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Transforming Clinical Decision Support with AI

A qualitative study of factors influencing adoption of Machine Learning enabled systems in healthcare

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ABSTRACT (MAX. 200 WORDS):
Machine learning, alongside other branches of AI have entered an era of rapid growth in several industries including healthcare, creating vast opportunities to advance several aspects of clinical practice. Specific to clinical decision support, despite the immense potential benefits of incorporating machine learning into clinical decision support systems, also known as machine learning enabled clinical decision support systems, there is a gap in literature and research shows that progress of adoption is still falling behind. This paper therefore aims to contribute to existing literature and practice by exploring influencing factors for adoption of these systems. This qualitative study used the TOE-framework as a reference to curate a conceptual research framework, including eight initial factors that guided the empirical research, from conduction of seven interviews with doctors and experts to data analysis. The study concluded that six of the ten examined factors – System Complexity, Transparency, Top Management Support, Regulations, Data Availability and Collaboration were influential, two factors – Technology Readiness and Market Trends were not influential and two factors – Financial Resources and Reliability were inconclusive for the adoption of machine learning enabled clinical decision support systems. Insights generated from this study can serve as a reference point for practice and further research.

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1 Introduction

For many decades, philosophers have tried to understand how a human mind works and the possibility of non-humans having minds (Negnevitsky, 2005). This triggered curious questions like "can computers think?" and ultimately led to some scientists taking up research regarding machine intelligence, with a purpose of developing machines that could recognise patterns, make predictions, learn, and basically have some sort of intelligence just like human intelligence (Negnevitsky, 2005). Whereas some philosophers argued that certain sophisticated intelligent human behaviours such as moral choice, learning, ethics were beyond the scope of machines, other schools of thought believed that machines were capable of doing everything humans can do. In as early as 1950, researchers such as Turing (1950) developed the "Turing imitation game" to demonstrate that machines can indeed pass a behaviour test for intelligence which significantly contributed to the initial development of machine intelligence that later morphed into present day Artificial Intelligence (Negnevitsky, 2005; Turing, 1950).

Artificial Intelligence (AI) as a branch in the domain of computer science, refers to the training of computer algorithms to perform tasks that typically are analogous to human intelligence (He et al., 2019; Russell & Norvig, 2021). AI has entered an era of rapid growth in several industries (Dopico et al., 2016; Oliveira, 2019), with vast possibilities of enhancing everyday lives in several areas, for instance healthcare, education, entertainment, and transportation (Stone et al., 2016). This is further evidenced by a sharp increase in AI related research publications, from 212 indexed globally in 1990 to over 1,153 in 2014 (Niu et al., 2016) and a sharp jump to 31,300,000 between 2016 and 2020 (Statista, 2022). Specific to healthcare and medicine, AI technologies have shown promises and broadening opportunities to aid multiple advancements in aspects such as diagnostics, triage, clinical decision support, treatment selection, planning of surgical procedures and disease monitoring (He et al., 2019; McKinsey, 2020; Yang, Ye & Xia, 2022). Research suggest that use of AI has the potential to perform even better than humans do. This has been evidenced in multiple situations, for example radiologists were outperformed by an algorithm at identifying malignant tumors (Haenssle et al., 2018), precision medicine that helped predict the most suitable treatment protocol for patients given a set of values for attributes (Davenport & Kalakota, 2019), and dermatologists have been outperformed by an algorithm at identifying skin cancer (Haenssle et al., 2018).

There are multiple branches of artificial intelligence such as Machine Learning (ML), Deep Learning, Neural Networks, Natural Language Process (NLP), and Robotics (Goodfellow, Bengio & Courville, 2016; Russell & Norvig, 2021). However, this paper will mainly focus on machine learning. Machine learning is an extensively used branch of AI and refers to the learning of a computer – i.e., an algorithm – using data to understand hierarchal concepts, without the need of explicit programming (Goodfellow, Bengio & Courville, 2016; Yang, Ye & Xia, 2022). Moreover, as there are many areas that have the potential to utilize machine learning in healthcare, this paper will focus on clinical decision support. This was motivated by the potential impact of machine learning enabled clinical decision support systems in transforming healthcare and existing success stories of where machine learning enabled clinical decision support systems have been noted to offer great benefits, such as the ability to use large amounts of data and information extraction from hospital electronic health records to learn from real-world use and provide personalised decision making insights to clinicians plus improve the decision making process through their ability to learn new clinical knowledge and provide intelligent behavioral patterns (Ji et al., 2021).

Traditionally, clinical decision support systems in healthcare are based on the predecessor of machine learning, namely expert systems (Davenport & Kalakota, 2019). These solutions are based on a large set of "IF-THEN" rules, that have been developed with the help of domain experts based on prior successful diagnostics, treatments and prognosis (Lysaght et al., 2019). However, as rules accumulate they tend to overlap, resulting in the system crumbling (Davenport & Kalakota, 2019). These systems are in the process of being replaced by more advanced technologies, such as machine learning, which depend on large amounts of data to train models (Pumplun et al., 2021) that provide better performance and insights. Nonetheless, the adoption of these technologies in healthcare has not been at the same pace as other sectors (Laï, Brian & Mamzer, 2020). Despite all the promises of using machine learning for clinical decision support, and in healthcare in general, the use of these types of solutions in practice is still quite low (Davenport & Kalakota, 2019).

1.1 Research Problem

Since 2020, when the World Health Organisation declared covid-19 a global pandemic (WHO, 2020), there has been a major shift in the adoption and use of digital technologies (Doyle & Conboy, 2020; Wade & Shan, 2020). Firstly, to control the spread of the virus, lockdowns and other stringent social distancing measures were implemented by governments around the world, making the use of digital technologies a preferred and more feasible option (Abed, 2021; Nah & Siau, 2020). Sectors such as education had to move their services to online, companies had to enable their employees to work from home, retail stores had to quickly scale up online capabilities and industries had to find new automated ways of maintaining production with a limited number of staff (Abed, 2021; Nah & Siau, 2020). The healthcare sector was not spared from this, it was rather at the centre of a record high influx of cases and needed to leverage technology to efficiently deal with the situation (Wang et al., 2021). This triggered a sharp increase in the use of technologies such as machine learning for vaccine development, contact tracing, diagnostics, and clinical decision support (Wang et al., 2021). Despite these drastic changes, researchers still argue that the adoption of machine learning and other AI technologies in healthcare is still lagging, compared to other industries (Davenport & Kalakota, 2019; He et al., 2019).

From a broad AI perspective, different approaches to investigating factors worth considering in the adoption of AI in organization have been researched and documented. Through this, factors such as data quality, regulation and legislation have been addressed (Hamm & Klesel, 2021). Research has further shown that legislation and regulation pose a challenge in adopting AI as healthcare is a heavily regulated space (Oliveira, 2019). In Sweden, and Europe, GDPR could slow down the pace of using these solutions in healthcare as it proposes informed consent and clarification of data ownership as minimum requirements (He et al., 2019). Secondly, as there is a dependency on access to medical data, previous research highlighted the challenge of data accessibility due to the heterogenous character of health data (He et al., 2019; Kaushik et al., 2020; Lai, Kankanhalli & Ong, 2021).

Lastly, co-operation and collaboration with health professionals poses various challenges such as trust relationship between health professionals and AI, health professionals' perceptions, and education of health professionals (Asan, Bayrak & Choudhury, 2020; Laï, Brian & Mamzer, 2020; Lysaght et al., 2019; Weber, Knop & Niehaves, 2022).

However, whereas previous research has extensively covered the notion of AI in healthcare from a broader perspective, minimal research has been done in relation to specific branches of AI, such as machine learning, in clinical decision support. As AI is a broad concept, there is need to enrich the existing body of knowledge by addressing gaps in literature regarding specific branches and industry applications that could potentially vary from the generalized AI approach. Additionally, as the covid-19 pandemic has posed changes to the dynamics of many sectors, the need for further exploration of its impact on the healthcare sector is crucial in order to identify factors influencing adoption of new technologies from both broad and specific contexts. This was further motivated by the potential of machine learning enabled clinical decision support systems to enable and translate uncertainty and complexity into practical suggestions that can enhance the clinicians' decision-making process (Asan, Bayrak & Choudhury, 2020; He et al., 2019). Consequently, this paper will focus on exploring the factors that influence the adoption of machine learning enabled decision support systems.

1.2 Research Question

Whereas there has been a drastic increase in the adoption and use of technologies such as machine learning, there is lack of granular level scientific literature to act as a reference point for understanding the factors that influence adoption of machine learning enabled clinical decision support systems. Consequently, to close this gap and provide valuable insights, this thesis will aim at answering the following research question.

What factors are influential when adopting machine learning enabled clinical decision support systems?

1.3 Purpose

The purpose of this thesis, through a qualitative approach, is to explore influencing factors in the adoption of machine learning enabled clinical decision support systems. The aim of this thesis is to identify and describe these influential factors through a theoretical lens based on the Technology-Organization-Environment (TOE) framework. The intended knowledge contribution of this thesis is to further provide a reference point for actors in the healthcare sector planning to adopt machine learning enabled clinical decision support systems, as well as provide insight for further research by providing an answer to the thesis' research question.

1.4 Delimitations

As mentioned, there are multiple ways of using AI in clinical decision support whereas this study is delimited to machine learning enabled clinical decision support systems. This was motivated by the existence of a gap in existing literature, which mainly focusses on AI in general. As healthcare covers a wide range of areas, this study is delimited to healthcare in hospital settings. Lastly, whereas this paper derived multiple factors with potential to influence the adoption of machine learning enabled clinical decision support systems, a selection of eight factors was highlighted and argued for in the theoretical background, mainly due to the limited time constraints.

1.5 Definitions

Technology Adoption: Adoption from an organizational perspective refers to “the assimilation of a product, service or technology new to the adopting organization” (Damanpour & Wischnevsky, 2006, p.272). Specific to technology, Rogers (1983, p.177) refers to it as “a decision to make full use of an innovation as the best course of action available”.

Artificial Intelligence: Whereas there is no single true definition of artificial intelligence, He et al. (2019) refers to it as the training of computer algorithms to perform tasks that typically are analogous to human intelligence. Additionally, Russel and Norvig (2021), argue that a rationality perspective – i.e. algorithms that think and act rationally needs to be considered in the definition.

Machine Learning: Refers to a branch of artificial intelligence that uses data, commonly known as datasets to learn and build hypotheses models that can solve a specific or multiple problems without the need for explicit programming (Russel & Norvig, 2021; Mitchell, 1997)

Clinical decision support systems: Refers to computer systems designed to improve healthcare delivery by supporting clinicians in making optimal medical decisions about individual patients by using patient information, targeted clinical knowledge, medical data, and other health information (Berner & La Lande, 2007; Sutton et al., 2020).

2 Theoretical Background

2.1 Artificial Intelligence

Artificial Intelligence is not a new concept, according to Russel and Norvig (2021), the field dates back to 1943 when present day AI was first conceived by researchers who drew inspiration and knowledge from physiology, functions of neurons in the brain, propositional logic and the Turing machine. Moreover, Russel and Norvig (2021) further noted that there are two main versions to the definition of AI that have been pursued by researchers, particularly when referring to intelligence. While researchers such as He et al. (2019) prefer to define intelligence in terms of fidelity to human performance, there are other researchers who prefer to define intelligence from a rationality perspective. This alternative version moves the focus away from viewing intelligence as building AI models that act or think like humans to AI models that act or think rationally (Russell & Norvig, 2021).

While there are many researchers who contributed to the foundations of AI, researchers in the field have suggested that Turing's vision of creating the Turing test, genetic algorithms, reinforcement learning, and machine learning, that would enable machines to learn as opposed to programming their intelligence was the most influential in advancing the field (Russell & Norvig, 2021). The term "Artificial Intelligence" was however first used by John McCarthy in 1956 during a two-month workshop by ten carefully selected top scientists at the Dartmouth College in Hanover with the aim of finding how to make machines use language, solve problems reserved for humans, and improve themselves (Russell & Norvig, 2021).

In the early years of the field, focus was on proving that machines could do certain tasks and researchers proved this by developing programs such as General Problem Solver (GPS) that imitated human problem-solving protocol, Geometry Theorem Prover that later became a precursor to modern mathematical theorem provers and Draughts that was a precursor to present day reinforcement learning (Russell & Norvig, 2021). However, AI did not really kick off then, mainly because earlier researchers based their AI systems predominantly on *informed introspection* – how humans perform tasks and did not consider *intractability* – complexities beyond microworlds (Russell & Norvig, 2021).

As funding increased in the AI field and researchers got over the 1980 *AI winter* – a period in which AI funding from governments and companies was cut due to failure to deliver on exaggerated promises, machine learning was invented – an approach that was grounded in existing theories, solid experimental methodology and used probabilistic reasoning and experimental results rather than hand-coding. This further bridged the earlier isolation gap between AI and other fields of computer science such as decision theory, statistics, operations research, and control theory (Russell & Norvig, 2021). Moreover, the new AI appreciation of data, optimization, statistical modelling, and machine learning trigged a reintegration with other fields such as robotics, speech recognition, natural language processing and computer vision that had earlier dropped away from core AI (Russell & Norvig, 2021).

2.2 Machine Learning

Machine learning is a field of AI that uses data, commonly known as datasets to learn and build a hypothesis model that can solve a specific or multiple problems without explicit programming (Russel & Norvig, 2021; Mitchell, 1997). With the increased availability of extensive online data, new learning algorithms and theory, machine learning has grown in popularity in healthcare, leading to an increase in adoption of data driven and evidence-based decision making (Jordan & Mitchell, 2015). A machine learning model is essentially trained by feeding it with data to learn and then tested with new scenarios to check it's learning progress. The process mostly involves splitting data into a *training set* used for training the model, a *validation set* use for evaluating the performance of the model(s) to aid with selecting the best performing model and a *test set* to perform a final unbiased evaluation of the selected "best" model (Domingos, 2012; Russell & Norvig, 2021). The models can either learn from scratch with no prior knowledge or from using transfer learning which involves transferring knowledge from another domain or already existing model. This kind of learning can be inductive where the model uses a set of observations to derive a general rule or deductive where are model bases predictions on a set premises (Russell & Norvig, 2021). As seen in figure 2.1 below, there are three main approaches to machine learning – supervised learning, unsupervised learning, and reinforcement learning.

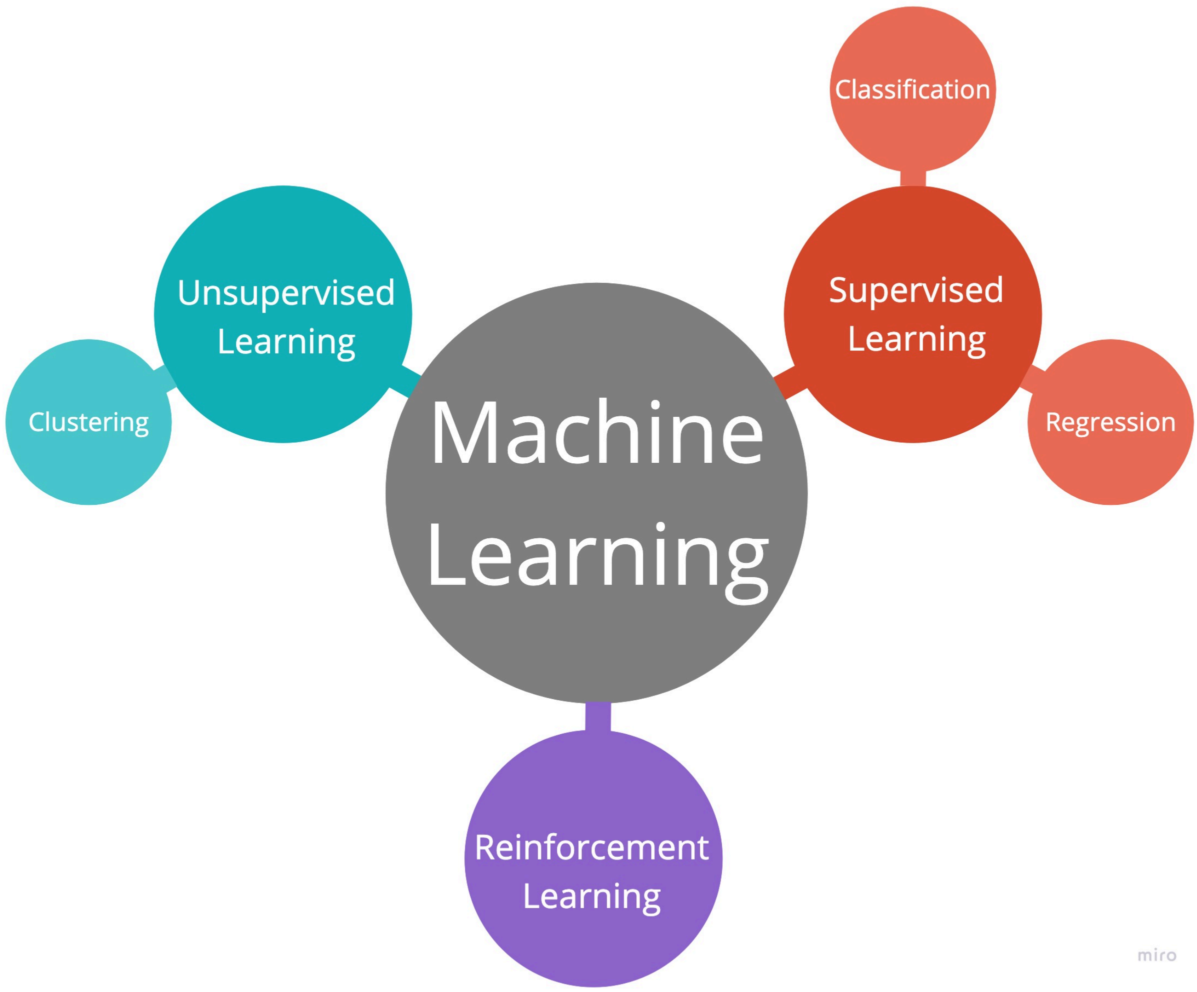

Figure 2.1 – Overview of Machine Learning, adapted from Mihailescu (2022, slide 18)

2.2.1 Supervised Learning

This machine learning approach uses labeled datasets to observe a set of inputs and corresponding outputs, learn overtime and thereafter perform tasks such as predicting outcomes or classifying data (Han, Pei & Kamber, 2011; Russell & Norvig, 2021). The commonest types of supervised learning algorithms include *Decision trees* – which use a vector of attributes and perform a sequence of tests corresponding to the input attributes, through an applicable set of branches until a decision is reached, also known as a leaf, *Random forests* – which use a multitude of decision trees, also referred to as base models to deal with issues such as bias that could be associated with using a single model (base model), reduce variance as it is less likely to misclassify with a collection of models than with a single model and ultimately make comprehensive predictions, plus other such as *Support vector machines*, *Linear classifiers, Linear regression, polynomial regression and logistic regression* (Han, Pei & Kamber, 2011; Russell & Norvig, 2021).

