIS-1 and the reference to VMWare being an *ancient system* shows that they are still not quite familiar with the new CDSS. The action of presenting their card to the card reader, typing their quick code and then having access to SP to make an MDT-note, is for most parts a frictionless process. As this had become an embedded routine, this login process occurred as a transparent action in their daily practice. On the contrary, getting familiar with not just a new technology, but also having to access this technology in a new manner, is seen as a disruption of known routines. AIS-1 is both the disrupter of their normal preparation routines, but also an entirely new routine they must integrate into their work practice. For the latter, AIS-1 is emerging as a new preparation routine as a new world is constructed through the surgeons' relation with the patient, with AIS-1 as a medium. The surgeons' perceptions of AIS-1 are crucial for developing a user–technology relation, allowing for a successful implementation by encompassing the attitudes and perceptions of the user, as stated in the article by Esmaeilzadeh et al. (2021). At this time, we observed a hard distinction between the users and the technology as it was not yet embedded in their routines nor deemed applicable to their practice, causing resentment towards the CDSS, inhibiting the development. As mentioned earlier, the development in the clinical practice is what is deemed effective for future research and advancement of CDSS in practice (Wang et al., 2021). We attribute their attitudes to the seeming lack of information regarding the login process delivered by the Data Science Unit. We saw how this lack caused confusion among the surgeons as to where to locate their passwords. In addition, there was a lack of information of the necessity for the high security levels, making the task of using AIS-1 an even more laborious task for the surgeons.

In a conversation with Surgeon 2 on the 8th of March, she told us how this was the second time for her preparing with AIS-1 and that she had some access issues, as a result of both updates and her being off work. These issues resulted in the Lead Data Scientist having to aid her by coming to the surgeons' preparation office. On the 19th of April, we had a peer-learning session with Surgeon 2, on her perception of the access to, and login issues with AIS-1, where she expressed the following,

> *“If you are in the black box and have to match the codes together and such, and you enter one space too many, then you’ll never get in, it’s completely hopeless. I’m no computer scientist or anything. I think it's annoying, that it can be a bit difficult, but luckily, I haven't had issues with it for a while now”*
>
> (Interview Surgeon 2, 19/4/23)

Accessibility to AIS-1 must be at the highest priority, for the AID-SURG project's ability to deliver useful knowledge on using CDSS in practice. The above quote expresses the development from the surgeon's previous frustrations with the login process, to the same surgeon talking about it two months later. The attitude shift is inevitable to see, as she both makes an outline of the tricky parts of the login process, and at the same time recognise that these issues are in the past, due to her regular use. Identification of where AIS-1 is causing the surgeon difficulties, is the result of a familiarisation with the technology. We saw a change in Surgeon 2 as she told us about her initial login issues on March 8th, in addition to the point of her not being a “*computer scientist”*, in the quote from April 19th. It can be interpreted as her perception of using AIS-1 is something which requires a better or different knowledge than what she possesses. We further saw that with the deployment of AIS-1, her relation with the practice of MDT preparation changed, as she was experiencing the model being intrusive in her practice. Looking at it from a different perspective, the duality of the technology’s ability to optimally change the way she sees the world, is obscured by the opacity of AIS-1 in use. We see this as the inseparability of her practice and technological interference. This issue is gradually alleviated as the surgeon gets more familiar with the technology, as it becomes more transparent in terms of use. This was observed through the duration of our field work, as we experienced the surgeon's relation with using AIS-1 as it developed into a routine. Instead of complaining about the login processes, she started reflecting on the prediction outcome’s effects on the patients.

5.1.3 More time for the patient and less time for the surgeon?

Going back to our field notes from the training session on the 26th of January, it was made clear by the Head of Research that the intention of AIS-1 was not to take time away from the patients. However, this did not seem to be the case as of when we conducted our field work. From an initial talk with Surgeon 1 on the 20th of February, he expressed that an AIS-1 preparation, for him, takes three times as long as a regular MDT preparation. On March 29th, during an MDT preparation with the same surgeon, we followed up on the time aspect, more specifically regarding if AIS-1 lives up to its intention of not taking time away from the patient, and where that time is supposed to come from. Surgeon 1 stated that he actually did not know and could not figure it out. According to him, the time surgeons have is limited as they, apart from the MDTs, have both conferences and meetings where they discuss patients. Based on our former knowledge, Surgeon 1 confirmed our impression of added documentation in healthcare, as he told us that the surgeons are assigned to considerably larger amounts of documentation and computer-based tasks, compared to 10 years ago. He further elaborated:

> *"If you have a look at how much I'm sitting in front of the computer opposed to how much we are with the patients, then it is a 1:5 ratio, being 1 with the patient and 5 at the computer".*
>
> (Interview Surgeon 1, 29/3/23)

He is well aware of his responsibility with both clinical guidelines for documentation, but also his attention and time towards patients.

> *"[...] for us surgeons, we, of course, use a lot of time at the operating table, but at ward rounds and administration, we use a rough amount of time at the computer."*
>
> (Interview Surgeon 1, 29/3/23)

It is hereby quite evident that the Department and surgeons are heavily loaded with computer-based tasks, making it difficult to see where AIS-1 is supposed to fit regarding the time aspect. With this perspective, we further observed that surgeons would often take work home, particularly the computer-based tasks, such as the MDT and AIS-1 preparations. We saw MDT as an established practice embedded within their work shifts, whereas AIS-1 was mostly "downgraded" to homework outside their normal 37-hours, unless they made time in their breaks or in between patients. With the surgeons considering this as part of their profession, it meant that we were unable to witness an AIS-1 preparation until our second to last day in the field. Regardless of the surgeons' considerations of professionalism by taking work home, their perception of AIS-1's use in practice was unequal to the intention of it. It was not clear to the surgeons where the extra time for the patient would come from, as they experienced AIS-1 predictions occupying more of their time. We elaborate with the intended use of AIS-1, being a support for the surgeons in their decision process, by creating change in patients' trajectories. This we find as constituting a mediation of the experience of patients as the change in patients’ trajectories are being mediated through AIS-1. Through our observations, we saw how there was a lack of clarification on the intended use of AIS-1 in order to avoid any confusions around the intentions of the model.