Supervised learning is further separated into two main types of machine learning problems. *Classification* - a type of supervised learning where the algorithm is used for assigning data into specific categories depending on the use case (Alloghani et al., 2020), ranging from tasks such as classifying patient's diagnostics into "tumor, no tumor" to more sophisticated multiclass classification and *Regression* - a type of supervised learning that uses algorithms to predict numerical values by understanding relationships between dependent and independent variables, basing on multiple data points.

2.2.2 Unsupervised Learning

This is a machine learning approach where a model observes, learns and discovers hidden patterns from unlabeled datasets (inputs) without any explicit corresponding outputs (Han, Pei & Kamber, 2011; Russell & Norvig, 2021). The ability of unsupervised learning to recognize patterns from large volumes of data, as inputs without explicit target attributes makes it ideal for clustering and association machine learning problems. *Clustering* – involves discovering hidden patterns and assigning unlabeled datasets into groups depending on their common features or differences and *Association* – involves using statistical techniques to discover relationships between variables in datasets (Han, Pei & Kamber, 2011; Russell & Norvig, 2021).

2.2.3 Reinforcement Learning

This is a machine learning approach where the model learns through interacting with the world and receives a reward or punishment that reflect how well it is performing (Russell & Norvig, 2021). The idea behind this kind of learning is to teach the model how to maximize rewards in the future by learning from their own experience and cogitating on their ultimate success or failure.

One of the challenges that come with reinforcement learning is the sparsity of rewards in the real world, making pseudo rewards a viable option for speeding up the learning. However, pseudo rewards introduce the risk of a model learning to maximize the pseudo rewards as opposed to the actual intended reward (Russell & Norvig, 2021).

2.3 Clinical Decision Support Systems

In an effort to improve patient safety and reduce human errors, Clinical Decision Support Systems (CDSS) were designed, to support clinicians with making decisions about patients at the point of care (Berner & La Lande, 2007). According to Sutton et al. (2020), clinical decision support systems use patient information, clinical knowledge, and other relevant health information to enhance clinicians' decision making. CDSS are not a new phenomenon, they can be traced back to the 1970s when they were first introduced and used mainly in academic pursuits (Sutton et al., 2020). At the time, the main concerns around using CDSS were ethical and legal issues that questioned their limited explainability and unanswered questions such as – "who is at fault if a wrong decision is taken about patient" after a CDSS is used (Sutton et al., 2020). However, research has shown that they do improve patient outcomes and cost of care (Berner & La Lande, 2007).

CDSS can generally be classified based on *Intervention timing* – dependent on whether they are used before, during or after a clinical decision is made, *Passive or Active* – depending on whether they only respond to a clinician's inputs or provide active alerts and insights to a clinician during decision making (Berner & La Lande, 2007; Sutton et al., 2020). Moreover, they generally fall under two broad categories as seen below:

2.3.1 Knowledge-based Clinical Decision Support Systems

Knowledge-based CDSS use rules (IF-THEN statements) created based on medical literature, clinical practice, or patient-directed evidence (Sutton et al., 2020). Spooner (2016) argues that whereas they are often based on if-then rules, it is not always the case. These systems generally comprise of a *knowledge base* – that contains compiled information and rules, an *inference engine* – that contains the logic that maps actual patient's data with system information to generate insights and *communication mechanism* – for clinicians to interact with the system when making the actual decision (Berner & La Lande, 2007; Spooner, 2016).

Furthermore, in earlier years, CDSS were predominantly used for diagnostic decision support, with the aim of providing information and insights to clinicians who were expected to actively interact with the system during decision making. (Berner & La Lande, 2007).

2.3.2 Non-knowledge based Clinical Decision Support Systems

Non-knowledge based clinical decision support systems are data driven systems that use artificial intelligence, machine learning and other statistical analytics to learn from past experiences or patterns in clinical data as opposed to being programmed to explicitly follow expert medical knowledge (Berner & La Lande, 2007; Sutton et al., 2020). The main advantage of non-knowledge based CDSS is their ability to deal with uncertainty (Hardin & Chhieng, 2007). Moreover, in contrast to knowledge based CDSS – which usually covers a wide range of diseases – non-knowledge based CDSS often tend to pay attention to more narrow signs or symptoms that are associated with a specific disease (Berner & La Lande, 2007). However, whereas they are growing in popularity, they are still facing challenges in relation to their blackbox nature and data availability (Sutton et al., 2020).

Machine learning enabled clinical decision support systems are part of non-knowledge based CDSS and are the type of clinical decision support system that this thesis aims to investigate. The terms “machine learning enabled clinical decision support system” and “ML-enabled CDSS” will be used interchangeably throughout the master thesis. Being part of non-knowledge based CDSS, ML-enabled CDSS share the characteristics just mentioned. In addition to this, one of the advantages of ML-enabled CDSS is that they phase out the need for developers to document and program the IF-THEN rules (Berner & La Lande, 2007). As entailed in the description of machine learning, when applied to clinical decision support, these systems can learn, and be trained from examples when the internal ML-algorithms are supplied with large amounts of data (Berner & La Lande, 2007).

2.3.3 Challenges of Machine Learning enabled Clinical Decision Support Systems

Despite the promises and progress made so far in using machine learning to assist clinicians with difficult decisions in complex clinical situations, issues of credibility and adoption still exist (Antoniadi et al., 2021; Shortliffe & Sepúlveda, 2018). This section of the master thesis will highlight some of the challenges associated with machine learning enabled clinical decision support systems.

Transparency: The black box nature of machine learning models makes it difficult for clinicians to understand the basis for offered recommendations, as it is often hard to explain how the model came up with the decision being suggested (Magrabi et al., 2019; Shortliffe & Sepúlveda, 2018), which has arguably contributed to issues of over or under reliance (Antoniadi et al., 2021). Additionally, as certain treatment requires clinicians to inform patients and obtain informed consent, inability to understand the logic behind a certain recommendation further poses challenges for clinicians (Gretton, 2018).

Automation bias and complacency: Clinicians become over-reliant on the ML-enabled CDSS, delegate full responsibility to them and do minimal verification, leading to an increase in errors when the algorithm is incorrect about a decision and the clinician fails to spot the miss or acts upon the incorrect diagnosis (Gretton, 2018; Magrabi et al., 2019).

A study conducted by Lyell et al., (2017) found that while CDSS significantly reduced omission errors, when they provided incorrect recommendations or suggestions, the clinicians’ omission errors increased by 33.3%. Another notable challenge is automation under-reliance, where the clinicians totally fail to trust a reliable CDSS, leading to errors (Gretton, 2018).

Data and Generalizability: Machine learning models are data driven and access to comprehensive data is critical. Consequently, according to Sanchez-Martinez et al. (2022), models are generally trained using randomized clinical trials, cohort, and clinical routine real-world data. Scholars have however highlighted multiple data related challenges. Firstly, when models are trained under conditions such as population demographics or curated data that differ from where they are deployed, they tend to underperform or fail to be generalizable, beyond the data upon which they were trained, especially with the contextual nature of medical practice (Gretton, 2018; Magrabi et al., 2019).

Time pressure: As time is a scarce resource in the clinical environment, Shortliffe and Sepúlveda (2018) argue that some CDSS do not blend well into the workflow, requiring clinicians to do data entry during critical emergency moments. This is time clinicians do not have during emergency situations, resulting into a rather slow uptake of the systems.

Bias: Susceptibility to placing patients at a disadvantage depending on socio-demographic backgrounds (Magrabi et al., 2019), representation in the training datasets and other data imbalance problems have been found to lead to bias. Moreover, studies have found that human cognitive biases incorporated in training datasets further leads to biases in model performance. Confounding, commonly observed in supervised learning where a model forces the output to match a given label rather than natural association within the data further creates bias (Sanchez-Martinez et al., 2022).

Regulatory: The use of machine learning enabled clinical decision support systems presents unique regulatory challenges, especially when a medical negligence is because of a machine learning failure. The legal and policy landscape is still not fully aligned with medical practice, presenting challenges for those that adopt ML-enabled CDSS (Sanchez-Martinez et al., 2022). Specific to Europe, the General Data Protection Regulation (GDPR) has been crafted to aid with regulation of processing personal data and in relation to ML related applications the compliance levels are still relatively low (Sanchez-Martinez et al., 2022).

Other notable challenges: Other challenges such as clinicians' perceptions, ethical issues, explainability, integration with existing medical systems, security and data privacy have also been associated with machine learning enabled clinical decision support systems (Sanchez-Martinez et al., 2022; Shortliffe & Sepúlveda, 2018).

2.4 Technology Adoption

Research of concepts regarding adoption has been carried out for quite some time. Liu, Min and Ji (2008) distinguishing that IT/IS adoption occur at different levels which are individual, group and organizational. Adoption from an organizational perspective refers to "the assimilation of a product, service or technology new to the adopting organization" (Damanpour & Wischnevsky, 2006, p.272), whilst individual adoption, usually refers to attitudes and behaviour at user level (Gallivan, 2001).

A more generic definition of adoption defines the term as "a decision to make full use of an innovation as the best course of action available" (Rogers, 1983, p.177), thus disregarding the adoption entity. Differentiating between pre- and post-adoption entail that the concept does not only refer to a single event of accepting, or not accepting new technology. According to Straub (2009) the decision to adopt innovation, or from this thesis perspective technology adoption, does not appear in a vacuum.

Consequently, different perspectives of the adoption process have been articulated. One of the most common views of the adoption process is the *Innovation Decision Process* articulated by Rogers (1995) in his book *Diffusion of Theory*, where a decision-making unit passes five steps ranging from getting knowledge about a technology to confirming and accepting it. Another view of the adoption process is a two-step process, which takes an organizational perspective through empathizing that user level adoption cannot occur until a primary adoption has occurred on management level (Zaltman, Duncan & Holbeck, 1973 in Gallivan, 2001). However these two views of the adoption process are not as explicitly tailored towards technology adoption in Jeyaraj and Sabherwals' (2008) view, which argues that the IS/IT-adoption process is affected by three different kinds of actions – actions within the context, actions by the adopter and actions by individuals who might influence the adopter – which occur over time, rather than just a set of actions performed by the adopter.

As this section has covered the description of technology adoption and its process, the following section touches upon frameworks developed and used within the IS discipline.

2.5 Choice of Reference Framework

Multiple frameworks have been proposed and used in the IS discipline to study and explain technology adoption based on the different levels expressed by Liu, Min and Ji (2008), and they include; *Technology Acceptance Model* (TAM) (Davis, 1989), *Theory of Reasoned Action* (TRA) (Fishbein & Ajzen, 1975), *Unified Theory of Acceptance and Technology Use* (UTAUT) (Venkatesh et al., 2003), *Diffusion of Innovation* (DOI) (Rogers, 1995) and *Technology-Organization-Environment* (TOE) (Tornatzky & Fleischer, 1990) among others. Out of these frameworks, Liu, Min and Ji (2008) argue that TRA, TAM, and UTAUT initially were used for studying individual adoption. TAM, along with its refined models such as TAM2 (Venkatesh & Davis, 2000) and TAM3 (Venkatesh & Bala, 2008), are indisputably the most used framework used in empirical studies of adoption and user acceptance (Baker, 2012; Liu, Min & Ji, 2008; Oliveira & Martins, 2011). The framework consists of psychometric variables whose measurement scales have been redefined over time (Davis, 1989), and in combination with empirical support, TAM is proven to be a robust framework for measuring user acceptance of technology (Liu, Min & Ji, 2008). As the phenomenon of research for this thesis is factors influencing adoption of machine learning enabled clinical decision support systems, the TRA, TAM and UTAUT frameworks are argued to not aid in the exploration of influencing factors from a holistic perspective.

On the contrary, DOI and TOE have both been viewed and used in the context of organizational adoption in previous IS-literature (Gangwar, Date & Raoot, 2014; Liu, Min & Ji, 2008). Comparing TOE and DOI, Oliveira and Martins (2011) emphasize that the constructs used in DOI are indistinguishable with the Technological and Organizational contexts in TOE. Thus, the TOE framework has been superior to study technology adoption among researchers as it encompass an additional context, namely the environmental context (Baker, 2012; Oliveira & Martins, 2011). Additionally, Baker (2012) and Oliveira and Martin (2011) state in their respective reviews of the TOE framework that it is one of most the repeatedly used theories in organizational adoption since its inception in 1990. Moreover, they explain that it has adapted to IT and IS-adoption and serves as a useful analytical framework for investigating the adoption of various types of technological innovations.

Thus, the TOE framework is found to be a suitable and holistic reference framework to use as theoretical guidance for an empirical study of factors influencing the adoption of machine learning enabled clinical decision support systems. The aforementioned reference frameworks for technology adoption are summarized in table 2.1 below. The TOE framework is described in more detail in the following section.

Table 2.1 – Overview of technology adoption frameworks

Framework	Curator (Year)	Adoption Level
Technology Acceptance Model (TAM)	Davis (1989)	Organizational
Technology-Organization-Environment (TOE)	DePietro, Rocco, Wiarda & Fleischer (1990)	Organizational
Theory of Reasoned Action (TRA)	Fishbein & Ajzen (1975)	Individual
Diffusion of Innovations (DOI)	Rogers (1995)	Organizational
Unified Theory of Acceptance and Technology Use (UTAUT)	Venkatesh (2003)	Individual

2.6 Technology-Organization-Environment (TOE) Framework

The technology-organization-environment framework was firstly described in the book, *The Process of Technological Innovation,* written by Tornatzky and Fleischer and was published in 1990 (Baker, 2012). As the book aims to address the extensive process of technological innovation, from what *defines* as technological innovation, to how its *developed*, *adopted* and *implemented* in an organizational context, DePietro, Rocco, Wiarda and Fleischer developed the TOE framework (Tornatzky & Fleischer, 1990). As emphasized by Baker (2012) the framework puts its attention to only one portion of the entire process of technological innovation, namely how an organization's context influences the adoption and implementation of a particular technological innovation. The framework constitutes of three elements – the technological context, the organizational context, and, the environmental context – which are all argued to influence new technologies and organizations' adoption of them (Baker, 2012). In figure 2.2 below, an overview of the TOE framework is depicted.

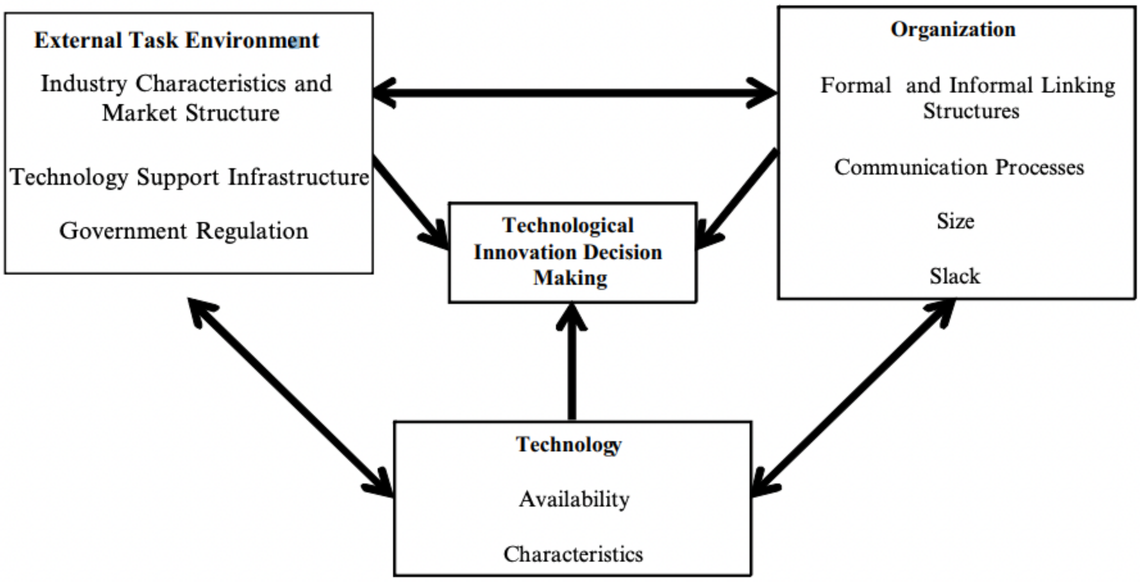

Figure 2.2 – The TOE framework in Baker (2012)

Due to its popularity, the framework has naturally gone through scrutiny and critique. One of the critiques is that the framework is broad (Zhu & Kraemer, 2005), to the extent that new research does not explore new influencing factors within the three different contexts (Baker, 2012). Thus, since the inception of the framework, few developments of the framework have been made due to having a wide range of freedom (Baker, 2012). However, the generic characteristics of the framework result in the framework being adaptable, the room for adaptability have been utilized among many researcher, thus varying factors within the three elements depending on the context and technology subject of study (Baker, 2012). In the following sub-sections, the three elements of the TOE framework are presented.

2.6.1 Technological Context

The element of technological context basically refers to all the relevant technologies for an organization, it includes used as well as external, non-used technologies (Baker, 2012). It is important for organizations to understand both internal and external technologies, Collins, Hage and Hull (1988) state that the former can act as an over limit of technical feasibly and cost from a technoeconomic perspective, while the latter can provide insight in regards to what is available on the market and in which way these innovation can enable them to evolve and adapt (Baker, 2012).

Moreover, the external innovations can be categorized into three types based on what kind of changes they are able to create, which are *incremental, synthetic* or *discontinues* changes (Tushman & Nadler, 1986). As stated, an organization should pay attention towards all technologies, however Baker (2012) put emphasis on the notion that the level of attention can be adjusted based on these three categories. Moreover, incremental changes are not usually bound to impact an organization’s competitive position or procedures to a large extent, thus allowing for controlled adoption. On the other hand, synthetic and discontinues changes may present more of a challenge, e.g., resulting in loosing competitive advantage in the case of not adopting the innovation (Baker, 2012). In these scenarios, organizations may be required to be nimble and account for the changing dynamics in the context they are operating to ensure adoption. Baker (2012) further elaborates that the impact of discontinues changes, also called radical changes needs to be considered, as they tend to create significant shifts in industries if change results in current procedures and competencies being obsolete. As demonstrated through the innovation classification, it is crucial to consider these characteristics of the technology as it impose potential impact on an organization, some will be more impactful than others (Baker, 2012).

2.6.2 Organizational Context

The element of organizational context refers to characteristics of an organization, including four areas; namely linking structures within the organization, communicational processes, organizational size and slack (Baker, 2012). Regarding *linking structures*, there are multiple mechanisms that promote innovation. Factors such as gatekeepers, product champions and cross functional teams are included here (Baker, 2012). Within *communicational processes*, top-management support has been a reoccurring factor, as it can encourage employees to embrace change (Tushman & Nadler, 1986). To promote adoption through top-management support includes making subordinates understand the innovation's role and relation to the overarching organizational strategy, thus enabling a compelling vision of the future throughout all levels of the organization (Baker, 2012).

However, within this context Baker (2012) highlights that researchers have not reached a unison conclusion of whether the respective factors promote adoption of innovations or if the factors hold little influential value for adoption. Organizational size is among the most occurring factors subject to discussion, where the relationship between them have not been able to be established (Baker, 2012). Whilst widely investigated, the mainstream suggested link is that larger organizations are more likely to adopt new innovations (Baker, 2012). However, Kimberley (1976) argues that size is too parsimonious, thus bundling and ignoring more purposeful organizational characteristics, for example if the organization is in a phase of rapid growth, decline or one of stability between the two. This is concurrent with Gangwar, Date and Raoot (2014) review of the TOE adoption in literature where size has been found both influential and trivial in the studies reviewed and analysed.

2.6.3 Environmental Context

The element of environmental context refers to three aspects, including the structure of the industry, the technology support infrastructure and the regulatory environment (Baker, 2012), meaning that the element and context put its attention towards the areas that an organization operates in (Gangwar, Date & Raoot, 2014).

Firstly, from Baker's (2012) review of literature shows that competitiveness and industry life cycle have been investigated within the context of industry structure. Fierce competition is proposed to stimulate adoption while industry life cycle, depending on its phase, does not propose any particular rationale for approaching innovation (Tornatzky & Fleischer, 1990). Baker (2012) elaborates on this, proposing that during an industry decline some organizations invest in innovation to enable entrance of new lines of businesses, while other disregard innovation to cut down costs. Moreover, technology support infrastructure also impacts innovation and refers to costs and availability of skilled labour, high cost and lack of availability may compel organization to bet on developing and adopting new innovation (Baker, 2012).

Lastly, government regulations could either benefit or hamper the adoption of innovation, constraints introduced by government on an industry have mandatory compliance and rigorous safety and testing protocols are examples of potential impeders of innovation (Baker, 2012). The environmental context thus provides a holistic perspective of external factors that have impact on new technologies (Gangwar, Date & Raoot, 2014).

2.6.4 Applications of TOE in a Healthcare Context

As stated previously, the room for adaptability of the TOE framework has been utilized by researchers (Baker, 2012). Thus, studies have been prone to use different factors for the respective contexts in the framework, some that are similar and others that are more unique to the technological innovation subject to study. Through an inspection of previous applications of TOE in healthcare, different technological innovations and set of factors have been identified for investigating adoption. The technological innovations studied include RFID (Chong & Chan, 2012; Lee & Shim, 2007), e-signature (Chang et al., 2007), Telecare (Liu, 2011), Cloud computing (Lian, Yen & Wang, 2014; Sulaiman & Magaireah, 2014), machine learning for medical diagnostics (Pumplun et al., 2021) and Big Data (Ghaleb et al., 2021) among others.

An overview of the factors investigated in prior literature of TOE conceptualizations in healthcare contexts can be viewed in table 2.2 below, factors with different naming that were found to be synonymous have been bundled into one factor to avoid redundancy in the table. Worth highlighting is that merely one research study that applied the TOE framework to machine learning (used for medical diagnosis) could be identified, which further emphasize the lack of previous research regarding the thesis' phenomena of research. Thus, the factors presented in table 2.2 may not account for the specific characteristics of machine learning enabled clinical decision support systems creating a need for further investigations to get a holistic overview of relevant factors. Lastly, from a healthcare context both qualitative and quantitative approaches have been taken when applying the TOE frameworks in previous research, in addition it has also been common to integrate TOE with other theoretical frameworks.

Table 2.2 – Healthcare factors used in TOE literature, an overview of research

	Factor	References
Technological	Security | Data Security	Sulaiman & Magaireah, 2014; Chang et al., 2007; Chong & Chan, 2012; Lian, Yen, Wang, 2014
	System Complexity	Chang et al., 2007; Chong & Chan, 2012; Ghaleb et al., 2021; Hung et al., 2010; Lian, Yen, Wang, 2014
	Reliability	Sulaiman & Magaireah, 2014; Pumplun et al., 2021; Venkatraman, Sundarraj & Seethamraju, 2015
	Relative Advantage	Lee & Shim, 2007; Chong & Chan, 2012; Hung et al., 2010; Lian, Yen, Wang, 2014; Liu, 2011
	Compatibility	Chong & Chan, 2012; Ghaleb et al., 2021; Lian, Yen, Wang, 2014; Liu, 2011
	Data Privacy	Sulaiman & Magaireah, 2014
	Cost	Chong & Chan, 2012; Lian, Yen, Wang, 2014
	Technology Optimism	Ghaleb et al., 2021
	Transparency	Pumplun et al., 2021
	System Set-up	Venkatraman, Sundarraj & Seethamraju, 2015
	Usage	Venkatraman, Sundarraj & Seethamraju, 2015
Organizational	Top Management Support	Sulaiman & Magaireah, 2014; Chong & Chan, 2012; Ghaleb et al., 2021; Pumplun et al., 2021; Venkatraman, Sundarraj & Seethamraju, 2015; Lian, Yen, Wang, 2014; Hung et al. 2010; Liu, 2011
	Organizational Size	Chang et al., 2007; Chong & Chan, 2012; Pumplun et al., 2021; Venkatraman, Sundarraj & Seethamraju, 2015; Hung et al. 2010
	Technical Knowledge	Lee & Shim, 2007; Chong & Chan, 2012; Hung et al. 2010; Liu, 2011
	Adequate Resources	Chang et al., 2007; Lian, Yen, Wang, 2014; Pumplun et al., 2021
	Benefits | Business Value	Lian, Yen, Wang, 2014; Venkatraman, Sundarraj & Seethamraju, 2015;
	Financial Resources	Lee & Shim, 2007; Chong & Chan, 2012; Ghaleb et al., 2021
	Training	Ghaleb et al., 2021
	User Involvment	Chang et al., 2007
	Presence of Product Champions	Lee & Shim, 2007
	Technology Readiness	Sulaiman & Magaireah, 2014
	Strategic fitness	Venkatraman, Sundarraj & Seethamraju, 2015
	Internal need	Chang et al., 2007; Liu, 2011
Environmental	Government Policy	Sulaiman & Magaireah, 2014; Chang et al., 2007; Lian, Yen, Wang, 2014; Ghaleb et al., 2021
	Competition	Sulaiman & Magaireah, 2014; Chong & Chan, 2012; Venkatraman, Sundarraj & Seethamraju, 2015; Lian, Yen, Wang, 2014; Liu, 2011
	Regulations	Sulaiman & Magaireah, 2014; Ghaleb et al., 2021; Pumplun et al., 2021; Venkatraman, Sundarraj & Seethamraju, 2015
	Vendor Support	Chang et al., 2007; Liu, 2011
	Medical Ethics	Pumplun et al., 2021
	Market trends	Chong & Chan, 2012

2.7 Conceptual Research Framework Based on TOE

A conceptual framework of TOE will be used to aid in the exploration of influencing factors of ML-enabled CDSS adoption. According to this thesis' delimitations all factors are not going to be subject for further investigation, which could be further evidenced in table 2.2 above highlighting a large set of factors. The disposable time for this study is a primary factor for this delimitation.

In total, eight factors were selected, as they were believed to relevant for the adoption in the research context. The selected factors are derived from table 2.2 and the theoretical background in general. Below each factor is described and accompanied with arguments for their inclusion. Lastly, the conceptual research framework based on TOE is illustrated in figure 2.3.

2.7.1 Technological Context

System Complexity: The level of system complexity has been documented by many researchers as one of the factors that influence adoption of innovative IT technologies (Chang et al., 2007; Chong & Chan, 2012; Ghaleb et al., 2021; Hung et al., 2010; Lian, Yen & Wang, 2014), including technologies such as machine learning (Pumplun et al., 2021). However, not all researchers share the same findings when it comes to its significancy in technology adoption. Whereas a study by Chong and Chan (2012) found system complexity as a significant factor, with a great effect on adoption, Chang et al. (2007) argue that system complexity is perceived as a low effect factor in healthcare, as many of the vendors provide comprehensive solutions that require minimal input from hospitals. A similar line of thought was highlighted by Ghaleb et al. (2021) who argue that system complexity difficulties are rather more predominate in developing countries. Since we could not find granular level literature specific to our research phenomena, we opted to include this factor for further investigation.

Reliability: Reliability is another factor that has been highlighted by multiple healthcare studies in relation to adoption of new technologies (Pumplun et al., 2021; Sulaiman & Magaireah, 2014; Venkatraman, Sundarraj & Seethamraju, 2015). According to Sulaiman and Magaireah (2014), availability of reliable data is perhaps one of the initial considerations healthcare organizations must check, as the industry grapples with many non-digitalized medical records and quite some challenges with existing heath records systems. Moreover, patients have also expressed concerns regarding the reliability of some of the technologies used in healthcare (Sulaiman & Magaireah, 2014), which further necessitates the need for our research to investigate this factor further, as clinical decision support systems are actively involved in day-to-day patient care.

Transparency: Looking at the challenges of machine learning in clinical decision support systems documented in the theoretical background – section *2.2.3 Challenges of Machine Learning enabled Clinical Decision Support Systems*, it is evident that transparency is a worthy factor to consider when investigating the factors that influence adoption. Furthermore, a study by Pumplun et al. (2021), found that the lack of transparency of machine learning systems still posed a major obstacle to healthcare providers' readiness to adopt machine learning solutions. This is majorly because of their black box nature and difficulty for clinicians to understand how certain recommendations are arrived at (Magrabi et al., 2019; Shortliffe & Sepúlveda, 2018). With the increased use of machine learning in healthcare, triggered by the covid-19 pandemic, this paper found it necessary to investigate transparency further.

2.7.2 Organizational Context

Top Management Support: When it comes to the organizational context, availability of top management support has been documented as one of the major factors for adoption of new technologies (Baker, 2012). Moreover, results from studies by Chong and Chan (2012), Pumplun et al. (2021), Ventatraman, Sundarraj & Seethmaraju (2015), Ghaleb et al. (2021) and Sulaiman & Magaireah (2014) specific to healthcare were further consistent with earlier studies regarding top management support. However, as noted in section *2.6.4 Applications of TOE in a Healthcare Context*, we could only find one specific study of machine learning adoption. Thus, the need to investigate and determine if results are still consistent with earlier generalized studies.

Financial Resources: This refers to the availability of financing and ability of the organization to fund the adoption and implementation of new technologies (Lee & Shim, 2007). Whereas some studies concluded that financial resources are a significant factor for adoption, studies by Chong & Chan (2012) & Lee and Shim (2007) argue that there is no significant role played by financial resources, as organizations with sufficient financial resources still face the issue of hesitation when it comes to adopting new technologies, calling for further studies to explore this phenomenon.

Technology Readiness: This refers to the IT infrastructure and human resource readiness to adopt new technologies, cutting across knowledge, awareness, training, perceptions towards the new technologies (Sulaiman & Magaireah, 2014). From a healthcare perspective, this paper will investigate whether technology readiness is a significant influencing factor regarding the adoption of machine learning enabled clinical decision support systems. This was motivated by the recent influx in the adoption of digital technologies across many industries triggered by the covid-19 pandemic (Doyle & Conboy, 2020; Wade & Shan, 2020).

2.7.3 Environmental Context

Regulations: Since healthcare is a heavily regulated space, supporting regulations have been argued to be a driver of innovation uptake (Ghaleb et al., 2021). As healthcare goes digital through electronic healthcare records (EHR), regulations of data sharing have gotten attention (Ghaleb et al., 2021; Pumplun et al., 2021; Venkatraman, Sundarraj & Seethamraju, 2015). However, when adopting ML in healthcare contexts Pumplun et al. (2021) emphasize that there are several regulations to account for when considering machine learning, such as accountability and approval. Moreover, ambiguity in existing regulations and misalignment with practice regarding CDSS (Pumplun et al., 2021; Sanchez-Martinez et al., 2022) calls for further exploration.

Market Trends: Expectations of market trends are expected to have an influence on the adoption, Chong and Chan (2012) argued that if a technology is part of the healthcare industry trends, more organisations within the industry are more likely to adopt it. This can be seen from the increased trends to adopt technologies such as mRNA technology for vaccine development and other artificial intelligence techniques to fight covid-19 (Wang et al., 2021). This paper will therefore aim to investigate and ascertain if market trends indeed have a significant influence on the adoption of machine learning enabled clinical decision support, as seen in other industries.

2.7.4 Conceptual Research Framework

The conceptual research framework is illustrated in figure 2.3 below, each of the factors described in the previous sections are placed within the respective contexts. The contexts have been updated to fit the empirical context.

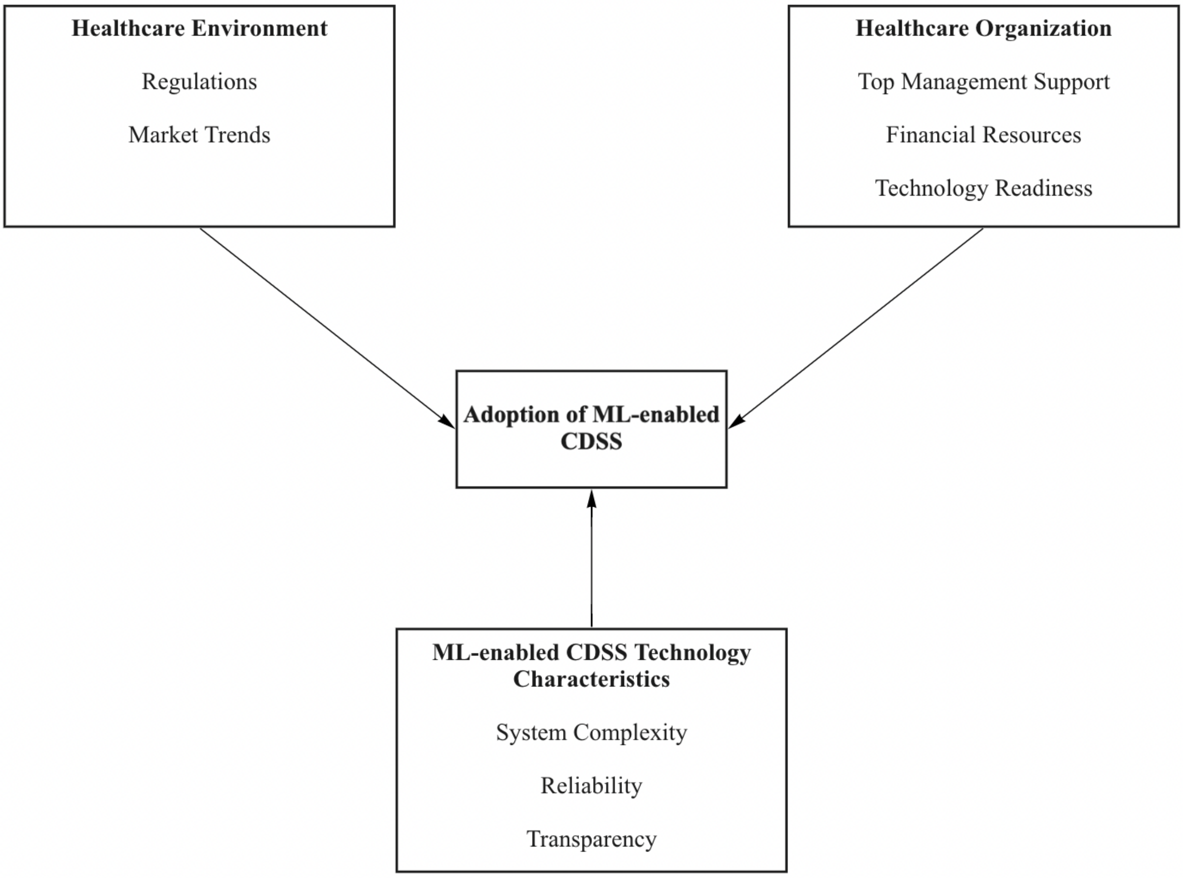

Figure 2.3 – Conceptual Research Framework based on TOE

2.8 Summary of Theoretical Background

As the theoretical background has covered different concepts with emphasis on various notions, table 2.3 below concludes the theoretical background section by providing a holistic overview. In combination with the conceptual research framework, the table is intended to guide the creation of the interview guide used for data collection.