To summarise, the surgeons found annoyance in the deployment of AIS-1 mainly due to the technical difficulties attributed to logging into the AIS-1 interface of VMWare Horizon. They further expressed issues with access to AIS-1 in comparison with their known routines of logging into e.g., SP, stating that AIS-1 was an *ancient system*. We saw this as due to the lack of information in terms of the extra codes needed for accessing AIS-1. Accessibility and user-friendliness were noticed as key factors in the surgeons’ willingness to adopt AIS-1. With Surgeon 2 stating she was not a *computer scientist*, it demonstrated how it requires the surgeons to attain different knowledge outside their speciality, constituting a need for clear information and the training sessions. Lastly, we saw how the integration of AIS-1 into their clinical practice, provided a greater workload. The time used on making AIS-1 predictions, was not equal to the timely aspects of not taking time away from patients, thereby resulting in more work outside their 37-hours.

5.2 Developing and Understanding AIS-1 within the Clinical Practice

The second section of the thesis analysis revolves around the theme of Developing and Understanding AIS-1 within the Clinical Setting. The presented subthemes are surgeons’ interpretation of patients through quantitative data, making sense through Surgeons’ visions, and the fruits of AIS-1

Initiating with surgeons’ interpretation of patients through quantitative data, we look at how surgeons transform their professional knowledge and subjective assessments into quantifiable data. The second subtheme, making sense through Surgeons’ visions, displays how their future visions on the development of AIS-1 contribute to a more complex understanding of the use of AIS-1 within their practice. The fruits of AIS-1, as the last subtheme, we see how AIS-1 can catch patients who previously would have been ruled out, by providing a second chance for undergoing curative elective surgery.

5.2.1 Surgeons’ Interpretation of Patients through Quantitative Data

Surgeon 2 asserted that her long education would be for nothing, if AIS-1 should assume a more decision-making role, rather than the intended support in her decisions. The power of intuition and experience matters (Gupta et al., 2022) and cannot be replaced by AI, as it is the surgeons' knowledge and experience accumulated over time that allows them to disseminate information about their patients and act accordingly in terms of patient treatment plans, something we also observed during our field work. However, it is precisely because of the accumulated experiences of the surgeons that AIS-1 cannot stand alone, as it requires an understanding of the relation between the covariates and their implications for the patients. Preparing an AIS-1 note requires extensive knowledge and understanding of the relation between, not only covariates, but also medical imagery, pathological results, and familiarity with locating further information in SP. With our observed perception of the surgeon's knowledge, we discovered how this configuration of knowledge is what enables them to utilise AIS-1 predictions in relation to the patient's treatment plan.

AIS-1 is not being put in opposition to the surgeon, as the clear organisation of their individual roles has been assigned from the beginning, enabling the surgeons' engagement with patients through AIS-1. Furthermore, the surgeons make use of two classification systems called ASA physical status and WHO Performance score, providing a result of respectively I-IV and 0-4, assessing a patient's health status. These two systems are already subjective estimates transformed into quantitative assessments. With AIS-1 intention to aid with personalised treatment, we wondered how the quantitative inputs in AIS-1, such as ASA and WHO score, as well as the prediction from AIS-1 in percentage and risk strata, affected the surgeons' perception of patients. Through our observations, we found that these difficulties were vocalised and considered, when speaking with Surgeon 2 about how different patients require different propositions to their treatment plan, and how AIS-1 could contribute to that matter:

> *"Of course, some fit better into the boxes than others. And that's nice, since it still provides us with the opportunity to use our professional knowledge as doctors, and we don't just have to click them into a scheme [...] That would be horrible."*
>
> (Interview Surgeon 2, 19/4/23)

What we can see from this quote, is how the surgeon can distinguish in which cases her professional knowledge is still required. In an environment, such as surgery, one could understand that if a patient would be able to fit into a certain box and follow the same treatment plan as 10,000 former patients, that would be the ideal for efficiency's sake. But patients are individuals, who require a specified treatment plan and, as the surgeon acknowledges, cannot be out into a certain box. The professional knowledge comes into play, with the patients who vary from the "norm" so to say, making way for personalised medicine with AIS-1 as a means to provide the perspective of this. But with Surgeon 2 stating "*That would be horrible"* to the schematic patient approach, and the former expression of how her long education would be wasted, we wondered how AIS-1 is supposed to support the surgeons with the angle of personalised medicine. As mentioned, AIS-1 is a CDSS and thereby only meant as a support for the surgeons, and not decision-making on its own. But besides support, we see how AIS-1 has brought a new perspective on the surgeons' practice by offering a new language, from which the surgeons can express their professional knowledge. Besides being able to distinguish, where AIS-1 is lacking skills (hence the quote), it is conveying a quantitative interpretation of subjective entities, being the patients. With the deployment of AIS-1, and through the course of our field work, we noticed progress in how they became more and more accustomed to using AIS-1 lingo, even in non-AIS patient cases. Here a mediation of the new language is constituted through AIS-1, as it was not a part of the surgeon's practice before the integration of AIS-1. The adoption of risk strata groups and percentage predictions as part of a new language, induced a way to quantify non-AIS patients, into the same categories as AIS-1 assigned patients. With this utilisation on a broader spectrum of patients, the surgeons implicitly justified the development of personalised medicine in the Department of Surgery.

Prompted by our presence at three MDT preparations, we asked if the preparing surgeon would make an estimate, from the brief survey of the available patient information in SP, of the patient's strata group. We included it in our field notes, with the intention to sort of "check" if their estimation matched the real prediction at the MDT the following morning - and they often did. Even in cases where they had guessed a patient to be e.g., strata B, and the patient, from the actual AIS-1 prediction, was strata A, the prediction score would be close to the dividing line of the two groups. In the following quote, we see how Surgeon 2 practised her professional knowledge, to make an estimation of the patient's strata group:

> *"She's going to be A or B. Because T1, and no lymph nodes, that looks ill, but T1 cancer, then it's early, and no comorbidities, so she's an A [...]"*
>
> (Interview Surgeon 2, 19/4/23)

Comparing to our field notes from the MDT on the 20th of April, we noted the following:

> P1 (Patient 1):
>
> [Surgeon 2] estimated P1 to be A or B
>
> The radiologist says it's difficult to see the tumour. (The radiologist) Looks at the same spot as [Surgeon 2] showed us yesterday at the preparation.
>
> Strata: 1.18%, B
>
> (Field note from MDT. 20/4/23)