Table 2.3 – Overview of theoretical background

Concept	Notions	References
Artificial Intelligence | Machine Learning	Supervised Learning Non-supervised Learning Reinforcement Learning	Russel & Norvig, 2021; He et al, 2019; Jordan & Mitchell, 2015; Domingos, 2012; Han, Pei & Kamber, 2011; Alloghani et al., 2020
Clinical Decision Support	Clinical Decision Support Systems Knowledge-based & Non-Knowledge based Clinical Decision Support Systems Challenges of Machine Learning enabled Clinical Decision Support Systems	Berner & La Lande, 2007; Sutton et al., 2020; Spooner, 2016; Hardin & Chhieng, 2007; Antoniadi et al., 2021; Shortliffe & Sepúlveda, 2018; Magrabi et al., 2019; Gretton, 2018; Lyell et al., 2017; Sanchez-Martinez et al., 2022
Technology Adoption	Adoption Process Technology Adoption Frameworks (TOE, DOI, TAM, UTAUT, TRA)	Liu, Min, Ji, 2008; Damanpour & Daniel Wishnevsky, 2006; Gallivan, 2001; Rogers, 1983; Karahanna, Straub & Chervany, 1999; Straub, 2009; Rogers, 1995; Jeyaraj & Sabherwal, 2008; Davis, 1989; Fishbein & Ajzen, 1975; Venkatesh et al., 2003; Tornatzky & Fleischer, 1990; Venkatesh & Davis, 2000; Venkatesh & Bala, 2008; Baker, 2012; Oliveira & Martins, 2011; Gangwar, Date & Raoot, 2014; Zhu & Kraemer, 2005; Collins, Hage & Hull, 1988; Tushman & Nadler, 1986 ; Kimberly, 1976
Technological Context	System Complexity Reliability Transparency	Chang et al. 2021; Ghaleb et al., 2021; Hung et al., 2021; Lian, Yen & Wang, 2014; Chong & Chan, 2012; Chang et al. 2007; Pumplun et al., 2021; Sulaiman & Magaireah, 2014; Venkatraman, Sundarraj & Seethamraju, 2015; Magrabi et al., 2019; Shortliffe & Sepúlveda, 2018
Organizational Context	Top Management Support Financial Resources Technology Readiness	Venkatraman, Sundarraj & Seetamraj, 2015; Sulaiman & Magaireah, 2014; Lee & Shim, 2007; Chong and Chan, 2021; Ghaleb et al., 2021
Environmental Context	Regulations Market Trends	Ghaleb et al., 2021; Pumplun et al., 2021; Venkatraman, Sundarraj & Seetamraj, 2015; Sanchez-Martinez et al., 2022; Doyle & Conboy, 2020; Wade & Shan, 2020; Chong & Chan, 2012

3 Methodology

3.1 Research Strategy

The aim of this study is to answer the research question – "What factors are influential when adopting machine learning enabled clinical decision support systems". This entailed conducting a descriptive study tailored to carefully observing and documenting (Recker, 2013) the factors, particularly regarding machine learning enabled clinical decision support systems, as they are currently not extensively documented in existing literature. According to Bhattacherjee (2012), descriptive studies are usually efficient when investigating "what" nature of research questions.

Furthermore, as the study required us to get a deeper understanding of the factors that influence adoption of machine learning enabled clinical decision support systems, interpretivism was chosen as the philosophical foundation for this research. This was motivated by the subjective nature of our research problem and the need to generate new understandings and knowledge from subjective and insider perspectives (Lee, 1991; Mingers, 2002). Other considerations such as pragmatism were assessed, but not chosen due to time constraints of the study period coupled with other factors. It was not feasible to be actively involved as outsider or active insider observers (Goldkuhl, 2012), thus the decision to stick with a more feasible interpretivist approach. Consequently, a qualitative method was used for this study to aid with generating the level of depth required since the demands of the research go far beyond just statistical representations of the findings, seen in alternative methods such as quantitative methods (Bhattacherjee, 2012). Moreover, as accentuated by Recker (2013), qualitative methods align well with interpretivism philosophical foundations as they emphasize a social constructionist ontology hinged on a viewpoint that phenomena are bound and molded by their social and historical context and therefore should not be secluded from that context.

Lastly, the approach used for this master thesis reminisce of an abductive approach. This is motivated by its foundation of scientific accounts being based on world views as precepted by the research participants (Bryman, 2012). Denzin (1978, cited in Patton, 2015) explained abductive analysis as a combination of both inductive and deductive reasoning. As the research strategy reminisce of an abductive approach, we argue that parts of research activates were characterized as either deductive or inductive. Firstly, opposed to a purely deductive approach – with an aim of testing current theory (Bryman, 2012) – we were able to conceptualize the TOE framework and use it as a reference framework to guide the empirical investigation. Moreover, the reasoning process when selecting the factors included in the conceptual research framework was similar to the process of abductive reasoning. This type of reasoning, often called informed guessing (Recker, 2013), was used to reduce the solution space to a more tailored set of factors as they were deemed to potentially influence the adoption of ML-enabled CDSS. Secondly, opposed to a purely inductive approach – with an aim of creating or generating new theory based on the empirical material (Bryman, 2012) – new factors could be identified and coded as the process of qualitative research often is non-linear (Bryman, 2012). Meaning that after a fist set of observations have been made, an attempt of approaching the collected data with an open mind could help in producing further interpretations, thus potentially identifying additional factors through letting the empirical material speak for itself. Thus, not being restricted to the initial set of factors included in the conceptual research framework.

3.2 Approach to Theoretical Background

This thesis journey was an iterative process, with a couple of adjustments as we continued to read existing literature and became more versed with our area of study. As seen in previous sections, we picked interest in the study area of AI in healthcare, specifically machine learning enabled clinical decision support systems. Among other factors, our interest in the study was inspired by the impact of the recent covid-19 pandemic on healthcare, and how technology was useful in alleviating its impact (Wang et al., 2021). This required reading extensive literature in relation to our subject area and to get a better grasp of what to look out for, we were guided by Bhattacherjee (2012) three-fold purpose of literature review as seen below:

1) examining the current body of knowledge in literature relating to our research inquiry, 2) identifying key authors, articles, theories, and findings related to our study area in the existing body of knowledge, and 3) identifying gaps or areas related to our research study that have not been sufficiently addressed in the existing body of knowledge (Bhattacherjee, 2012).

As recommended by Bhattacherjee (2012), we used computerized keyword searches in online data sources such as IS Basket of eight journals, Google scholar, Lund university LUBSearch, Scopus, Web of science, and other associated medical journals to generate a shortlist of relevant articles and books that we then initially skimmed through to determine their suitability for our study. Some of the keywords used in the search were:

- ("AI" OR "Artificial Intelligence") AND ("Healthcare")
- ("ML" OR "Machine learning") AND ("Healthcare")
- ("ML" OR "Machine learning") AND ("Clinical Decision Support Systems" OR CDSS)
- ("Machine learning") AND ("Adoption") AND ("Clinical Decision Support Systems")
- ("TOE" OR "technology-organization-environment framework") AND ("Machine Learning") AND ("Clinical Decision Support Systems")
- ("Technology Adoption") AND ("Machine learning") AND ("Clinical Decision Support Systems")

Once suitable articles and books were determined, we proceeded with a detailed review or literature to get a deeper understanding of what already exists in literature in relation to the adoption of machine learning enabled clinical decision support systems. Moreover, as our study involved investigating adoption factors, we also reviewed multiple technology adoption frameworks to determine a suitable reference framework for the study.

As seen in table 3.1 below (also found in appendix 10), whereas there is extensive literature regarding AI and machine learning in healthcare, it is evident that there is still a gap when it comes to granular level literature concerning the adoption of machine learning in clinical decision support, further motivating the need for research in this phenomenon.

Table 3.1 – Overview of available literature

Search Keywords	Google Scholar	Web of science	Scopus	LUBsearch
("AI" OR "Artificial Intelligence") AND ("Healthcare")	2 280 000	11 843	8 183	31 382
("ML" OR "Machine learning") AND ("Healthcare")	3 550 000	28 815	13 378	45 283
("ML" OR "Machine learning") AND ("Clinical Decision Support Systems" OR CDSS)	28 800	400	1 195	1 049
("Machine learning") AND ("Adoption") AND ("Clinical Decision Support Systems")	3 230	13	38	34
("Technology Adoption") AND ("Machine learning") AND ("Clinical Decision Support systems")	289	0	0	0
("TOE" OR "technology-organization-environment framework") AND ("Machine learning") AND ("Clinical Decision Support systems")	121	0	0	0

3.3 Data Collection

3.3.1 Interviews

According to Recker (2013) interviews are the most dominant data collection technique in qualitative IS research inquiries. Through interviews, we are expected to gain a deeper understanding of the topic. Schultze and Avital (2011) mentioned that interviews distinguish themselves from other data collection techniques through engaging both the research participants and the researchers. Moreover, they can be of different nature – *descriptive*, *exploratory,* and *explanatory* (Recker, 2013)– in the setting of this master thesis, we employed interviews of descriptive nature as data collection technique. This is argued to be a suitable choice since descriptive interviews can provide rich descriptions of individuals' perspective regarding the phenomena subject to study, thus enabling a subjective understanding (Recker, 2013).

However, all data collection methods have shortcomings that need to be addressed and potential remedies that may need to be considered. Patton (2015) and Recker (2013) put emphasis on the fact that the act of interviewing is unnatural and artificial – opposed to an everyday conversation for instance – which entail that careful planning and interviewing skills are required in order to conduct a good interview. Another shortcoming regarding interviews is the relationship between the participators, reflexivity is one of the most common issues, this phenomenon refers to the respondents feeling pressured to answer what the researchers wants to hear (Recker, 2013). The interviews were conducted over Zoom, a video conference and communication tool, as it was the most convenient approach. It gave us the flexibility of conducting interviews with people situated outside of Lund. However, this meant that the interviews' social setting was different from interview to interview which we find to be one of the drawbacks with Zoom-interviews. The unnatural nature and setting of a regular face-to-face interview, expressed by Patton (2015) and Recker (2013) is altered even further, which also needs to be accounted for.

In order to remedy these shortcomings, a balance between being neutral and empathic had to be established (Patton, 2015), despite conducting them in a digital setting. Battling reflexivity, also called the interviewer effect, was done through validating that the respondents were suitable research participants and felt comfortable talking about the research topic. This was done through describing the aim and research question of the study to every potential respondent, where they would have to decide whether they felt comfortable talking about the research phenomena or not. Moreover, we argue that the conduction of digital interviews did not hinder us to capture social cues, since Zoom meetings to some extent can replicate a physical face-to-face setting through having a web camera activated.

Lastly, Patton (2015) states that the quality of the interviews is highly dependent on the interviewer. Meaning that a large responsibility was put on us when it came to preparations and conduction of this data collection activity. As literature in social science research (Bryman, 2012; Patton, 2015; Recker, 2013) provides a vast set of principles for conducting qualitative interviews, such as being present, not asking leading questions, etcetera, we did our best to consider these.

3.3.2 Target Sample and Respondent Selection

As this study is of qualitative characters, there is a call for a purposive sampling process in contrast to a randomized one that is often applied in quantitative studies (Recker, 2013). Thus, when looking for potential respondents to interview, they had to have knowledge or experience of machine learning enabled clinical decision support systems and be part of or involved in the process of adopting these kinds of systems. This acted as a fundamental precondition to be considered for an interview to ensure that the respondents could provide rich answers of the potential influential factors.

Two groups of respondents were approached – namely doctors and experts – these two groups were argued to enable a varying holistic perspective of the potential influential factors when adopting machine learning enabled clinical decision support systems. Experts were argued to be people with a substantial role in relation to initiatives or project of machine learning enabled clinical decision support systems in a healthcare context. Thus, project managers, machine learning developers, clinical researchers, etcetera are all grouped into the expert-group, with the hope of having the ability to provide with interesting insight regarding the adoption of this type of decision support systems. Moreover, doctors are expected to have more insight into the clinical practice and process compared to the expert-group.

With these criteria and groups in mind, we sought to reach out to as many as possible in order to ensure that appropriate number of respondents participated within this master thesis' relatively short time horizon. Patton (2015) argues that the number of respondents necessary when conducting qualitative research depends on various aspects, including the notion that it should be based on the trade-off between breadth and depth of knowledge that the study aims for, as well as the resources and time available. However, an important note is that the insights generated and their meaningfulness depends on other aspects than solely on the sample size (Patton, 2015).

All of the respondents were contacted through e-mail, they were mainly found through their organizations and other healthcare innovation platforms. Whereas many interesting candidates were approached, the majority did not have the opportunity, time or did not find themselves fit for this study, thus not all prospects could partake in the research study. In the end seven respondents were available and were thus invited to partake as interviewees in this study. In table 3.2, an overview of the interviews can be found, showing the group we identified them as, date, length, and type of interview.

Table 3.2 – Overview of respondents and interviews

Respondent	Group	Date	Length	Type	Transcript
R1	Expert	14th of April	35 min	Zoom	Appendix 3
R2	Doctor	18th of April	30 min	Zoom	Appendix 4
R3	Expert	19th of April	45 min	Zoom	Appendix 5
R4	Doctor	25th of April	30 min	Zoom	Appendix 6
R5	Doctor	25th of April	30 min	Zoom	Appendix 7
R6	Expert	26th of April	30 min	Zoom	Appendix 8
R7	Doctor	27th of April	35 min	Zoom	Appendix 9

3.3.3 Interview Guide

Researchers usually makes use of detailed or less detailed protocols during the execution of interviews (Recker, 2013). The protocol, also called interview guide, is created prior to the data collection. Moreover, different types of qualitative interviews can be distinguished, namely *structured*, *semi-structured*, *unstructured* or *group interviews* (Myers & Newman, 2007). An unstructured interview has some fundamental concepts planned out, but certain sub-concepts are devised as the interview progresses. In contrast, a structured interview has a strict set of questions with no room for improvisation (Myers & Newman, 2007). Neither of these two types were deemed to be appropriate for this study compared to the semi-structured type. A structured interview would risk omitting parts of individuals' perspectives as they may not be addressed in the predefined interview guide, whilst an unstructured interview is argued by us to require more experience of academic research and expertise of the research phenomena, thus, also potentially omitting parts of individuals' perspectives. Thus, as a trade-off, semi-structured interviews were performed for this research. Interviews of this nature, accompanied with unstructured formats, are the most commonly used types in qualitative IS research and allow for new questions to be addressed as the interviews progress, while still following a pre-defined structure (Bryman, 2012; Recker, 2013).

The creation of the interview guide was based on the theoretical background section. To begin with, the conceptual overview in table 2.3 was used as a guideline for developing questions. Moreover, following some of the steps suggested by Bryman (2012) for preparing the interview guide ensured that the interview guide was not created in a loose unstructured manner. For instance, a set of introductory questions (Question 1-4) established the setting of the interview and descriptive information of the interviewee. The main section of the interview guide was guided and based on the theoretical background, where an order of topic areas was mapped out (Bryman, 2012). This part is constituted of the three different contexts from the conceptual research framework (Question 5-15). As highlighted, the order of addressing topic areas could be altered as the interviews progressed, this is due to the semi-structure nature such as asking follow-up question or getting into related topic areas naturally (Bryman, 2012). Additionally, depending on the respondent's group and role, different questions were prioritized which can be seen by the added "Group"-column with colour codes in the interview guide (see appendix 2). Lastly, a set of ending questions (Question 16-17) concluded the interview and posed questions of reflective nature to validate if the interviewee had something to add or believed that something had been missed out on during the interview. The interview guide in its entirety can be shown in appendix 2.

3.4 Data Analysis

3.4.1 Transcription

The sensemaking process of analyzing and interpreting the data generated through the interviews is crucial. However, there were activities that had to be performed prior to this. A substantial amount of generated verbal data had to be converted into text, having this large amount of data generated is not unusual, but rather expected in the context of qualitative research approaches (Patton, 2015). After each interview was conducted, the next step included the development of comprehensive transcriptions, as well as synchronizing them with the accompanying notes taken during the interview.

The interview transcriptions were created as soon as possible, after the interviews were conducted. An AI-based transcription tool, called Otter.ai, was used to automate the conversion from audio to text, thus creating an initial transcription. This transcription was later revised by us manually, by going over the recording in order to correct for potential mistakes, such as erroneous interpretations and punctuation, made by the service. During this process a set of transcription-guidelines were implemented and upheld. Firstly, information of disclosing nature was replaced with "*…*" to ensure anonymization of research participants. Moreover, brief pauses were marked, and conversational context were highlighted in brackets. The transcriptions are of verbatim nature, however, in accordance to Bhattacherjee (2012), we refrained from full-verbatim to increase the readability of the transcripts but still without changing the meaning and overall structure of the interviewees responses.

3.4.2 Coding

Recker (2013) addressed that an abundance of data is generated in qualitative research, therefore we dove deep into the generated data, concluded what information was relevant or not, and essentially made sense of it (Patton, 2015). This part of the research process was a very time consuming and a mentally demanding activity, mainly due to the nature of the semi-structured interviews. These circumstances called for a systematic way of processing the data, we opted for choosing coding, among the other available techniques, as analysis technique (Patton, 2015; Recker, 2013). One of the primary reasons for choosing coding as technique, is that it enables categorization and organization of data (Recker, 2013). The process of coding means eliciting a chunk of information, such as entire, words, sentences, entire statements, etcetera and assigning them descriptive labels, also called codes (Recker, 2013). Additionally, coding is one of the most used and commonly recognized analysis techniques in qualitative studies (Recker, 2013). However, it is important that the manner of approaching the coding process is established and explicitly discussed. Firstly, the coding process was conducted independently and repeated iteratively among the two researchers. Through dual coding at an initial stage, the aim was to generate complementary insights when comparing where codes had been elicited between one another. Secondly, there are further coding approaches that need to be considered, since different approaches have special prerequisites for analyzing and interpreting data (Recker, 2013).

In accordance with previously described research approach, the data collection was based on the set of factors presented in the conceptual research framework (see figure 2.2), these factors were used as an initial set of codes. An overview of the factors abbreviated into codes can be found in table 3.3 below. Based on this, it is evident that this initial stage of the coding process is characterized with what Recker (2013) calls selective coding. This approach is often taken when having a deductive approach, whereas coding is based on a few central concepts in order to enable validation of existing relationships, theories, etcetera (Patton, 2015).

Table 3.3 – Initial set of codes for data analysis based on the Conceptual Research Framework

Context	Factor	Code
ML-enabled CDSS Technology Characteristics	System Complexity	SC
	Reliability	REL
	Transparency	T
Healthcare Organization	Top Management Support	TMS
	Financial Resources	FR
	Technology Readiness	TR
Healthcare Environment	Regulations	REG
	Market Trends	MT

However, following the research approach, another angle was taken after the initial codes had been used in a first iteration of data analysis. This time around, the collected data was approached once again with an open mind, with an aim of identifying additional factors emerging from the empirical material. In contrast to the initial step of analysis, this part of the data analysis is characterized as open coding (Recker, 2013). This approach is often applied when having an inductive approach, whereas coding is based on the empirical material rather than having existing theories in the backbone, thus not limiting the data to existing findings (Patton, 2015).

Once both steps of data analysis had been performed, we arranged a set of themes with accompanying concepts and codes to provide an overview of the entire coding process. This overview is shown in table 3.4 below, which also acted as a foundation for the structure of the result section. This further emphasizes how the abductive approach – of applying a mix of both deductive and inductive logical underpinnings – was performed for this study. Consequently, this resulted in multiple iterations of coding the collected data, the approach of dual coding and multiple iterations are argued by us to add a more interpretive character to the analysis.

Table 3.4 – Overview of themes, concepts and codes after completed data analysis

Theme	Concept	Code
ML-enabled CDSS Use Casses	Use Case	UC
ML-enabled CDSS Technology Characteristics	System Complexity	SC
	Reliability	REL
	Transparency	T
Healthcare Organization	Top Management Support	TMS
	Financial Resources	FR
	Technology Readiness	TR
Healthcare Environment	Regulations	REG
	Market Trends	MT
Emerging Findings	Data Availability	DA
	Collaboration	COL

3.5 Research Quality

According to Recker (2013), quality of the research starts with making sure that the selected research question is relevant in the sense of adding value to the existing body of knowledge or addressing a relevant identified gap, achievable and in alignment with ethical principles. For this thesis, attention was placed on reviewing existing literature and current state of IS research to ensure that the chosen research phenomenon is within the IS field, addresses a gap in existing IS literature, and is creditable (Stenfors, Kajamaa & Bennett, 2020). There are many factors that can impact the quality of a scientific study and it is therefore important to be cognizant of them, prevent or address them. Reliability refers to the extent the used variables are consistent in their measurement, while validity, which usually is divided into external and internal validity, refers to what extent the collected data measures what the researchers sought out to do in the first place (Recker, 2013). However, these criterions are not as suitable in a qualitative context compared to a quantitative one (Recker, 2013).

Recker (2013) states that this does not mean that rigor cannot be achieved for these methods in a qualitative study, but rather that the means to ensure high research quality and rigor are different.

Furthermore, as emphasized by Bhattacherjee (2012), the context, data collection and analysis process have been documented to give other researchers the opportunity to understand and validate if need arises to further develop the area of study. This helps establish the *dependability* of the study, as other researchers can reach similar conclusions if considering collection and analysis of similar data (Recker, 2013), thus, addressing the reliability of the study from a qualitative viewpoint. Moreover, this also allows for *transferability* of the research to other settings or contexts (Stenfors, Kajamaa & Bennett, 2020). As this is a qualitative study, the master thesis is cognizant of the fact that the exact interview contexts and scenarios cannot be replicated (Bryman, 2012) and was thus limited within the constraints of providing full documentation of all steps taken in data collection and analysis. This is argued to be equivalent to the external validity often applied in quantitative contexts.

Moreover, to ensure collection of high-quality data and *credibility* of the study, the findings are supported by an audit trail, showing where and how findings have been derived from, in the transcriptions. Additionally, as the transcripts have been sent out for validation by the research participants, giving them the opportunity to independently verify their answers, can further establish the credibility of findings (Recker, 2013). Thus, ensuring that internal validity checks were done.

3.6 Ethical Considerations

Qualitative studies, such as this master thesis, face a set of various ethical considerations that need to be accounted for (Recker, 2013). Within the context of academic research, ethical considerations could be viewed as a set of rules or principles that researchers are expected to follow (Recker, 2013). To begin with, our aim was to be as transparent and upfront with the research participants hence an invitation with information and a consent form was sent out to each research participant shortly after participation had been confirmed, see consent form in appendix 1.

The principle of *voluntary participation* was followed by informing the participants that they had the choice of withdrawing their participation at any time during the research process, without any consequences (Recker, 2013). This principle was further based on the notion that there should be something to gain for both parties when partaking in this research study (Patton, 2015).

The principles of *Anonymity* and *Confidentiality,* meaning that research participants cannot be identified through the collected data or through research disclosure (Recker, 2013), this was ensured through informing the research participants of that their data and information will be stored and managed in manner that anonymity and confidentiality are upheld. Moreover, information deemed as disclosing information was removed from the transcript provided in the appendices. Beyond ethical considerations of the research participants Recker (2013) addresses *honesty* and *complete reporting* of data analysis and how it has been conducted as an ethical principle, consequently undesired or unexpected results and findings still require full disclosure. To ensure that this principle was followed findings were presented in an objective manner, despite of potential misalignment with expected findings.

4 Results

4.1 ML-enabled CDSS Use Cases

Table 4.1 provides a holistic overview of the empirical findings from the ML-enabled CDSS use cases theme. The table illustrates respondent and row details from transcriptions where the respective factors were coded.

Table 4.1 – Overview of the ML-enabled CDSS Use Cases theme

Theme	Code	R1	R2	R3	R4	R5	R6	R7
ML-enabled CDSS Use Cases	UC	15, 17, 19	23, 25	17, 19, 23, 29	16, 20, 22, 75	19, 25	13, 15	30, 45, 41

When starting out with the interviews, the respondents were asked about their background and relation to the research phenomena at hand. Getting this additional context served as a foundation for the remaining parts of the conversation and interview questions. The set of respondent resides in or are related to different hospital departments that all are in different stages of adopting machine learning enabled clinical decision support systems. Hence, there are different ways of utilizing ML-enabled CDSS within specific healthcare contexts to support clinical care among the respondents. Thus, to provide a holistic view of the respondents' organizations and their adoption of ML-enabled CDSS, a brief description of the different use cases and adoption follows.

As Respondent 1 (R1) has a background in research, they have enabled collaboration with various organizations that are trying to explore the use of ML and AI in general to improve patient value by making clinical decisions more efficient (R1.15; R1.17). The initiatives and projects that R1 has been involved in revolved around the use of ML and AI in various healthcare settings, such as cardiovascular and cancer diseases (R1.15). Moreover, when addressing the use of ML in healthcare from the respondent's perspective, but also AI in general, the respondent states that not many systems or applications are currently up and running and that many organizations are currently in the process of trying to understand how to implement these technologies (R1.19).

Respondent 2 (R2), as doctor and researcher, is involved in projects that investigate the use of machine learning based tools for breast cancer (R2.23). The projects are shaped in the form of clinical research projects which investigate ML-algorithms' ability to assist in diagnosis and post-assessment of breast cancer based on Magnetic Resonance Imaging (MRIs) (R2.25). Currently, one of the ongoing projects has been assessing the use of such a tool at a hospital, where R2 has been part of leading the project from the start (R2.23).

Respondent 3 (R3) works as a business developer at a hospital, and they were part of a project as a project manager that included the development and implementation of an ML-enabled clinical decision support system for risk assessment and prediction of ambulance-need among incoming calls to their dispatch centre (R3.17; R3.19). The project was amongst the first initiatives of utilizing machine learning based models at the hospital (R3.19). However, foundational preparations for these kinds of projects had been done prior to project start. The organization's operations manager had spent a lot of time and resources to curate a large dataset, with data from the various systems – such as from the dispatch centre, the ambulance service and hospital systems – that the patient goes through in the emergency care workflow (R3.23). The project is over and was spanned out over two-three years, the self-developed machine learning enabled clinical decision support system is currently up and running (R3.19), where dispatchers get suggestions from the CDSS of which patients to prioritize especially when the demand of ambulances are high (R3.29). R3 was highly involved in the project, as the respondent was part of developing the software-tool, from conceptualizing of how to make use of the available data to a finished self-developed product. After the project, part of R3's day-to-day tasks consist of quality development to maintain the CDSS (R3.19).

Respondent 4 (R4) has three roles consisting of, treating patients as a doctor, teaching at a university as a professor and lastly investigating AI and ML-enabled CDSS among other clinical topics as a research leader (R4.16; R4.20). As the respondent's hospital has implemented rule-based CDSS, the intent is to introduce ML-enabled CDSS to be used within the emergency care department where R4 is specialized (R4.20). In this setting the, ML-enabled CDSS can support in the initial risk assessment, the triage process, for all incoming patients as well as for specific patient groups after the initial risk assessment (R4.22). Moreover, R4 stated that these types of CDSS are relevant and of high interest since emergency physicians are driven by decision-making as this specific clinical environment requires decisions to be made at an intense pace (R4.75).

Respondent 5 (R5) is a doctor specialized in infectious diseases, moreover, as a PhD R5 is interested in the use of ML-algorithms to predict sepsis through using data from electronic healthcare records (R5, 5.19). The prediction of this infection is important, R5 stated that sepsis is common among hospitalized patients and is associated with high mortality (R5.19). Currently, the development of this ML-algorithm is in a research phase. However, R5 has also been involved in projects with the adoption and use of ML-enabled CDSS at hospitals around Europe through collaboration with a company that sells an ML-enabled CDSS as a medical device (R5.25). This implemented CDSS provides suggestions of which type of antibiotics to use for treating patients with acute infections (R5.25).

Respondent 6 (R6) is an engineer and PhD, they have been involved in projects that investigate the use of ML-enabled CDSS for detecting drops in blood pressure during surgeries (R6.15). Moreover, R6 is currently working on his PhD where he develops an ML-algorithm used in a CDSS for prediction of sepsis (R6.13). R6 role has been tied to data management, designing and reporting of ML-models (R6.13).

Respondent 7 (R7) is a doctor and research leader within the field of unspecific pain. R7 has been part of a project using machine learning models to predict diagnoses based on pain drawings (R7.30). The aim is to be able to enable the patient to use an app where the pain drawing is digitized and fed to the machine learning model, which the clinicians can use as a decision support (R7.45). The project has spanned over a long time, however it is still in the initial stages of adoption, whereas the digital pain drawing app has been developed but have not been released yet (R7.41).

4.2 ML-enabled CDSS Technology Characteristics

Table 4.2 provides a holistic overview of the empirical findings from the ML-enabled CDSS technology characteristics theme. The table illustrates respondent and row details from transcriptions where the respective factors were coded.

Table 4.2 – Overview of the ML-enabled CDSS Technology Characteristics theme

Theme	Code	R1	R2	R3	R4	R5	R6	R7
ML-enabled CDSS Technology Characteristics	SC	27, 31,33	29, 31	23, 27, 51, 57, 59, 61, 65	24, 26, 65, 67, 79	27, 53, 62	21, 25, 27	37, 45
	REL	23, 29	29	-	28	51	25, 29	-
	T	23	33	29	30	-	21, 31, 35	39

4.2.1 System Complexity

When it comes to system complexity of machine learning enabled clinical decision support systems, there are several angles to look into. This is mainly because clinical decision support systems touch upon several branches of clinical care. According to R1, these kinds of decision support systems are complex to implement, as they tend to have an effect on other parts of healthcare, thus the need to be carefully considered before adoption to ensure that potential negative changes to patients' workflows and the way clinicians work with patients are prevented (R1.33).

Moreover, R3 also expressed similar concerns regarding the need to ensure that machine learning enabled clinical decision support systems are integrated with the existing dispatcher system in the right way (R3.57). According to R4, the traditional rule-based decision support systems are relatively simple and easy to implement, opposed to machine learning enabled clinical decision support systems that are difficult, take a lot of time and require a lot of coordination with IT departments, and integration with systems such as patient records systems (R4.24). On the issue of integration, while R7 continues working towards having their application that allows patients to draw their own discomfort or pain areas moved from paper version to using algorithms with the same sensitivity and specificity (R7.37), a major technical problem was observed to come from the complexity of integrating their system with the hospital journal system (R7.45).

The other issue that came up was the model training process. R2 highlighted that some of the models they use were trained on a different population, in another country and the radiology equipment they used for training the models (GE) are different from those being used by the hospital (Hologic):

> *GE-image looks different from a Hologic-image of the same breast. So there is definitely something different in the images, so I think it's probably important. (R2.31)*

However, despite these system dynamics, R2 mentioned that the models still work just fine (R2.31). A similar notion was further supported by R4 and R6 who highlighted complexities such as the need to retool, reset, readjust, and revalidate modes at new sites, that come with training models in one hospital and trying to spread them to other hospitals or regions (R4.65; R6.25), as the parameters used at one hospital may not work in another due to various aspects such as difference in IT-systems, culture if located in a different country and treatment practices (R6.27).

Away from system complexities associated with setting up and integrating machine learning enabled clinical decision support systems, R5 mentioned that other system complexities arise from underestimating the importance of sufficiently involving clinicians in the initial stages of the adoption process (R5.62), making the systems less user friendly and more complex to implement. Additionally, unlike simple rule-based decision support systems where it is possible and relatively simple to predict what models are going to output given certain inputs, R6 expressed concerns regarding complexities associated with difficulty of knowing how the nonlinear models are going to behave (R6.21). This was further intimated by our conversation with R3 who highlighted that if the model fails to identify a patient who needs an urgent ambulance and one is not sent, the kind of damage can be extensive (R3.57).

4.2.2 Reliability

Regarding reliability, from R1's perspective, a lot of the data extracted from medical systems is noisy and contains errors, mostly resulting from wrong inputs into systems where this data is picked:

> *I mean, so all data that we use are noisy [Laughter]. Because they all contain errors, because things are entered wrong into the system, and so on and so forth. You can't really avoid that, there is always going to be noisy data, error in the data (R1.29)*

Thus, R1 finds it important to put some safeguards in place to ensure that the machine learning enabled clinical decision support systems have a way of dealing with the unclean data (R1.29).

According to R3, ensuring reliability of data involves a lot of work, spanning from creating combined datasets into some sort of quality development database (R3.23) where the data can be centrally cleaned to handle issues such as missing values, formatting, and data handling issues (R3.25). Additionally, R6 highlighted reliability issues resulting from using small datasets that do not sufficiently address underlying predictive signs of the desired outcome, which could result into false high model scores that do not address underlying mechanisms in actual practice (R6.29).

In the process of empirical data collection, it was noted that whereas previous literature and our conceptual research framework placed emphasis on reliability of data as a factor that influences adoption of machine learning enabled clinical decision support systems, the respondents seemed to place more emphasis on data availability instead. Section *4.5 Emerging Findings* of this results section will therefore cover the factor of data availability in more detail.

4.2.3 Transparency

According to R1, in order to build clinician's trust in the machine learning enabled clinical decision support systems, transparency has become more and more important and there is an increasing demand for reasonable explainability of why the systems came up with the kind of diagnosis or predictions they provide (R1.23). This was further supported by R6 who mentioned that the issue of transparency and interpretability is a big one and extremely important (R6.21; R6.35), citing examples where doctors tended to prefer systems or algorithms that had a slightly lower accuracy score but more transparent over algorithms that had a higher accuracy score but black boxed, even when both systems are trained via the same randomized control trials (R6.31).

From R2's point of view, depending on the type of decision, suggestion, or prediction provided by the ML-enabled CDSS influences transparency aspects differently:

> *So I mean this, like binary decision itself is very easy to understand, like, it's yes or no, basically. It's flagging something suspicious or not (R2.33).*

However, providing explanations to why the models came up with the predictions or suggestions is not always an easy task, R2 elaborated by explaining that ML-models used for their application can give other types of suggestions that are not binary, such as marking specific areas in MRIs that are suspicious, which are not as easy to understand (R2.33).

From perhaps another point of view, R3 mentioned that whereas they incorporate transparency in their systems by offering a functionality where users (clinicians) can press a button and get some additional information about how the model is thinking and how it came up with the recommendation it provided, the users tend not to really look at these explanations especially due to high emergency patient numbers at their centers (R3.29). In accordance with this, R7 further stated that the average clinician in most of cases will not have enough time to go into depth of how the machine learning model came up with its suggestion (R7.39).

Moreover, R4 who is a medical doctor among other responsibilities provided a similar interesting context regarding transparency, citing some situations and examples regarding different circumstances at play in a clinical setting:

> *It depends on how established the decision support is. If I know, for example, that it has been used for three years, by my colleagues, all over the country, then I don't need to really understand what happens. But if it's new, and if it looks complicated, if I knew it's AI or machine learning or something then I will feel the need to understand what's happening (R4.30).*

R7 also stated that as long as the managers or someone dependable tells the clinicians to use the system they will do so without critical need for further transparency (R7.45). Despite this though, it is still important to provide a user interface that gives users enough information regarding the basis for the recommendations to optimize trust in the system (R4.30).

4.3 Healthcare Organization

Table 4.3 provides a holistic overview of the empirical findings from the healthcare organization theme. The table illustrates respondent and row details from transcriptions where the respective factors were coded.

Table 4.3 – Overview of the Healthcare Organization theme

Theme	Code	R1	R2	R3	R4	R5	R6	R7
Healthcare Organization	TMS	-	35, 37	23, 39	40, 42	35	37	-
	FR	46	39	19	50	37, 39, 41, 47	43	26, 30, 43, 59
	TR	35	-	37	24, 53, 55	43	45, 47	45

4.3.1 Top Management Support

R2 mentioned that top management interest in a project or initiative makes a big difference and sometimes it does not necessarily have to be from far higher up in the hierarchy (R2.37). The importance of top management support was further emphasized by R4:

> *We need support from the entire system, from the clinical managers, from the IT department to some extent, from the *...*, but mostly from the clinical side of the clinical leadership, the IT clinical people. So, we need a lot of support (R4.40)*

Moreover, R3 highlighted their hospital operation manager's efforts to coordinate activities regarding data storage, which enabled the ability to take on the project of developing a machine learning enabled clinical decision support system in the first place (R3.23). Additionally, R5 also found top management support as important, as they often are in contact with the CEO of the medical device company that they have been collaborating with, who is very much involved into the details of the system as well as the process of developing the machine learning models used in the clinical decision support system (R5.35).

4.3.2 Financial Resources

According to R1, financial resources is not a big factor when it comes to adopting machine learning enabled clinical decision support systems. This was based on the notion that there are various external funders that can be approached to fund good ideas and initiatives. Moreover, whereas it can take quite some time to apply for the external funds, it is still doable, and many funders exist in the field (R1.46). This was further collaborated by responses from R2, R3 and R5 who mentioned that funding for some of their projects came from external funders (R2.39; R3.19; R5.39) while some costs are funded internally (R2.39; R3.19).

Furthermore, R4 mentioned that when it comes to financial resources, whereas:

> *The hardware is cheap, the people are expensive and there are no specific budgets for this and in the *...* IT department. So, we have to get the money (R4.48).*

R4 elaborated on this emphasizing that they have to find funding from some special grants that they need to apply and compete for (R4.50).

Lastly, while external funders exist, R5 and R6 acknowledged that a lot of financial support is needed for these machine learning enabled clinical decision support system projects at various stages of the process and funding in the initial phases can be quite difficult to get (R5.47; R6.43). This is also evidenced by the project that R7 is involved in, where at times they struggled with external founders and currently only rely on financing it internally and privately (R7.43).