For clarification, strata A has predictions below 1%, and strata B has from 1-5% (see figure X in section 2.1.2), meaning that her estimation was miscalculated by 0.18%. This can have a higher significance, if the patients were to score on the edge of being B or C, or more severe in the case of strata C or D groups. This observation connected our very first experience of the MDT on the 16th of January, before the deployment of AIS-1, to how it impacts, not only the MDT's, but the surgeons' ability to exercise their professional knowledge as well. Visible in the above quote of the interview with Surgeon 2, she used a professional, clinical jargon, such as *T1 cancer*, *ill lymph nodes* and *comorbidities*. Some of them can be transferred to other areas of specialisations, but articulated within the clinical setting of CRC surgery, these words have a specific meaning, and a specific resolution in terms of treatment strategy. We hereby accentuate that a certain clinical and professional knowledge is a necessity to translate the patient's information into a meaningful and cohesive treatment plan, thereby underlining the surgeons' position in the use of AIS-1 as well. In the surgeon's explanation of her estimated prediction, she clarifies e.g., that *T1* means a tumour in the early stage, giving us the opportunity to assimilate the knowledge she has, to the reasoning of her final estimation. Knowing the language of the AID-SURG project, strata groups, and prediction scores are intended to initiate tailored interventions of care, commits us to have a specified knowledge, to which we can interact with the surgeons. However, we remain outsiders of the clinical jargon and its implications used by surgeons, as this requires an extended field work concerning their practice as a whole. AIS-1 becomes the language we share, and from which we, us and the surgeons, can converge a common understanding of the patient. The effect the quantification has on the surgeons' professional knowledge can be seen in the two-edged attitude they have towards AIS-1. On the one hand, they are reluctant to its sudden appearance in their practice. The reluctance occurred in their immediate annoyance, with it taking a larger chunk of their time, in contrast to what they experience the model can compensate for in return. On the other hand, they implicitly ascribe AIS-1 with a level of trust, in terms of translating their professional knowledge into a general quantifiable answer, as well as strengthening the knowledge they have achieved through clinical experience. Upon the latter, the perception of trust, implicit or not, can be identified as a significant ethical reflection in the implementation of AI and ML in surgeon-patient relations.

5.2.2 Making sense through Surgeons' visions

Moving on, we observed how the immediate feedback on what the model compensated for in their practice, provided the foundation for the following section, as we elaborate on the surgeons' proposals for the development of AIS-1.

> *"When it gets this complex, then I think we can use it for something, then I believe we will get some value out of it. Right now, it is so simple, that our brains can keep up."*
>
> (Interview Surgeon 1, 29/3/23)

During the training session on the 16th of January, the Lead Data Scientist stated that AIS-1 would remain in its current static form with no room for development within the first year of deployment. This, along with AIS-1 being perceived as nothing, but a consumer of time, shaped the surgeon's initial encounter with the model. In the quote by Surgeon 1 from the 29th of March, we saw how he believes the model to be too simple and that it was only by adding more complexity to the model that real value could be attained. However, through the ongoing experience with AIS-1, we saw how the surgeon's encounter had changed over time, becoming more accustomed to AIS-1. We noticed a change in the surgeon’s attitude from that of annoyance to seeing the possibilities offered to him.

Through our peer-training, we experienced how each surgeon had a vision of what they believed would transform AIS-1 into a more usable model for them in the future. Firstly, Surgeon 3 expressed an interest in seeing the one-year mortality rate brought down to a 30-day mortality and went on by saying that a lot can happen to the patient within one year. We see how this entails a low level of complexity, as the surgeon’s suggestion is focused on the model's timeframe of the prediction, rather than changing covariates. However, he is still reflecting on the limitations offered to him by the one-year mortality, and so finds more value in a more immediate time frame of 30 days.

Elaborating on the previous point and adding more depth, Surgeon 1 expressed that he would like to see more covariates, particularly on the biology of the tumours and immunology levels. In our observations at the MDT preparations, we saw how the surgeons often watched through CT and MRI imagery, to get an impression of the severity of a tumour. This proposal would provide a deeper level of complexity offered by AIS-1, as support in areas outside their immediate expertise. Surgeon 2 agreed that a shorter prediction timeframe would benefit, though she proposed a 90-day mortality rate, as she deemed 30 days to be too short. She further expressed an interest if AIS-1 could aid her in predicting the risk of an anastomotic leakage. This would support her in the case of offering the choice between intestinal continuity (anastomose) or a stoma to her patients. This was also presented in our problem analysis as there was a 20-25% risk of relapse in the first 5 years post-surgery (Vogelsang & Gögenur, 2018). With this vision for AIS-1, we see an even more complex level, as it would advance to support in predicting the risk of a surgical intervention. Here, she wished to make significant changes in the core setup of AIS-1’s current mortality prediction capability, to a prediction on a specific surgical intervention instead. All three visions enclose the surgeons’ attitudes towards the future development of AIS-1 within their practice. The surgeons' ability to make proposals for the development of AIS-1, shows us that they are moving towards an acceptance of the technology’s presence in their practice. With their sequence of future improvements, they attribute AIS-1 with a greater potential than previously detected through this analysis.

We saw a progression in the perception of AIS-1’s capabilities, evolving throughout the pilot project phase. This was showcased through their reflections, developing from their login complaints to the above reflections on the future development of AIS-1. We saw how they were adapting the opportunities of bringing AIS-1 into their workflow, through its contributions as a CDSS. This was also seen, in our literature review, as an advantage in the use of AI in healthcare. Using a CDSS was identified as a means to improving the surgeons' workflow, as it assists in specifically decision-making processes (Grote & Berens, 2021). We discovered how the deployment and integration of AIS-1, generated a new awareness in the surgeons through their reflections on both their normal practice, and the use of AIS-1. By deploying AIS-1 in CRC surgery, it made way for entering Big Data into their practice, providing new perspectives on their practice, to reflect on. This was also pointed out by Surgeon 1, when we addressed his willingness to make predictions, even if it meant he had to do it as homework, as we previously described as part of their practice:

> *“[...] we want to leave the surgery a better place than when we arrived, so we would like to do things like this, [...] I mean, if it makes sense, then we would like to do it. And with all of this Big Data and personal medicine, it makes sense in several cases, and we would like to have an impact on that. So, we hope to point towards something that will be applicable in real life, right.”*
>
> (Interview Surgeon 1, 29/3/23)

By the introduction of AIS-1 into the surgeon’s practice, we experienced the initial stubbornness towards the model. As time went by, the surgeon began to see how the perspectives of AIS-1 and Big Data could benefit through the predictions. With Surgeon 1 saying “*I mean, if it makes sense, then we would like to do it”*, it is evident that thorough information on the purpose of AIS-1 can make a great change in the surgeons’ adoption of the model. Observed through our various field trips to ZUH, we saw how different surgeons were involved in the process at different times. Surgeon 1 was present on the 16th of January at the first AIS-1 introduction. He further told us that he, before this, had helped the Data Science Unit by filling out a questionnaire about covariates to be included in the model. In the above quote, along with his contributions to the different parts of AIS-1’s development and launch, has affected Surgeon 1’s ability to reflect on AIS-1. In his vision of AIS-1 this sentiment is further expressed in Surgeon 1’s quote whereby he expressed "*we want to leave the surgery a better place than when we arrived”* and so sees how the application of AIS-1 can shape future possibilities offered by AIS-1 and by extension possibilities that can benefit future patients. Together with the surgeon’s perception of AI’s entry in their field, we saw his wish for making an impact on this development as well. Pointing towards the applicability of AIS-1 in other areas shows the broader scope the surgeon has on the general development of AI in healthcare. Here we expand this point with the recent AUH cancer case (Steenberger, 2023), as an area that could benefit from the implementation of an AI such as AIS-1. Furthermore, we observed how integration of such a model requires a thorough training and information on both the model's structure and its use in practice. We saw how the surgeon’s reflection provided an awareness for AI to become a more integral part of their work in the future, meaning that with his present knowledge of AIS-1 he finds the use of AIS-1 meaningful. We see this as an example of mediation.

We observed how all three surgeons developed a more constructive attitude to the deployment and use of AIS-1. Stated in the above section, Surgeon 1’s willingness to take assignments home and for him to endure these initial difficulties of AIS-1 was due to the wish to leave CRC surgery in a better place than where they found it. However, this does not imply that the surgeons were not still annoyed with the added workload associated with the model. This had become a more secondary focus as they were now more at the point where they recognised AIS-1’s potential and room for development.

5.2.3 The fruits of AIS-1

Summing up the surgeons’ experience with AIS-1, it was clear from the beginning of our field work that the surgeons were hesitant over the deployment of AIS-1. On this matter, Surgeon 1 stated that they were unable to *“harvest the fruits of this already”*. Seen as a time-consuming technology and the initial problems with the login process, little value was seen in what AIS-1 had to offer the surgeons. However, over the course of the field work we noticed a change in the surgeons' attitude as the routines of opening and filling out the AIS-1 interface became less of an issue. Incorporating a familiarisation with the model, we observed how stratifications became a more integrated part of the MDTs. Here we see how the reinterpretation of the patient through the mediation of AIS-1 is seen in multiple social situations, such as the MDT.

A crucial aspect of the deployment of AIS-1 was the model's ability, in association with the AID-SURG project, to enable more fragile patients the opportunity of curative elective surgery. This we saw as the intended use of the model and aligned well with a previous statement from the Head of Research during the training session, stating that the model should *“change patient trajectories”*. The prediction in itself is a form of personalised medicine, as the prediction score takes the known variables of the specific patient and makes a prediction relevant for this specific patient's outcome. In this sense, AIS-1 changes the patient’s trajectory by offering an optimised treatment plan by comparing the patient's data with the statistical data. In our interview with Surgeon 1, if AIS-1 constituted a prioritisation of patients, he told us that a common understanding before the deployment of the AID-SURG project and AIS-1, was that:

> *“Some (patients) are ruled out when they are over 80 years old, even though there is nothing wrong with them, there are just some things that rule them out [...]”*

(Interview Surgeon 1, 29/3/23)

Patients were ruled out due to their fragility, as surgeons had this shared understanding, that patients above 80 years old, would not be able to undergo surgery with a worthy result afterwards. A wrong assessment from the surgeons of performing surgery or not can have a fatal outcome for a patient. Throughout our observations at the MDTs, we noticed how surgeons discussed patients' fragility and their ability to recover from a surgery or not. This was both present for AIS-1 assigned patients, and ‘normal’ patients. AIS-1 patients were at times changed back to being normal patients, as the MDT discussions ended in a change of the patients' status from surgical to non-surgical treatment. By this, we saw how the multidisciplinarity of MDT’s came into effect as patients were discussed from both a surgical, pathological, radiological, and oncological perspective, and how these different professions’ knowledge was used to provide the best suggestion for treatment. They could transfer a patient, initially referred to the department of surgery, to the oncological department, if it was deemed more effective for the patient's restoration of health. In extension of this knowledge sharing notion of MDTs, we involve Surgeon 1’s further utterance of the above quote the impact of AIS-1 prioritisations, by saying:

> *“[...] it’s more a stratification of the patients' fragility, where the ones who are now at the back of the queue, previously would have been completely left out of this queue.”*
>
> (Interview Surgeon 1, 29/3/23)

With this statement, we see exactly what the Head of Research had stated, that AIS-1 should change patients' trajectories. AIS-1 constitutes that fragile patients get a second chance, instead of being denied surgery, they now have the opportunity to receive and recover from CRC surgery. With the deployment of AIS-1, we observed how the surgeons’ practice changed drastically in terms of patient treatment. Through the model's quantitative outcome, we saw the benefits of decision support and how this aided in assessing the one-year mortality of patients. In addition, the support also lifted a part of the surgeons’ burden from their shoulders when ruling patients above 80 years out of surgery. By further placing these fragile patients in strata groups, it helps not only surgeons, but all the involved care personnel to know what initiatives are needed to ensure the patient's restoration of health. It was evident in such types of cases, where AIS-1’s interpretability of Big Data came into play and thereby had a significant outcome for both surgeon and patient. With the processing of DCCG data into AIS-1 predictions, the surgeon was equipped with previous patients' surgical histories, and as AIS-1 interpreted it could compare their current patient through its prediction. For the fragile patient, this meant that they were being assessed up against the statistical odds for their recovery of surgery, in comparison with a multitude of similar patients regarding age and performance status. With this comparison, through the prediction, patients could be considered to undergo surgery, rather than being ruled out considering their age. As for the patients, we see how the AID-SURG initiatives are already a valuable resource, for changing their trajectories.