4.3.3 Technology Readiness

R1 mentioned that whereas technology readiness has to be taken on a case-by-case basis, most clinicians are already used to using some sort of decision support systems in their work all the time, making the readiness to transition to machine learning enabled clinical decision support systems much more apparent (R1.35). Moreover, R4 highlighted similar sentiments regarding clinicians using decision support systems already, mainly the simple rule-based kind (R4.55).

According to R4, clinicians are relatively ready for the new machine learning enabled clinical decision support systems:

> *Oh, they're ready. They're ready. And we are very computerized in the clinical work (R4.53)*

R5, R6 and R7 associate this kind of technology readiness to the rapid breakthroughs happening in the medical world and the continuous introduction of new technologies (R5.43; R6.47; R7.45). Moreover, according to R6, there is a high interest among clinicians in understanding how technologies work and how they can personally use them, influenced by general technology information published about the impact of AI and machine learning (R6.45).

4.4 Healthcare Environment

Table 4.4 provides a holistic overview of the empirical findings from the healthcare environment theme. The table illustrates respondent and row details from transcriptions where the respective factors were coded.

Table 4.4 – Overview of the Healthcare Environment theme

Theme	Code	R1	R2	R3	R4	R5	R6	R7
Healthcare Environment	REG	44, 50	42	43, 47, 49	59, 61, 63	45	51, 53	32, 47
	MT	19, 39, 44	44	51	69, 71	49, 56	56	-

4.4.1 Regulations

The statement of healthcare being a heavily regulated space was shown evident among all of the respondents when asked to what extent they are considering regulations in terms of adopting ML-enabled CDSS. These regulations have been shown by the respondents to impact two major areas of ML-enabled CDSS adoption, namely the use of medical data that are being fed to the ML-models and ML-enabled CDSS that are classified as a medical device.

The first aspect, the use of medical data, is expressed by the respondents to be governed by different regulations and authorities. Firstly, R1 and R2 mentioned, from a Swedish perspective, that the Swedish Ethical Review Authority must approve any research initiative, which is among the first steps of adopting ML-enabled CDSS as medical data is very sensitive (R1.50; R2.42). Additionally, R2 mentioned the *patient safety act* and the *public access to information and secrecy act* are important regulations that are impacting their adoption (R2.42). However, from R1's point of view, the process of getting ethical approval is not really that big of an issue compared to other aspects. The respondent elaborated by saying: "I think the biggest hurdle in Sweden today is actually to get access to it once you have got it approved (R1.50)". R1 based this statement on that hospitals and regions are using different systems for storing and accessing medical data (R1.52).

Moreover, in regard to storage, access and usage of medical data, GDPR was mentioned by the majority of respondents as impacting the adoption as it poses requirements on the management of data used for the machine learning models. R6 elaborated ways in which it has been impacting from their perspective:

> *Yes, impacting for the best and for the worst. Of course, the GDPR laws, they impose certain constraints about how you should handle your data and they make you feel like you're responsible for what you're doing. For real. If you leak data, it's going to be your fault. In the past, you wouldn't have this kind of pressure in a sense. But it's not a bad thing, it's good that you're able to build a system that's actually robust, that you can share data safely within the hospital and so on. For that aspect, it has impacted but I think positively rather than negatively (R6.51).*

As evident in the statement, R6 mentioned that it has impacted how certain tasks have been done to make sure that the regulation is followed. Both R3 and R7 align with this statement, as they in their projects have taken a set of actions to ensure that the directions of GDPR is uphold. In R3's project all activities were conducted on hardware that is owned or servers hosted by the hospital (R3.41). Additionally, for R7 in the development of their app, they spent both a lot of time and financial resources to ensure that the constraints imposed by GDPR were followed (R7.47).

The second aspect is governed by the European Union Medical Device Regulation (MDR), R1, R3 and R4 stated that this poses a lengthy process to get the ML-enabled CDSS approved, which enables distribution of the CDSS as a medical device (R1.44; R3.47; R4.59). R4 expressed that simple rule-based clinical decision support systems could be used without taking any regulations into account, since its complexity level of the system is equivalent to being able to implement it on pen and paper (R4.57; R4.59). Moreover, the MDR poses that medical devices require a CE marking, showing that the CDSS conforms to all the directives posed by the MDR (R1.44; R3.47; R4.59).

However, R3 and R4 stated that the MDR regulation was updated quite recently, about two-three years ago, as a result there are ambiguities and technicalities in the current regulation (R3.47; R4.59). As R3 was part of developing the CDSS, the respondent said:

> *if you have an […] medical device that you develop yourself, it needs to fulfill the same requirements as a CE marking, but you don't need to go through all the legal kind of formalities to do it. […] We still have to produce evidence that it's safe, and that it does what we say it does. But we don't need to go through all the formal kind of application processes to get things approved, the "Läkemedelsverket", CE marking, and all these things (R3.47).*

Having developed the ML-enabled CDSS on their own has enabled them to use it without going through some of the extensive steps of the process. R4 strengthened this further by addressing that this somewhat undiscovered territory as they could not get clear answers when seeking regulatory advice (R4.59) and that there are various aspects that are unclear at the time (R4.63). However, R3 stated that they still have their ML-enabled CDSS CE marked and in the case of distribution to other hospitals it would have to go through the entire process (R3.37; R3.39). R5 also conformed to regulations being influential for the adoption of as the process of a CE marking is cumbersome work that requires both financial and human resources (R5.45).

4.4.2 Market Trends

According to R4, whereas market trends and major events, such as the pandemic, increased the incentive for adopting machine learning enabled clinical decision support systems and other technologies, it is rather curiosity that was the main driving factor for their team (R4.69). R4 stated that as the development for these systems has been relatively slow and going on for a couple of years, long before the pandemic:

> *But I mean, these ideas were... have been present for a long time. For at least 25 to 30 years, the development has been slow, and it comes and goes (R4.71).*

Moreover, the respondent also mentioned that curiosity has been driven and inspired by sudden breakthroughs in certain areas of medicine as possible explanation to the sporadic development of these kind of systems (R4.71).

Additionally, R2 and R5 mentioned that the curiosity (R2.46; R5.49) and desire to use the vast amounts of data being collected by hospital systems and possibilities of how it can be used to improve patient care inspired them to adopt machine learning enabled clinical decision support systems (R5.49). However, on the contrary side to curiosity being more prominent than market trends, R6 acknowledged that the recent covid-19 pandemic also increased the incentive for using ML-enabled CDSS as a result of availability of multiple grants to conduct studies and enhancements (R6.56).

4.5 Emerging Findings

Table 4.5 provides a holistic overview of the emerging findings theme. The table illustrates respondent and row details from transcriptions where the respective factors were coded.

Table 4.5 – Overview of the Emerging Findings theme

Theme	Code	R1	R2	R3	R4	R5	R6	R7
Emerging Findings	DA	17, 25, 27	-	23, 27, 35, 53	28, 75	56	-	-
	COL	17, 52, 54	-	49, 55	40	25, 33, 51	45	32

4.5.1 Data Availability

According to R1, availability of a good structure of healthcare data, most of which already existing in the healthcare systems and collected during patient visits with the aim of improving patient value by having more precise decisions along the patient care workflow, was a big influencing factor for embarking on using machine learning enabled clinical decision support systems (R1.17). This was further supported by R4 and R5, whose teams were also influenced by the availability of great databases (R4.74; R5.56).

From a Swedish context, integrating machine learning enabled clinical decision support systems with other systems such as the journal system that potentially contain historical data, new data and recently added data present a great opportunity for access to the much-needed data (R1.27). Lastly, as seen from below interview extract, R3 further emphasized that the availability of data as a precondition motivated their project to implement the machine learning enabled clinical decision support system. Moreover, they were already working on a comprehensive dataset long before adopting machine learning enabled clinical decision support systems (R3.35).

> *Like I mentioned that even before the project, they were working on developing this dataset, right, that the machine learning based system is based on. So we have the data from dispatch center, ambulance and hospital. And really, the reason we started with a project was that we needed to use this dataset for something in a way (R3.35).*

4.5.2 Collaboration

When asked what aspects the respondents found the most influential while considering the adoption of machine learning enabled clinical decision support systems, collaboration was found to be critical as seen in extract below from one of the respondents.

> *I think the most important thing is in a single word collaboration [Laughter]... the only way we can work towards adoption is that all involved partners collaborate (R1.54)*

R1 has taken this into consideration in his choice of employer, as the respondent's current roles at different organization enables collaboration and access to medical data (R1.17), thus enabling initiatives of machine learning enabled clinical decision support systems to take place. From a bigger perspective, the collaboration between hospitals was found to be important to the adoption. From a Swedish perspective, one of the challenges resides with the collaboration between the different regions and making use of the large set of quality registers that contains information of specific diseases for small patient populations (R1.52). This is further evidenced by R3 who stated that as they currently have been able to adopt their CDSS internally, constraints regarding collaboration in combination with other regions among other aspects – such as regulation and system complexities previously addressed – have impeded further collaboration to take place (R3.49).

R1 stated that the current challenges of machine learning enabled clinical decision support systems is something that can be resolved, but it will not be realized if organizations work in silos (R1.54). Internal collaboration between the IT department and the clinicians is found by R4 as an important pre-requisite for the adoption of machine learning enabled clinical decision support systems (R4.40). Additionally, when R3 reflects upon their finished project, the respondent finds that there could be more synergies to make use of by offloading some work and collaborating with the IT department (R3.55). The factor of collaboration being important has its foundation in that professionals from different fields intervene, thus a need to establish a common understanding of their different professions. R5 spoke of how this intervention takes place from the perspective of a clinician, where R5 makes sure to help the developers to make sense of the medical parameters used in the machine learning models (R5.51). On the other hand, as R6 has a developer's perspective, they found the need to establish a common understanding of the generic concepts that fall under the field of machine learning and how the design and development process takes place between the respondent in question and the clinicians he collaborates with (R6.45).

5 Discussion

5.1 ML-enabled CDSS Technology Characteristics

5.1.1 System Complexity

System complexity is not a new factor in studies researching influencing factors for the adoption of new innovative technologies in healthcare, even though scholars have varying findings when it comes to its actual influence on adoption (Chang et al., 2007; Chong & Chan, 2012; Ghaleb et al., 2021; Hung et al., 2010; Lian, Yen & Wang, 2014). Firstly, in regards to system complexity when adopting machine learning enabled clinical decision support systems, respondent R1, R3, R4, R7 noted that the systems were complex to implement at various levels, ranging from complexity to integrate with existing systems, complexity of ensuring that the new systems have no negative impact on the patient workflow or associated downstream processes and the amount of time they take to implement.

Moreover, ML-enabled CDSS are data driven and require significant model training. However, as noted from our empirical data collections, R2, R4, and R6 highlighted complexities associated with training models in one context, hospital or population and trying to scale the same model to another context or hospital. Whereas models trained using different machines and on a different population managed to work without significant issues for the case of R2, the difficulty to scale from one setting to another was a concern raised by several of the respondents. This is consistent with a study by Chong and Chan (2012) which found that system complexity was a significant influencing factor for adoption of new technologies (Chong & Chan, 2012). Furthermore, opposed to findings by Chang et al. (2007) that supported the notion of system complexity being perceived as a low effect adoption factor in healthcare, citing reasons such as – many of the vendors providing comprehensive solution that require minimal input from hospitals, the respondents of this study did not acquire already made solutions from vendors but rather worked proactively on them.

Consequently, based on feedback from the respondents and existing literature, this paper argues that system complexity is an influencing factor for the adoption of machine learning enabled clinical decision support systems, especially when the hospital does not procure an already made ML-enabled CDSS.

5.1.2 Reliability

Reliability has been acknowledged in literature as a factor to address when adopting new technologies in healthcare, especially in relation to the reliability of data in the Electronic Health Record (EHR) systems (Sulaiman & Magaireah, 2014). This finding can also be found in the empirical material as multiple respondents – R1, R3 and R6 – were cognizant of the fact that the data from EHR systems are prone to errors and contains noisy data. The main reason behind the respondents' realization of reliable data is most likely due their knowledge of machine learning and the fact that the EHR systems in many cases constitutes the basis for the data to be used for training of the models used, or to be used in the clinical decision support systems.

However, the respondents for this study rather put an emphasis on other factors that influence the adoption instead of elaborating how data reliability had an impact, indicating that other factors were more prominent on the adoption. One possible explanation to this is that many of the respondent are still in the initial steps of adopting these types of clinical decision support system. R3 and R5 being exceptions as they are part of or collaborating with hospitals that currently use machine learning enabled clinical decision support. In these situations, they both work with maintaining the machine learning models through ensuring that the data is reliable.

As evident, reliability has been highlighted as important. However, based on the empirical material indicating that many of the respondents are in the initial stages of adopting machine learning enabled clinical decision support systems reliability is found inconclusive if it in fact is influential of the adoption machine learning enabled clinical decision support system, despite being found influential in previous studies (Pumplun et al., 2021; Sulaiman & Magaireah, 2014; Venkatraman, Sundarraj & Seethamraju, 2015).

5.1.3 Transparency

A couple of studies have highlighted the significancy of the black box nature of machine learning systems and the difficulties faced by clinicians in regards to understanding the logic behind the recommendations provided by these systems (Magrabi et al., 2019; Shortliffe & Sepúlveda, 2018). The respondents however had mixed opinions regarding transparency. Firstly, according to R1 and R6, the issue of transparency is a big and important factor when it comes to adopting machine learning enabled clinical decision support systems. Majorly because transparency has been perceived to increase trust in the system and the recommendations provided as clinicians have an understanding of how and why the system came up with the kind of insights it provided. This is in line with findings from a study conducted by Pumplun et al (2021) that found transparency as a influencing factor of adoption of machine learning systems.

On the other hand, R7 was of the view that the average clinician will not have time to go into details of why an algorithm provided a certain recommendation or insight. Moreover, according to R3, even though their system incorporates a button that clinicians can press to get more details regarding insights provided by the system, it is barely used due to high numbers of patients. This further made us question whether transparency is indeed an influencing factor for the adoption of ML-enabled CDSS, especially after one of the respondents voiced a point of view that if the managers advise clinicians to use a particular system, more often than not, they will do so without critical need for further transparency.

Subsequently, given that different respondents provided varying views regarding the influence of transparency in the adoption of machine learning enabled clinical decision support systems, this paper found that whereas a couple of respondents acknowledged the notion that often times the average clinician has no time to check details of why a system provided certain recommendations, majority of the respondent expressed that is was still an important and influencing factor of adoption and building trust in the systems.

5.1.4 Data Availability

One of the factors that kept coming up during our empirical data collection that respondents felt was an influencing factor for their adoption of machine learning enabled clinical decision support systems was availability of data – "Data availability". Prior to the empirical data collection phase, while reviewing literature regarding adoption of machine learning in healthcare, data availability was not explicitly mentioned as an influencing factor, as scholars highlighted other data related factors such as data privacy, data security and data reliability (Chang et al., 2007; Chong & Chan, 2012; Lian, Yen & Wang, 2014; Pumplun et al., 2021; Sulaiman & Magaireah, 2014). As such, it was not included in our initial conceptual research framework. This could be as a result of previous research focusing more on data related issues such as privacy, security, reliability, generalizability and not the actual availability of data as influencing factors.

According to R1 one of the motivating factors for their project was the availability of a good structure of healthcare data that made it easy to access data to be used for their ML-enabled CDSS project. Additionally, a collaboration with over seven other entities under one umbrella further provides access to even more data collected from various places.

A similar viewpoint was provided by R3, where the availability of a combined dataset collected and combined in a quality development database arguably influenced their adoption as mentioned by the respondent. Moreover, R4 referred to their access to data as a big goldmine and like R5, one of their influencing factors for embarking on their ML-enabled CDSS as availability of great databases.

Subsequently, whereas this factor – Data availability was not included in the initial conceptual research framework, feedback from the respondents makes it a novel addition to the factors that influence the adoption of machine learning enabled clinical decision support systems.

5.2 Healthcare Organization

5.2.1 Top Management Support

When faced with the question to what extent top management support was impacting the adoption of machine learning enabled clinical decision support systems, both R2 and R4 stated that it was important for their project and initiatives, thus in some way embracing change to take place through adoption. This aligns well with Tushman and Nadlers' (1986) argument of top management support acting as a facilitator of adopting new innovation. Moreover, as R2 and R4 to some extent already poses the role as managers in their current projects or initiatives they conform with top management support being influential for the adoption as they are part of driving the process. Additionally, from another perspective R3 and R5 found the support from the medical director and operations manager of the hospital and the CEO of the medical device company respectively as impacting the adoption in a positive manner.

However, in some instances, top management support did not seem to be that influential as expected, for instance, in comparison to establishing a supportive environment throughout the entire organization. R4 mentioned they require a lot of support, especially from the IT clinicians and IT department indicating a more prominent need for technical competence and collaboration rather than top management support. Thus, parts of the empirical findings deviate from the latter part of Tushman and Nadlers' (1986) arguments of managers successfully promoting the organizational strategy in order to create a compelling vision throughout all the organizational levels. Despite this small deviation in our empirical findings, the factor of top management support is argued to influence the adoption, which is in accordance with previous literature (Pumplun et al., 2021; Ghaleb et al., 2021; Chong & Chan, 2012).

5.2.2 Financial Resources

Financial resources refers to the availability of funds or ability of an organization to fund the adoption of new technologies (Lee & Shim, 2007). This encompasses both internal and external funding. According to R4, R5 and R6, a lot of funding is needed for the adoption of machine learning enabled clinical decision support systems and is sometimes difficult to get, to the extent that a project being run by R7 is currently relying on self-financing.

Despite the challenges though, R1, R2 and R3 acknowledged that there are many grants and external funders that are accessible and willing to fund the ML-enabled CDSS projects. Based on this, it is not clear if indeed financial resources is an influence factor for adoption or not. This therefore neither confirms nor reject findings from studies by Chong and Chan (2012) and Lee and Shim (2007) that argued for financial resources not being an influencing adoption factor.

5.2.3 Technology Readiness

With the recent increase in adoption of new technologies across several industries including healthcare triggered by events, such as the covid-19 pandemic (Doyle & Conboy, 2020; Wade & Shan, 2020), this paper sought to investigate if technology readiness was an influencing factor for the adoption of machine learning enabled clinical decision support systems. The aim was to investigate the readiness of clinicians, IT infrastructure and healthcare organizations in general to adopt these systems.