Despite being in its pilot phase, the potential for AIS-1 is recognised through the surgeons’ reflections on its development. Recognised by Surgeon 1, he sees AIS-1 as a possible future collaborator to support them during the MDTs, as an additional discipline. In terms of AIS-1 the surgeons reap the benefit of it easing the decision-making burden from their shoulders, through its supportive setup. Even though they are pleased by using their professional knowledge, at times it is down to minor values of covariates that could alter the prediction outcome. Through this analysis, we observed how they acknowledged the decision support AIS-1 could provide in such distinct cases, and thereby be a contribution to their professional knowledge. Together with the surgeons’ perspectives of adding more complexity and variety of knowledge into the model, the usability of AIS-1 becomes more apparent, thus ensuring the continued sustainability of AIS-1.

In summary, we now know that filling out AIS-1 is more than just copy-pasting information from SP into the interface. It requires a clinical understanding of the relation between the covariates and their implications for the patients' treatment plan. The understanding of this means that surgeons are not dispensable, but rather are a necessity for the interpretation of the predicted score to be applicable to the clinical context. The surgeons, now past the initial technical difficulties, see both the potential and future of AIS-1 and so add to the sustainability of AIS-1 by compiling proposals intended for the model's future. With these factors in mind, the surgeons recognise the role of AIS-1 as to embrace non-AIS patients. Here we can see how the mediation through AIS-1 extends to patients beyond non-AIS patients. Our observations further demonstrated how their reflections of their use of AIS-1, can expand beyond the borders of their department.

6. Discussion

As presented in the analytical framework chapter, we draw on a post phenomenological understanding of our field and data. This understanding is rooted in the mediating role of AIS-1 in the relation between the surgeons and patients and evaluates these relations and their meaning for integrating a model such as AIS-1 into the clinical practice of CRC surgery. The following discussion will contribute to answering the thesis's problem statement:

> *How can the experiences of Colorectal Cancer surgeons shape the continued use of AIS-1 in the clinical setting? And how can these experiences translate into knowledge for the sustainability of AIS-1?*

Our analytical results are being discussed, against literature review findings and the presented extended literature.

6.1 Discussion of development and understanding of AIS-1 in the clinical setting

In this section, we discuss the development and understanding of AIS-1 in the clinical setting. The results of the analysis chapter and that of existing literature found within our literature review are discussed. This is supplemented by postphenomenological and ethical perspectives for the understanding of the present role of AIS-1 now and in a larger context. Further, we make recommendations for possible future implications on how AIS-1 may develop to achieve sustainability and usability of the model.

From the onset of our thesis, we explore the surgeons' experiences with the deployment of the new CDSS, as we, from postphenomenology, understand the inseparable nature between technology and the surgeon. This is seen in surgeons' interpretation of the patient through the mediation of AIS-1. Postphenomenology also states that human-world relations are enacted through technologies (Verbeek, 2016), which we correlate to the world of surgeons as enacted through the deployment of AIS-1 into their field.

From the literature, we found that the attitude and acceptance of AI is crucial for the successful implementation as by incorporating users' attitudes can aid in avoiding potential misuse of the technology (Cheng, Li, & Xu, 2022; Esmaeilzadeh et al., 2021; Rundo et al., 2020). Training of staff was also found to benefit clinicians as this would result in a faster implementation whereby clinicians would be more sensitive to potential outcome errors (Cheng et al., 2022; Lynn, 2019). From our analysis, we understand how the initial login and technical difficulties influenced the surgeons' initial perception of AIS-1 and how they were hesitant in their adoption of the model. As such, we could argue whether AIS-1 was successfully implemented, as the surgeon had little choice but to use AIS-1 in its current form. It is beyond the scope of this discussion to clarify if the training session on the 26th of January had the desired effect of creating a successful implementation. However, we can discuss if the training session could be considered to be a real training session.

Through our participation in the training session and observations, the training session served more as a presentation of AIS-1 whereby surgeons could ask clarifying questions about possible workflow implications with the integration of the model. Contrary to the training session, we saw that on the 16th of January was where surgeons could experience logging into AIS-1, and finding their codes, thereby constituting more of a training or practice session. From our field work, we observed how surgeons who were both present on the 16th of January and 26th of January had a more profound understanding of the intentions behind AIS-1. Surgeon 1 and Surgeon 3 were both present on both dates, whereas Surgeon 2 was only present on the 26th. Unsurprisingly, Surgeon 2 is the surgeon who during our peer-learning sessions and small talk remained the most critical of AIS-1, this we attribute to a lack of information and training of Surgeon 2. A lack of training could also lead to a lack of transparency whereby the use and explainability behind AIS-1 prediction scores remains unclear and so resulting in a lack of trustworthiness, furthering the lack of adoption of AIS-1 by the surgeons (Lekadir et al., 2022). From our analysis, time, or the lack thereof, was seen as a resource and something that the surgeons spend on MDTs, conference meetings, patient discussions, and out-patient clinics. The practice of surgeons and the amount of time available to them outside their normal practice was limited. This we can relate to a general healthcare issue, by including the recent AUH cancer case. Here the long waiting list, an increase in number of referred patients, lack of personnel and time pressure entails the extended delay in cancer surgery, exceeding the treatment guarantees (Steenberger, 2023). From our attained knowledge, we see that the issue of time constraints could benefit from the implementation of a technology such as AIS-1. Here we emphasise how the stratifications of patients could aid surgeons at AUH with prioritising patients, both in severity of cancer stage, but also with the notion of the initiatives from the AID-SURG project. With the implementation of these initiatives, we see how these could alleviate the lack of personnel, as they offer a framework for the extra care needed by these C and D patients. From this, we foresee the benefits of the department at AUH being able to allocate the necessary resources in the handling of patients (Esmaeilzadeh et al., 2021). As presented in the analysis, Surgeon 1 expressed how AIS-1 had helped in catching patients, who previously would have been disregarded for surgery. Without further insights concerning the AUH cancer case, we can neither reject nor confirm if this would aid their current problems but find it worth noticing in the connection of future and broader perspectives of AIS-1. That being said, the importance of training and information is, based on our understanding, crucial for the implementation of CDSS within the clinical practice and as such proper resources should be allocated to train and inform the users of a CDSS. In this regard, an extra session for surgeons who were not present on the 16th of January would have benefitted the surgeons and so helped in the alleviation of potential misuse and adoption of AIS-1.

Misuse is also stated in the literature as one of the seven risks and should be understood as the incorrect usage of AIs that may lead to incorrect medical assessment and decision-making processes (Lekadir et al., 2022). An incorrect medical assessment is not possible for us to judge as we lack the medical expertise necessary, and AIS-1 does not have any decision-making capabilities. The gradual adoption of AIS-1 was seen in the surgeon's development of a new routine due to regular use of the model. With the increased familiarisation of AIS-1 the surgeons were less inclined to be annoyed by the model and instead were able to see its potential. However, as also noted by Surgeon 2, misuse of AIS-1 could still occur as she pointed out the potential pitfalls of adding an extra space in the login process. However, as our analysis pointed out, the surgeons' attitudes changed over time whereby they became more familiar with the workings of AIS-1 and how the model could add to their existing practice. This is also reflected through their visions for AIS-1 and how a CDSS could benefit their field. In this regard, future versions of AIS-1 that accommodate the surgeons' desires for changes to the model, may supersede the current model and so attribute AIS-1 more decision-making capabilities. Here we identify a future risk of automation bias and deskilling. Surgeons' skills are rooted in attained experience (Gupta et al., 2022) and used to perceive symptoms of patients and so act on them (Ploug & Holm, 2022). This is something that we also noticed during our MDT observations, where surgeons would discuss the best course of treatment based on their experience with other similar and previous patient cases. Although the risk of automation bias and deskilling as future consequences are difficult to predict with updates to the AIS-1 model, there may still be the risk of overreliance on AIS-1. In our analysis, the surgeons were able to predict the patients' strata group very close to that of where AIS-1 would stratify the patient. This is no surprise, as the covariates used within AIS-1 are similar values used by the surgeons when discerning information about their patient. As the prediction score of AIS-1 matches so closely to that of the surgeons, it could possess a risk that the surgeons will unwittingly stop relying on their intuition and so just use the prediction scores. Thus, the surgeons may develop an overreliance on the prediction scores and a deskilling occurs. In this regard, we maintain the importance that the surgeons remain critical of the prediction outcomes of AIS-1 and to continue to rely on their own clinical judgement.

Should AIS-1 attain a larger degree of decision-making capabilities, it could also blur the line of accountability as to who is then responsible for medical errors. As of the time of writing the thesis, the surgeons were required to check the box for *"I understand that the final decision rests with the healthcare professional"* before being allowed by the system to proceed to the final prediction score. In this case, the surgeons are held systematically responsible for the errors of AIS-1 which may result in the reluctance in the adoption of future technologies such as AIS-1 (Lekadir et al., 2022). In addition, a multi-actor problem exists as there are multiple-actors involved in both the development, implementation, and use of AIS-1, thus making the identification of responsibility difficult (Lekadir et al., 2022). We saw these multiple-actors involved being the Data Science Unit, CSS consulting, project management, and surgeons. However, according to our literature there is a distinction regarding responsibility whereby clinicians cannot be held responsible for software malfunctions and developers cannot be held liable for misdiagnosis (Denecke & Baudoin, 2022; Esmaeilzadeh et al., 2021). Recommendations in this area are outside the confines of this discussion. However, we recognise that regulatory authorities are needed in the regulation of AI in healthcare as to minimise potential harm to patients.

From the above notions regarding accountability, we raise an ethical query, as the surgeons are required to use AIS-1 in their practice to help support their decisions. By extension, they are required to take responsibility for the prediction scores predicted by AIS-1 as they are required to check the box. As noted in section 2.1.3 the data from which AIS-1 is based on national databases, and so it assumes the characteristics of the population in this data. However, we argue that because the data was only assumed to contain characteristics of the population and was not highlighted in greater detail during our field work, that surgeons are taking responsibility for prediction scores based on incomplete data. In addition, we cannot say with any certainty what implications the adoption of AIS-1 would be, if the surgeons were made aware of this fact, but we are aware that none of the covariates in AIS-1 are based on socio-economic data. If we assume this statement to be true, then surgeons may be held responsible for incorrect medical assessments based on the prediction scores. This becomes even more of an issue if we assume, as previously stated, that an overreliance of AIS-1 may occur as the prediction resembles the surgeons' own assessments. If AIS-1 is to support the surgeons' decision regarding treatment of patients, but does so on incomplete data, how then can the surgeons trust that the prediction score to match their assessments? As this thesis is confined to the pilot phase of the implementation of AIS-1 the depth of trust the surgeons attribute to AIS-1 is unknown at this time. However, we know from our analysis that the surgeon does attribute a level of trust in AIS-1's ability to translate their clinical knowledge into a quantifiable result. This is also seen in the acknowledgement of AIS-1's potential to give patients a second chance. This was what we identified in the analysis as the intended use of AIS-1. As the mediation through AIS-1 was able to change the surgeons' perception of patients while at the same time being able to lift a burden off the surgeons' shoulders.

AI also has the potential to change the historical paternalistic patient-surgeon relationship into a shared decision-making due to increased transparency (Lekadir et al., 2022). This is also supported by Lorenzini et al. (2023) where AI can indeed support the shared decision-making paradigm if carefully implemented. However, if attention is not given to how AI may influence doctors' and patients' communication and autonomy, this could lead CDSS back to a paternalistic relation between patient and surgeon (Lorenzini et al., 2023). This can also be seen in a previous statement where we highlight how the covariates in AIS-1 do not contain socio-economic data and as such, we do not see the mediation of patients' values or preferences expressed in the prediction score. Within the shared decision-making paradigm, respect for patients' autonomy is considered a professional obligation (Lorenzini et al., 2023). Although it may be considered to be a shared value to maximise the lifespan of patients by offering the best treatment, some patients with terminal diseases may opt for palliation rather than having to undergo chemotherapy or an operation. This was noticed a few times during the MDT’s where surgeons would discuss if it would be ethically right to submit the patient to further treatment. Using AI to help support diagnostics means that the AI’s suggestion is part of the evaluation. By this, it raises the question of who is responsible for the decision-making, thus running the risk of a paternalistic relation as an algorithm knows-best situation (Lorenzini et al., 2023). AIS-1 does not have diagnostic capabilities but is acknowledged by Surgeon 1 as a possible new discipline within the MDT. Here there is a possible future scenario where AIS-1 as discipline could have the same properties as a diagnostic AI and so would run into an AIS-1 knows-best situation in terms of overreliance. From this position, we recognise the importance of a shared decision-making paradigm as an ethically responsible approach as this allows the patients to exercise their autonomy and values.