According to R5, R6 and R7, the continuous introduction of new technologies and rapid number of cutting-edge technological breakthroughs happening in healthcare has significantly increased the technology readiness and clinicians' willingness to embrace new technologies. Moreover, the general consensus this paper derived from feedback received from our respondents indicates that technology readiness from clinicians' perspective is evident and present, especially with the viewpoint that clinicians already work with some sort of clinical decision support systems and thus transitioning to machine learning enabled systems is perceived as a relatively smooth task.

Consequently, this paper argues that whereas technology readiness is an important factor when it comes to adoption of new technologies, the feedback received from respondents indicates that it is not an influencing factor for the adoption of machine enabled clinical decision support systems.

5.2.4 Collaboration

As described by Baker (2012), organizational context elements such as linking structures within the organization, communication process and factors such as cross functional teams tend to have an impact on the adoption of new technologies in various ways. To this end, our empirical data collection found similar viewpoints from the respondents.

According to R3, collaboration between medical experts, IT, machine learning experts and other departments is perceived as a big enabler for adoption of these systems. This is further aligned with R4's submission regarding needing support from clinical managers, IT department, that region, and overall clinical leadership. Moreover, this was emphasized by R1, citing that the only way to overcome the obstacles in adopting ML-enabled CDSS is if there are no silos and giving an example of a collaboration they have with seven companies that has aided with making things such as access to healthcare data from various places easier, and thus creating the potential to offer clinicians more precise decisions alongside offering patients better value.

On these grounds, whereas collaboration was not indicated in the initial conceptual framework, this paper found it important to include on the list of influencing factors for adoption of machine learning enabled clinical decision support systems, based on the feedback received from respondents.

5.3 Healthcare Environment

5.3.1 Regulations

Regulations could either support or hamper the organizational uptake of innovation and technologies (Baker, 2012). All the respondents were cognizant of regulations impacting their organization's adoption of machine learning enabled clinical decision support systems as they addressed the impact of GDPR and the MDR in regard to their adoption extensively.

The finding of Sanchez-Martinez et al. (2022), that machine learning based applications currently do not follow the constraints of GDPR aligns partially with the respondents' answers. From the respondents' perspective it differs as R3, R6 and R7 expressed that they have actively taken actions to ensure that the constraints of GDPR are upheld – such as seeking legislative advice and ensuring procurement of secure hardware – thus indicating that progress regarding compliance of the strict requirements posed by GDPR have been made. Additionally, the MDR regarding the extensive process of getting the ML-enabled CDSS a CE mark, since they are classified as a medical device, is a cumbersome and time-consuming process. In addition to that, the current ambiguities in the MDR further impacts this process as it is unclear for how to proceed in certain situations. These regulatory impacts are argued to be hampering as these activates have slowed down the adoption speed. However, supportive characteristics was also found in relation to GDPR, as R6 expressed the constraints ensures the creation of robust system from the get-go. Hence, both signs of regulations being supportive and hampering, as argued by previous literature (Ghaleb et al., 2021; Baker, 2012), were found from the respondents.

Moreover, other regulations regarding the respondents' clinical research projects, which constitutes the very first steps of adoption for many of the respondents' hospitals were touched upon. In this setting, regulations are impacting as it is required to get ethical approval to perform clinical studies that will utilize medical data. Consequently, regulation is argued to be an influential factor of the adoption of machine learning enabled clinical decision support systems, as the empirical findings show that regulations mostly slow down uptake of these kinds of systems. In accordance with Pumplun et al. (2021) proposition, which is that uncertainties and strict requirements will impede adoption, aligns well with the empirical findings in this study.

5.3.2 Market Trends

From our empirical data collection, it was noted from respondents that market trends were not an influencing factor for their adoption of machine learning enabled clinical decision support systems, contrary to findings from a study by Chong and Chan (2012) stating that if a technology trend makes its way to the healthcare industry, more organisations within the industry are more likely to adopt it.

The most prevalent reflection that came up was "curiosity" for trying to find ways of improving the clinical environment. Moreover, from R4 and R6 point of view, whereas trends and events such as the covid-19 pandemic increased the incentive and grants for new technologies, the ideas, and projects they are working on have been around far before the pandemic. However, according to R3, the covid-19 pandemic made them reevaluate their models as changes in patient population and other dynamics presented a potential risk of impacting the accuracy of their models. Therefore, based on feedback from the respondents, this paper argues that market trends are not an influencing factor for the adoption of machine learning enabled clinical decision supports but can act as an incentive for further development in the area.

Table 5.1 – Overview of findings

Factor	Finding	Category
System Complexity	Influential	ML-CDSS Technology Characteristics
Transparency	Influential	ML-CDSS Technology Characteristics
Data Availability	Influential	ML-CDSS Technology Characteristics
Top Management Support	Influential	Healthcare Organization
Collaboration	Influential	Healthcare Organization
Regulations	Influential	Healthcare Environment
Reliability	Inconclusive	ML-CDSS Technology Characteristics
Financial Resources	Inconclusive	Healthcare Organization
Technology Readiness	Not Influential	Healthcare Organization
Market Trends	Not Influential	Healthcare Environment

After elaborating on each of the factors, table 5.1 gives an overview of this research study's findings, putting an emphasis on whether they are influential, not influential, or inconclusive regarding the adoption of machine learning enabled clinical decision support systems.

5.4 Implications for Practice

In accordance with Recker (2013), this section highlights how the derived findings impact the work of clinicians and other important stakeholders of our study in actual practice. Firstly, this paper set out to investigate influential factors in the adoption of machine learning enabled clinical decision support systems and as seen from table 5.1 showing a summary of the findings, factors such as system complexity, transparency, top management support, regulations, data availability and collaboration were found to be influential in adoption. This implies that as hospitals and other healthcare entities work towards adoption of ML-enabled CDSS, these factors can be referred to and strategies put in place to ensure that they are addressed which can arguably aid with a smooth adoption process. For instance, most of the respondents expressed concerns around integration of ML-enabled CDSS with existing systems and workflows which can be a major stabling block in the adoption of these systems. This paper argues that awareness of such influential factors can aid with ensuring that practitioners take time to perform a comprehensive review of all surrounding systems and ensure that potential integration complications or complexities are identified and mitigants or comprehensive plans are put in place to have smooth adoption. Moreover, as noted from the respondents and previous researchers regarding the highlighted influential and non-influential factors, this paper argues that confirmation of these factors as influential or non-influential provides a good reference point for key stakeholders to know which areas to prioritize when working towards adoption of ML-enabled CDSS.

It is also important to note that whereas previous literature covered many factors associated with the adoption of new technologies in a healthcare context, this paper limited its investigation to only eight initial factors and two additional factors that were derived during empirical data collection, due to time constraints, meaning that there are other potential factors that practitioners can consider outside the listed ones.

6 Conclusion

This master thesis set out to explore factors that influence the adoption of machine learning enabled clinical decision support systems in a healthcare hospital setting, as well as to contribute with an understanding of their rationale when adopting this specific type of technology, through attempting to answer the research question:

What factors are influential when adopting machine learning enabled clinical decision support systems?

The qualitative approach taken to provide an answer to the research question was mainly constituted of curating a conceptual research framework based on existing literature on the well-known TOE framework along with its previous applications in healthcare contexts. The curated conceptual research framework facilitated as theoretical guidance for the empirical data collection and analysis. As previously highlighted, it was delimited to eight initial factors derived from literature that were argued to be suitable for investigating the adoption of machine learning enabled clinical decision support systems. Building on the theoretical background, curated framework and selected factors, a comprehensive semi-structured interview guide was generated that aided with empirical data collection. Post this, coding and analysis were done to derive required insights for the study and as seen in the result and discussion section, parts of analysing the data enabled identification of additional factors.

This research study found that six factors – *System Complexity, Transparency, Top Management Support, Regulations, Data Availability and Collaboration* – were influential to the adoption of machine learning enabled clinical decision support systems. Moreover, – *Financial Resources and Reliability* – were inconclusive. Lastly, the remaining factors – *Technology Readiness and Market Trends* – were not influential to the adoption of this kind of clinical decision support systems. In summary, out of ten examined factors, six of them were identified to be influential, two factors to be inconclusive, and two to be non-influential.

Based on the derived findings and insights, the contribution of this master thesis thereby resides in firstly, contributing to closing the gap in existing literature regarding adoption of machine learning enable clinical decision support systems, as this research phenomenon was found to not be covered extensively. Our findings indicate that the *system complexities* of these machine learning systems, including integration challenges with existing hospital systems and workflows plus model training to enable transfer of ML-models to other patient populations, alongside strict and somewhat ambiguous *regulations* are key considerations for hospitals when deciding to adopt machine learning enabled clinical decision support systems. *Collaboration* is perhaps another factor that was found to be important for bridging the gap between clinicians, technical departments, and overall project teams to aid with adoption. Secondly, as discussed in the implications for practice section, this study can contribute to partitioners by shading light on factors to consider before or during adoption of ML-enabled CDSS. Lastly, as the study was limited to ten potential adoption factors, it can serve as a reference point for future research investigating additional adoption factors.

6.1 Future Research

Clinical decision support systems are not in any sense new in clinical care, however embedding machine learning mechanism into these systems and existing healthcare systems are still relatively new. Despite research regarding their potential and challenges, there is still room for further exploration of this topic.

As previously mentioned, this study was limited to eight factors in its initial stages, which acted as theoretical guidance for the empirical research, and two additional factors derived during analysis. It is important to highlight that other technology adoption factors were identified within the healthcare context as seen in table 2.2 but were not included in the conceptual research framework. These factors are still unexplored within the setting of machine learning enabled clinical decision support and can be explored by future studies to further enrich the existing body of knowledge. Thus, we believe that this research study could potentially work as a reference for future research looking into examining influencing adoption factors.

Moreover, since this research study used the TOE framework as a reference, future research can consider using other technology adoption frameworks which would further facilitate conduction of studies within the same research phenomena using other theoretical lenses.

Appendix 1 – Consent Form

Interview Consent Form

LUND UNIVERSITY
School of Economics and Management

Firstly, we would like to thank you for accepting to participate in this research study.
In accordance with previous communication, the interview is scheduled for:

[Date] at [Time]

The interview is estimated to take 30 minutes and we do not anticipate or identify any risks associated with participating in this study. Furthermore, there is no requirement to answer all the interview questions.

Ahead of the upcoming interview, this consent form provides information regarding the principals of ethical conduct that we aim to uphold. This is provided to ensure that research participants know why information will be gathered and how it's intended to be used in the master thesis. Please make sure to read them through:

- The interview will be recorded, and a transcript will be produced based on the recording
- Once produced, the transcript will be sent to you, where you'll get an opportunity to correct any factual errors.
- As a research participant you have the right to withdraw from the study at any time, until one week after the interview transcript has been shared with you for review.
- The transcript will be analyzed by the researchers, and will be included as an appendix in the master thesis
- Your identity will be kept anonymous, direct quotes and resumes of interview content will be anonymized in all types of research disclosures (the transcript and the thesis)

When starting the interview, we will make sure that this information has been understood through mutual confirmation, which will be reflected in the transcription.

If there are any concerns or question in relation to this, do not hesitate to contact us by answering this email.

Appendix 2 – Interview Guide

Concepts	Question	Group
	Introduction	
	1. Did you have the opportunity to look through the consent form? Any particular questions or concerns? If not we'll proced with starting the recording of the interview.	All
	2. To summarize, this research study is focusing on the factors that influence the adoption of machine learning enabled clinical decision support systems.” This entails looking into the factors that were or are being considered when adopting machine learning in any area of clinical decision support and associated systems.	All
Clinical Decsion Support Systems | Machine Learning	3. Could you tell us about your role in your current organization and any previous applicable roles?	All
	4. In what ways is your organisation utilizing or planning to utilize machine learning enabled clinical decsion support systems?	All
ML-enabled CDSS Technology Characteristics	**System Complexity**	
	5. How complicated was it/are you finding it to comprehend and implement machine learning enabled clinical decision support systems?	Expert
	6. How does the clinical decsion support system(s) relate with other systems? *If needed to elaborate on the question: mention integration with current systems as an example.*	Doctor
	Reliability	
	7. Machine learning enabled clinical decsion support systems require large amounts of medical data, how reliable is the data you are using/used?	Expert
	8. How reliable are the system (CDSS) recommendations and insights?	Doctor
	Transparency	
	9. Are you able to understand the logic behind the system (CDSS) suggestions? How important is it for you to understand this logic?	Doctor
	10. Transparency of machine learning models have seemed to be a hot topic, how important have you found it when conducting these projects/initaives?	Expert
Healthcare Organization	**Top Management Support**	
	11. To what extent is/was top management involved in the adoption process of the machine learning enabled clinical decsion support systems?	All
	Financial Reosurces	
	12. Was/is the iniative of adopting ML-enabled CDSS percieved as costly and was it funded internally or externally?	All
	Technology Readiness	
	13. How prepared was/is the orgainzation for the machine learning enabled clinical decsion support system(s)?	All
Healthcare Environment	**Regulations**	
	14. What kind of regulations were considered and how did they impact the project/iniative?	All
	Market Trends	
	15. Was the project/initaitave based on a particular market trends or demands? *Follow-up:* What were they?	All
	Closing questions	
	16. In your opinion, what influenced the the decsion to adopt machine learning enabled clinical decision support system(s) the most?	All
	17. Would you like to add anything or provide any particular feedback?	All

Appendix 3 – Transcript Respondent 1

Speakers:

HK = Herman Joseph Kambugu

AS = Axel Svansson

R1 = Respondent 1

Date: 14th of April 2022 Length: 35 min.

Row	Transcription	Code
1.1	**AS:** Hello, *…* !	
1.2	**R1:** Hello.	
1.3	**HK:** Hi.	
1.4	**AS:** How are you?	
1.5	**R1:** I'm fine. It's soon Easter vacation.	
1.6	**AS:** Yeah yeah, definitely. We tried to make sure that we didn't book anyone during Easter. It would be really unfortunate.	
1.7	**R1:** Friday is gonna be tricky for you if you're gonna book people.	
1.8	**AS:** Yeah, definitely. Are you in *...* currently?	
1.9	**R1:** I'm in *...* now, yes.	
1.10	**AS:** Nice. So, just to double check, we saw that you read the consent form and all of that, and it seemed okay?	
1.11	**R1:** Yep.	

1.12	**AS:** Good. So then we'll just start the recording. You will hear Zoom announce it, just for your awareness. And then we'll get to know a bit more about you and then we start the interview essentially. Also, in interest of time, and everything like that. **[Zoom: Recording in progress]** So, yeah. Great. So, just to begin with, we would just to super briefly just mention the purpose of the interview and what we're studying. That will sort of be the foundation and something to reflect upon when answering questions, essentially. So we're focusing on the factors that influence adoption of machine learning enabled clinical decision support systems. So, we think this essentially entails looking into all kinds of factors, technical, environmental/external, organizational, that are being considered when adopting these kind of new technologies. We sort of tried to find appropriate people to talk to and you came up. And that's essentially it. So first off, we would just like to know a bit more about you, what current roles you've been having or initiatives or projects that you've been involved in. So you can just go ahead and tell us briefly about it.	
1.13	**R1:** I will just start with a question. From what department are you running this at the university?	
1.14	**AS:** Oh, we're from LUSEM, so Lund University School of Economics and Management, and we're part of the informatics department. So we're a bit of in the mix of being super technical and a bit more management.	
1.15	**R1:** Yeah. Okay, so, I started as, studying physics [laughter] back in 1986. I started then in 1990, with my PhD. But then very early on in my PhD, I was focusing on machine learning as we call it today, but at that point, it was all on artificial neural networks and very early in my PhD, we started to collaborate with physicians at *...* hospital, trying to help them classify various kinds of medical datasets, often into things like "healthy", "not healthy" and it was a lot about ECGs and in connection with infarction. So it had a medic, a clinical, point to it. But as you say, all the studies that we, that I did, during my PhD that was connected to medicine. None of these things actually got implemented in any way. It was retrospective studies that ended up in a journal, but no concrete action at the clinical floor due to these publications. And I think that's still, as you hint here, if you look at the studies, that's still the case today. There is a lot of studies on the potential of AI and machine learning in healthcare, but there is still much more to do when it comes to the implementation of it. So that's what I did, and then I have been continuing to working with medical people during the years and have been involved in various kinds of projects trying to see if there is potential for using AI and machine learning in a quite range, big variety of clinical applications lately. But a little bit focused on cardiovascular diseases, some cancer related projects and so on.	UC

1.16	**AS:** Alright, so the ways that these applications are intended to be used is essentially for to improve decision making for doctors, I guess?	
1.17	**R1:** Some of the studies are more on the pre-clinical side trying to figure out biomarkers, trying to understand the disease more, while some of them are really focused on helping physicians at some very specific decision point in order to improve, in the end improve for the patient's right. Improve and diagnostic situations, make predictions that perhaps avoids surgery or something like that, but it has a very clinical side to it. I would like to mention that 2018, I joined *...*. So, I'm currently 50/50 at *...* and *...*. The reason why I did that is because *...* and *...* has a very good collaboration. *...* has very good... structure of healthcare data. So it's very easy in *...* to have access to healthcare data, basically all the data that you collect when patients are visiting the healthcare system, including primary- and also in hospital care. So it's convenient of them to do studies like that, because it's so easy to get access to the data. Also at the university, there are people studying implementation science. We have, and when you ask that in the beginning here, what kind of projects am I involved in and so on, we are having quite a big, we call it a research profile. So it's a collaboration between the *...*,*...*, and seven companies under the umbrella of what we call *...*. Which is for me... it's utilizing all the healthcare data that is collected in various places and try to, in the end, improve patient value by for instance, having better, more precise decisions along the flow. In that project, in that *...* as we call it, we have implementation science persons trying to understand a little bit of what you're trying to understand; "What are the obstacles?", "What are the hurdles, when you actually want to implement something at the clinical side?", "What organizational challenges are needed?", "What do the physicians need in terms of the AI systems, just besides the fact that it can produce a good prediction?", "Do we need something else?", and things like that. So we are actually focusing a little bit on there. If you have time, and if you want to interview more people, I could probably suggest a couple of persons that are implementation science persons at *...* if you want to understand more of their field.	UC, DA, COL
1.18	**AS:** I see. Yeah, that sounds super promising actually. Because we sort of also got that realization that it isn't super easy to find people who actually have implemented something that's up and running. So that's always something to consider, especially when doing research, you can't be speculative.	
1.19	**R1:** And to be honest, we are in some of the projects that we are running up there are now in the phase of actually understanding this implementation process. But we cannot say that we have many systems that are actually up and running. I think if you want to understand that, you should also look from the medical device company's point of view. Because of course medical device companies that are in the medical device area, they have to understand also, when they are selling devices, how they should be used. Right. So there's also that side from it.	UC, MT