Although this thesis is confined to the experience of surgeons and how this can be translated into sustainability for AIS-1, it is important to recognise that the receiver of the prediction scores is the patient. As such, through our analysis and through the surgeon's mediation of AIS-1 we see the implications of possible future versions as having an impact for patients and so recommend that future versions of AIS-1 be kept in the same format as a CDSS. This also aligns with the report by *National Strategy for Artificial Intelligence* where they emphasise how AI should be used to supplement decision-making and not compromise patient values (Ministry of Finance & Ministry of Industry, Business and Financial Affairs, 2019). Furthermore, the surgeons clinical judgement in evaluating the prediction score and their presence in promoting patient preferences and values is invaluable as AI lacks human touch and some patients preferring human-human contact (Gupta et al., 2022; Lynn, 2019). As such, through our analysis and through the surgeons’ mediation, we hope to have opened an avenue for future research in the deployment of CDSS within the clinical practice.

7. Conclusion

The following is the result of the generated empirical data derived from our selected ethnographic methods, which have formed the backbone of the analysis in Chapter 5. Our analytical points have been discussed up against the presented literature review findings, as well as further extended literature. This has all resulted in the following conclusion of our raised problem statement:

> *How can the experiences of Colorectal Cancer surgeons shape the continued use of AIS-1 in the clinical setting? And how can these experiences translate into knowledge for the sustainability of AIS-1?*

AI in healthcare is becoming more prevalent as time goes on. In the report *National Strategy for Artificial Intelligence,* AI is seen as being able to aid in analysis, understanding and improved decision-making. In this thesis, we see how AIS-1 as a CDSS can create change in patients' trajectories through the interpretation of Big Data by offering patients a second chance. Furthermore, AI has the potential to reverse the paternalist patient-surgeon relation into a shared decision-making paradigm. However, the implementation of AIS-1 into the practice of surgeons has not been without its problems.

The lack of information and training has had an impact on the adoption of AIS-1 and shaped the surgeons' attitude towards the model. This lack of information and training was seen present in the technical difficulties of logging into the AIS-1 interface through VMWare Horizon. Furthermore, the use of AIS-1 required considerable knowledge in understanding the relation between the covariates used within the model and its implications for the patients.

It can hereby be concluded that the experience of using AIS-1, formed a familiarisation of the model, and thereby shaped the surgeons' perception and their willingness of adoption in terms of the continued use of AIS-1. It was further extended, that with their adoption of AIS-1, they recognised the model's potential, by implying future visions of the model. We further conclude that these visions have encompassed the complexity of the surgeons' field and so should be considered as part of the surgeons' development of the sustainability of AIS-1 in the future. A point of concern in this consolidation is that great patient care must be taken into consideration to ensure that future versions of AIS-1 remain as a CDSS to minimise potential misuse and overreliance of the model.

It is beyond the scope of this thesis to predict the future outcomes of AIS-1 and future implications for patients. We do, however, recommend that future versions of the model reflect patients' values and preference, thereby recognising the patients' autonomy. During this thesis, we have concerned ourselves with a postphenomenological standpoint, to make an account of the surgeons' experiences with AIS-1. With our investigation of the inseparability of surgeons and AIS-1, we saw this was present in the mediation through AIS-1, as it enabled the surgeons with new perspectives of the patients.

Understanding how the mediating role of AIS-1, were of great significance for the surgeons' understanding of patients, we see how our research contributes to the future of the deployment of CDSS by offering knowledge on the experiences of surgeons in a clinical context.

References

acm.org. (n.d.). About the ACM organization. Retrieved from https://www.acm.org/about-acm/about-the-acm-organization

Beam, A. L., & Kohane, I. S. (2018). Big data and machine learning in health care. *JAMA : The Journal of the American Medical Association, 319*(13), 1317-1318. doi:10.1001/jama.2017.18391

Bernard, H. R. (2006). *Research methods in anthropology - qualitative and quantitative approaches* (Fourth Edition ed.) AltaMira Press.

Bertrand, A., Belloum, R., Eagan, J., & Maxwell, W. (2022). How cognitive biases affect XAI-assisted decision-making: A systematic review. Paper presented at the doi:10.1145/3514094.3534164 Retrieved from https://hal.telecom-paris.fr/hal-03684457

Braun, V., & Clarke, V. (2006). Using thematic analysis in psychology. *Qualitative Research in Psychology, 3*(2), 77-101. doi:10.1191/1478088706qp063oa

Bräuner, K. B., Rosen, A. W., Tsouchnika, A., Walbech, J. S., Gögenur, M., Lin, V. A., . . . Gögenur, I. (2022). Developing prediction models for short-term mortality after surgery for colorectal cancer using a danish national quality assurance database. *International Journal of Colorectal Disease, 37*(8), 1835-1843. doi:10.1007/s00384-022-04207-6

Cheng, M., Li, X., & Xu, J. (2022). Promoting healthcare workers' adoption intention of artificial-intelligence-assisted diagnosis and treatment: The chain mediation of social influence and human-computer trust. *International Journal of Environmental Research and Public Health, 19*(20) doi:10.3390/ijerph192013311

Columbia University. (2022). Understanding MeSH terms and navigating the MeSH database. Retrieved from https://library.cumc.columbia.edu/kb/understanding-mesh-terms-and-navigating-mesh

Daronnat, S., Azzopardi, L., Halvey, M., & Dubiel, M. (2021). Inferring trust from users' behaviours; agents' predictability positively affects trust, task performance and cognitive load in human-agent real-time collaboration. *Frontiers in Robotics and AI, 8*, 642201. doi:10.3389/frobt.2021.642201

Denecke, K., & Baudoin, C. R. (2022). A review of artificial intelligence and robotics in transformed health ecosystems. *Frontiers in Medicine, 9*, 795957. doi:10.3389/fmed.2022.795957

elsevier.com. (n.d.). Embase - A biomedical research database. Retrieved from https://www.elsevier.com/solutions/embase-biomedical-research

Emani, S., Rui, A., Rocha, H. A. L., Rizvi, R. F., Juaçaba, S. F., Jackson, G. P., & Bates, D. W. (2022). *Physicians' perceptions of and satisfaction with artificial intelligence in cancer treatment: A clinical decision support system experience and implications for low-Middle–Income countries* JMIR Publications Inc. doi:10.2196/31461

Esmaeilzadeh, P., Mirzaei, T., & Dharanikota, S. (2021). Patients' perceptions toward Human–Artificial intelligence interaction in health care: Experimental study. *Journal of Medical Internet Research, 23*(11), e25856. doi:10.2196/25856

Flora, J., & Andersen, A. O. (2018). Taking note: A kaleidoscopic view on two, or three, modes of fieldnoting. *Qualitative Research, 19*(5) doi:10.1177/1468794118782897

Grote, T., & Berens, P. (2021). *How competitors become collaborators—Bridging the gap(s) between machine learning algorithms and clinicians* Wiley. doi:10.1111/bioe.12957

Gupta, A., Singla, T., Chennatt, J. J., David, L. E., Ahmed, S. S., & Rajput, D. (2022). Artificial intelligence: A new tool in surgeon's hand. *Journal of Education and Health Promotion, 11*(1), 93. doi:10.4103/jehp.jehp_625_21

Hansen, D. L., Shneiderman, B., Smith, M. A., & Himelboim, I. (2019). Chapter 11 - twitter: Information flows, influencers, and organic communities. In D. L. Hansen, B. Shneiderman, M.

A. Smith & I. Himelboim (Eds.), *Analyzing social media networks with NodeXL: Insights from a connected world* () Morgan Kaufmann. doi:10.1016/B978-0-12-817756-3.09988-X

Jacobsen, B., Tanggard, L., & Brinkmann, S. (2015). Fænomenologi. In M. Shilling, & D. Steiness (Eds.), *Kvalitative metoder* (pp. 217-239) Hans Reitzels Forlag.

Lazar, J., Feng, J. H., & Hochheiser, H. (2017). *Interviews and focus groups* Elsevier. doi:10.1016/B978-0-12-805390-4.00008-X

Lekadir, K., Quaglio, G., Garmendia, A. T., & Gallin, C. (2022). *Artificial intelligence in healthcare applications, risks, and ethical and societal impacts.* ().

Lin, V., Tsouchnika, A., Allakhverdiiev, E., Rosen, A. W., Gögenur, M., Clausen, J. S. R., . . . Gögenur, I. (2022). Training prediction models for individual risk assessment of postoperative complications after surgery for colorectal cancer. *Techniques in Coloproctology, 26*(8), 665-675. doi:10.1007/s10151-022-02624-x

Lorenzini, G., Arbelaez Ossa, L., Shaw, D. M., & Elger, B. S. (2023). Artificial intelligence and the doctor–patient relationship expanding the paradigm of shared decision making. *Bioethics, 37*(5) doi:10.1111/bioe.13158

Lynn, L. A. (2019). Artificial intelligence systems for complex decision-making in acute care medicine: A review. *Patient Safety in Surgery, 13*(1), 6. doi:10.1186/s13037-019-0188-2

Ministry of Finance, & Ministry of Industry, Business and Financial Affairs. (2019). *National strategy for artificial intelligence.* ().

National Library of Medicine. (n.d.). Pubmed overview. Retrieved from https://pubmed.ncbi.nlm.nih.gov/about/

Oerther, S. (2021). Analysis methods in hermeneutic phenomenological research: Interpretive profiles. *Chinese Nursing Research, 7*(4), 293-298. doi:10.2478/fon-2020-0038

Papadopoulou, E., & Exarchos, T. (2022). *An ethics impact assessment (EIA) for AI uses in health & care* ACM. doi:10.1145/3549737.3549755

Ploug, T., & Holm, S. (2022). The right to a second opinion on artificial intelligence diagnosis—Remedying the inadequacy of a risk-based regulation. *Bioethics, 37*(3) doi:10.1111/bioe.13124

Rosenberger, R., & Verbeek, P. (2015). *Postphenomenological investigations essays on human-technology relations* Lexington Books.

Rundo, L., Pirrone, R., Vitabile, S., Sala, E., & Gambino, O. (2020). Recent advances of HCI in decision-making tasks for optimized clinical workflows and precision medicine. *Journal of Biomedical Informatics, 108*, 103479. doi:10.1016/j.jbi.2020.103479

Spradley, J. P. (1979). *The ethnograhpic interview* Harcourt Brace College Publishers.

Spradley, J. P. (1980). *Participant observation*. United States of America: Holt, Rinehart and Winston.

Steenberger, A. (2023). Mave- og tarmkirurgisk afdeling i aarhus kæmper med mange ting. Retrieved from https://ugeskriftet.dk/nyhed/mave-og-tarmkirurgisk-afdeling-i-aarhus-kaemper-med-mange-ting

Sundhedsstyrelsen. (2005). *Kræftplan ii - sundhedsstyrelsens anbefalinger til forbedringer af indsatsen på kraeftområdet.* ().Sundhedsstyrelsen.

Thieme, A., Belgrave, D., & Doherty, G. (2020). Machine learning in mental health. *ACM Transactions on Computer-Human Interaction, 27*(5), 1-53. doi:10.1145/3398069

Upol Ehsan, Q Vera Liao, Muller, M., Riedl, M., & Weisz, J. (2021). *Expanding explainability: Towards social transparency in AI systems.* (). Ithaca: Cornell University Library, arXiv.org. doi:10.1145/3411764.3445188 Retrieved from Publicly Available Content Database Retrieved from https://search.proquest.com/docview/2477836709

Verbeek, P. (2016). Toward a theory of technological mediation - A program for postphenomenological research. *Technoscience and postphenomenology: The manhattan papers* (pp. 1-23) Lexington Books.

Vogelsang, R. P., & Gögenur, I. (2018). *Intenderet kurativ kirurgisk behandling af patienter med kolorektal cancer (2018)*

Wagner, M., Schulze, A., Haselbeck-Köbler, M., Probst, P., Brandenburg, J. M., Kalkum, E., . . . Müller-Stich, B. P. (2022). Artificial intelligence for decision support in surgical oncology - a systematic review. *Artificial Intelligence Surgery, 2*(3), 159-72. doi:10.20517/ais.2022.21

Wang, D., Wang, L., Zhang, Z., Wang, D., Zhu, H., Gao, Y., . . . Tian, F. (2021). *Brilliant AI doctor in rural china: Tensions and challenges in AI-powered CDSS deployment.* (No. 18). Ithaca: Cornell University Library, arXiv.org. doi:10.1145/3411764.3445432 Retrieved from Publicly Available Content Database Retrieved from https://search.proquest.com/docview/2475611046