1.20	**HK:** Yeah, that's I think very helpful. And like you've mentioned, it's very hard to find people that have actually implemented this kinds of projects and my question regarding the *...* project that you mentioned, how complicated is it at the moment for you to sort of come up with a grasp of trying to get it started?	
1.21	**R1:** Get it implemented?	
1.22	**HK:** Yes. Like, how complicated is it? Oh, what are some of those things that are stopping you from driving it from concept to implementation?	
1.23	**R1:** Yeah. So if I look from my side, when it comes to AI and machine learning, there is a more and more increasing demand of what is called explainability. Which I could probably boil down to what is called trustworthiness of the AI-solutions and things like that. But it is becoming apparent that when you are using a decision support, that is providing you with a suggestion for a diagnosis, that tool is also trying to provide an explanation for why it came up with that kind of specific diagnosis or a specific prediction. So this field of Explainable AI is becoming more and more important, also, when it comes to the implementation. Because it's going to build trust for the ones that are using the system, if it also can provide reasonable explanations. This is of course tricky, because none of the systems so far developed are 100%. Which means that there is always going to be errors involved here, and how do users perceive when a system is providing you with a wrong predictions. So there are complications, but this field of XAI, that is important, and that is also then as you say, becoming one of the challenges that we have to cross.	T, REL
1.24	**AS:** I see. But then you also mentioned the abundance of data, at least accessible in *...*, right? But these systems, they are very dependent on these datasets?	
1.25	**R1:** Yes. So then comes another challenge and that's more on the technical nature, which means that one... you need to understand the situation, exact in time, location, where you're going to provide this possible decision support. You need to know that, you need to make sure that the data is available, so the system can actually have access to the data needed for the predictions.	DA
1.26	**HK:** Right.	
1.27	**R1:** And that... In... I guess, we have one company aboard in-house that is *...*. You probably know that Cerner is going to try to introduce a new journal system at *...* which is called Millennium. It has been a lot in the news that this has been delayed and so on. But the journal system is, of course, the perfect place to also	DA, SC

	have these kinds of decision support systems. Because if you attach a decision support system directly to the journal system, you have the possibility to access all the data that is needed, all the data that the journal system can have, historical data, new data that is just recently entered into the system, all that can be accessed at the journal level. And then of course, a decision support has to be attached to that in some way or another, if it's going to be able to provide you the data that is needed exactly when you want the decision support to happen.	
1.28	**HK:** Right. So in terms of... so you've touched upon availability of data, but in terms of reliability how would you say it's reliable, the data that is available right now?	
1.29	**R1:** No, I mean, okay, so all data that we use are noisy [Laughter]. Because they all contain errors, because things are entered wrong into the system, and so on and so forth. You can't really avoid that, there is always going to be noisy data, error in the data, so it's a little bit up to the system... to the ones that developed the AI system to make sure that there at least there are some kind of fail safes in that. So that I cannot enter an age that is 256, because that doesn't make sense. these kinds of failsafe has to be built into the systems, other noisy data is just so that you have to cope with, you have to live with that. So, I don't think there is a quick fix to increase the reliability of the data. It's rather so that you have to build systems that cope with the fact that data is noisy.	REL
1.30	**AS:** And I also assume here, that's maybe a bold move, but as in terms of explainability, like the transparency in between how this entire process has been conducted, I guess, it's important for everyone to understand it... in order to become like, achieved this level of trustworthiness that you're, you mentioned.	
1.31	**R1:** Yep. Then, my next... and this obstacle to overcome, I think it's more... I mean... okay, we had the challenge of understanding other possible organizational change when you use the decision support. Let me take an example, I mean, if I have a fairly "clean" decision support, like providing you with an aid of interpreting a medical image. That's kind of "clean" to me, it doesn't really change so much of the workings. Because there is going to be a person looking at an image trying to make a diagnosis that person is going to get help with a system, that is helping with getting a better diagnosis. But then you can have other kinds of systems that is actually suggesting an alternative treatment. There could be systems that indicates that, okay, now that I'm going to discharge this patient from the hospital system, I have a system that says, oh, no, don't do that, because this patient is going to come back within 30 days.	SC
1.32	**HK:** Okay.	
1.33	**R1:** And you know, these decision support, they are more trickier, because then you	SC

	need to make an action, something, you need to do something once you have that information, and that action may not be easy to understand. That will have effects on other parts of the healthcare. So these decisions supports that are more... that changes the way people work, they are, of course, much more trickier to implement, because they potentially will change the way the patient flows and the way you work with patients. While some, as I see it, some decision support systems, like the ones that are helping you to diagnose images, they are a cleaner in that sense. They don't influence so much the workings of the at the clinic.	
1.34	**HK:** Yeah, that's a very good point. So, I just wanted to understand if I've got you correctly, does that mean that in terms of technology readiness, the people and the systems that are in place in hospitals and regions right now and not as ready for these new implementations? Is that what you're saying?	
1.35	**R1:** I think that cannot be... I think that has to be a case-by-case study. I mean, people are of course, I mean, physicians are of course used to using technical aids, right. They have them all the time. Physicians are searching the web and are using various kinds of risk scoring models that are used. I mean the readiness of using anything to some extent is already there and then if I add a new decision support system, I don't think that is an obstacle, that has to be solved case-by-case. I think. That's just my opinion.	TR
1.36	**HK:** Right? That's, perfect. Sorry?	
1.37	**R1:** But what I think is the trickiest hurdle is how do you spread... So let me take an example. I'm involved in a project here at *...*, it's about treating breast cancer patients. If you get a breast cancer then one of the most common path series, that of course, you do surgery, you remove the tumor. But during that operation, you in many, many cases, today, you do what is called a sentinel node biopsy. You go into your armpit, and you remove some sentinel nodes in order to see if the cancer has spread. Doing that is in many cases unnecessary and it's not without side effects, so you can get numb feelings, and you can get swollen arms and things like that. So, that's one of these... it's the term de-escalation is becoming popular, you want to deescalate healthcare. You want to avoid unnecessary stuff. So we have developed a small tool that can do that prediction, whether or not the cancer has spread to the arm to the sentinel node. And we can then say that for some set of patients we can with high confidence say that it hasn't spread, so you can avoid that operation.	
1.38	**AS:** Right.	
1.39	**R1:** Now comes the next question. "How do we implement this?" We can try to	MT

	implement it, we have developed an app that can be used here. But in what way can we spread this system in the rest of Sweden? The way I understand that landscape is that I can probably fairly easily spread it within *...* as something called "egenutvecklad". So I think they have the path for actually using inventions like that. But then it stays within, limited to *...*, if you want to spread it across Sweden and across the world, then the current path is building a company that is trying to sell this as a medical device.	
1.40	**HK:** Right.	
1.41	**R1:** That is, of course, a huge hurdle for most people, because most researchers are not are not equipped with the correct genes to build companies [Laughter].	
1.42	**AS:** I see [Laughter].	
1.43	**HK:** Right?	
1.44	**R1:** For me this is actually quite tricky... and I don't understand that... so that becomes another hurdle, right. You need to mark your product and that's of course very important because if it's a medical device, it has to be evaluated, and you have to make sure that it can resolve the requirements and so on. But it also becomes an additional hurdle when it comes to implementation. Because that's the only way it's going to be used if you sell it as a medical device.	REG, MT
1.45	**HK:** Right. You touched upon something and I have two questions in one actually. One is in regards to top management support, like how important or to what extent has like management in some of these projects been essential for helping you navigate the whole research towards implementation and also how important or to what extent has financing been, you mentioned... has financing or financial resources been in some of these projects? Are they founded internally? Are they funded externally? Yeah, so basically, two in one like in terms of management support and also in terms of financing.	
1.46	R1 So if we go financing, I don't think... there are I mean, you search for external money, and that's the common approach here, right? If you're at *...*, research projects take external funding for doing basic research, once you come more and more towards trying to implement things, well, then you can find additional external funders that are more biased towards that. I don't necessarily see that funding is a huge problem. If you have good ideas, and if you have the correct team and so on, I think that it's fairly straightforward to find external money for a project. So it's always takes time to apply for money for your research projects	FR

	and things like that. But I think that it’s doable. And there are a lot of external funders for these kinds of projects.	
1.47	AS Okay, so in terms of the external environment, there seems to be at least a positive trend, if you can say so, if funding isn't an issue. But I guess there are high demand? I guess we have an abundance of AI companies just like popping up to left and right and trying to innovate new stuff. But also, in terms of this data that you use, it's medical, the healthcare sector at least, it's bound to have a bunch of regulations, right?	
1.48	R1 Yes, yes.	
1.49	AS So like, they, how impactful are they for these kinds of initiatives? Like especially when doing research, maybe it's..., I don't know, from the perspective of research how you approach this kind of legislation? How restricted are you in that sense?	
1.50	R1 So, I'm restricted. So to do research on healthcare data, you always need an ethical approval. Because it's sensitive data, right. I cannot start a research project with healthcare data, unless it has been approved by an ethical board, or the Swedish "Etikprövningsmyndighet". So all projects need to go through that and be approved. So that's the kind of legal, I have to... and then of course, with GDPR and all that it has become slightly more complicated to actually store and manage sensitive data. But still, I don't think the ethical approval and all that is a huge hurdle. I think the biggest hurdle in Sweden today is actually to get access to it once you have got it approved.	REG
1.51	AS Okay?	
1.52	R1 Because I mean, in *...* they have been working with this for several years. So they have a good system for collecting all the healthcare data that is produced in their health care system. But in Sweden we have 21 regions, and if I were to use healthcare data from all 21 regions, that would be super tricky, right. Fortunately, in Sweden, there are also a lot of "kvalitetsregister". So there's a lot of registers collected for all kinds of diseases, for all kinds of special patient populations like that. That you can also use. But these are special, specially collected databases that only reflects a small portion of a patient for instance, while the data that is collected by the regions, they reflect the day-to-day workings of the healthcare system. But nowadays of course only a small part where a lot of healthcare related data or patient data is collected by ourselves and things like that [Laughter]. Like sensors and so on. So I think that a huge	COL

	hurdle here is the fact that we have these 21 regions and that all of them have different systems when it comes to storing and accessing data.	
1.53	AS All right. I see. We actually only have one question left, and also in interest of time, so just based on our brief conversation here and your experiences especially, in your opinion, what do you think is the most important aspects in terms of adoption, or a potential adoption of these kinds of decision support systems? It could be based on what we talked about.	
1.54	R1 I think the most important thing is in a single word collaboration [Laughter]... the only way we can work towards adoption is that all involved partners collaborate. I think that's... I mean, there are obstacles, these obstacles can all be overcome, but we cannot overcome them if we try to work in silos. As an AI researcher, you cannot do anything unless you collaborate with the correct... So I think collaboration will be, is really key to the fact that we're gonna have adoption. Then we have all these challenges, but I cannot really single out a single of them as the key one. It's case to case dependent here, some specific cases have one of these challenges is more prominent than others, and so on. But unless we work together, we are not going to solve anything.	COL
1.55	HK All right. I see that we are one minute past time, and we want to respect your time. So probably, if you have any feedback for us, or any concluding remarks, that would be good. Otherwise, we are so grateful for taking time to talk to us.	
1.56	R1 Okay. Yeah, nice talking to you. And I hope... I would like to see a copy of this master thesis, it's a master thesis, right?	
1.57	AS Yes, it is. Yeah, we will. We'll take a note of that. And then as you said, if you know about any people in *...*, feel free to contact us with names and we could contact them or whatever.	
1.58	R1 So who have you interviewed in *...*?	
1.59	AS We are going to interview more people. I think you may be related to them in some way or another.	
1.60	R1 Because I collaborate a lot with *...* or *...*. You may know them?	
1.61	AS Yeah, we have contacted them.	

1.62	R1 Yeah. There is one person from the social science point of view that is very interested in the way AI and ethics works. Also in connection to AI implementation. His name is *...*.	
1.63	AS Okay.	
1.64	R1 If you can get a hold of him and get an interview with him, you will hear a lot of very intelligent things [Laughter].	
1.65	AS Thank you for the tips. But we'll make sure to make a transcription, we send it out to you and you can have a quick review. And then we also make sure that you get a copy of the thesis one once finalized.	
1.66	R1 Yeah. Okay.	
1.67	AS Thank you.	
1.68	HK Thank you very much. Have a good day and Easter!	
1.69	R1 Yeah, the same to you.	
1.70	HK Okay. All right.	
1.71	AS Bye bye.	

Appendix 4 – Transcript Respondent 2

Speakers:

HK = Herman Joseph Kambugu

AS = Axel Svansson

R2 = Respondent 2

Date: 18th of April 2022 Length: 30 min.

Row	Transcription	Code
2.1	**R2:** Ja hejsan.	
2.2	**AS:** Hello *...*!	
2.3	**HK:** Hello.	
2.4	**R2:** Hi.	
2.5	**AS:** Is it okay if we speak English?	
2.6	**R2:** Yes, it is.	
2.7	**AS:** Great. So to start with, I'm Axel and this is...	
2.8	**HK:** Herman.	
2.9	**AS:** We're from the Department of Informatics at Lund University.	
2.10	**R2:** Okay, nice to meet you.	
2.11	**HK:** Nice meeting you too.	

2.12	**AS:** Did you have an opportunity to look at the consent form? And all of the practical stuff?	
2.13	**R2:** No, I actually didn't. So maybe I should do that then.	
2.14	**[Summary of consent form prior to starting the recording, the research participant okayed recording of the meeting.]**	
2.15	**AS:** Good, so then we will start the recording, and then we officially start the interview.	
2.16	**R2:** Yeah, let's do that.	
2.17	**[Zoom: Recording in progress]**	
2.18	**AS:** Yeah, Zoom announced it, I hope you heard it.	
2.19	**R2:** Yes.	
2.20	**AS:** Good. So, I will just start to summarize our topic, or our research inquiry in short. So, we want to focus on the factors that influence the adoption of machine learning enabled clinical decision support systems. And for us, this entails looking into the potential factors that are being considered when adopting these kind of systems. And they could be technical, environmental, and organizational. So that's some sort of structure we had when we created our questions. And... it's into all kinds of clinical decision support. So it could be from radiology where you reside, and other fields within healthcare, essentially. So this is what will act as a foundation for our conversation here today. So it's something to keep in mind when we have our conversation and answering questions. But when we were in this process, we were looking for people to talk to and your name came up. So we'll start there. So it would be nice if you could tell us briefly about your roles and your current organization. A little bit brief about your background, essentially.	
2.21	**R2:** Yeah. Okay. Thanks. So, just to be clear. I have to leave slightly before 4.30. Because I have another meeting at 4.30.	
2.22	**AS:** Yeah, good.	

2.23	**R2:** You have to control the time, since I don't know exactly what you want to ask. My background then, *...*. And then I worked for *...*, for a few years and also started a company on my own. *...* I started studying medicine and *...* I started my specialization in radiology. I started doing my research about, like one year after I would say, and then I was done. So I was a specialist in *...* and PhD in *...*. Since then, I worked with breast imaging like all the time, but more or less half the time clinically and half the time with research. Now since *...* I'm a docent at *...*, and I've worked at the *...* all the time since *...*. I guess that's the educational and professional background to some extent and then when it comes to research. It's totally focused on the use or development of AI or machine learning algorithms and their use in breast cancer imaging. So it's a mix of evaluating algorithms from elsewhere and developing algorithms *...* Right now I'm involved or heading a project *...* for AI algorithms in breast imaging *...*.	UC
2.24	**AS:** All right, so it seems that we came in contact with the right person.	
2.25	**R2:** Yeah, and I'm also conducting two prospective studies now, probably the first ones of each kind, so one is using AI *...*, making like binary decision if there is something suspicious or not in the image.*...* And that's one study called *...*, and then we have another study called *...* at *...* where we use AI as a, let's call it like post-assessment. So after the radiologists have already concluded, there is nothing in the mammogram, no cancer signs in the mammogram, we evaluate the images with algorithms that we have developed, like in this research collaboration. And then the purpose is to select women that could have cancer even though it was not seen on the mammogram. So to offer MRI, magnetic resonance imaging. *...*	UC
2.26	**AS:** Nice.	
2.27	**R2:** But that's what's going on.	
2.28	**AS:** We could just jump into a little more about the technical aspects when it comes to these systems that you're researching about. So how complicated are you, or the group that you're in, are finding it to comprehend and implement these kinds of systems from a large perspective, like... is it complex?	
2.29	**R2:** Well, I think you have to break it down a little bit. I mean, it's you can't really say yes or no, but so when you implement it as independent reader, it's quite straightforward in the way that it makes a binary decision. It's not visible. I mean, the other radiologists can just consider it as another radiologist making a binary decision as well. And since the rule is that if they get any positive assessment, it will go to consensus discussion, this will just be another, like it's pretty easy to	SC, REL

	integrate into the workflow. But it has to be before you do that it's a little bit more complicated because you have to kind of calibrate it's... calibrate it to your setting, or at least that's what we did. So we wanted to give like... yeah, make it possible to implement it in the workflow, which means that we did not... Well, first of all, that it's a clinical study, so we had to calibrate it *...*. So we had to calibrate it to have the same sensitivity, to find as many cancers together with one radiologists as two radiologists would have found. So that's one aspect, the sensitivity. The other one is that it can't flag too many because if it flags too many cases, it will create an unrealistic amount of downstream workload for the consensus discussion. So we were lucky enough that this algorithm that we use, when we calibrate it to reach the same sensitivity, it was also a realistic workload. But if you just take the abnormality threshold that is kind of delivered, or suggested by the company, you might have like higher sensitivity which sounds really good, but maybe it's not realistic because it could mean that you have to handle a lot of cases downstream that you would normally not do. So I mean, that's the important, I think that's the tricky part, when you do it as a least kind of binary decision, because the decision is made by the algorithm without any human intervention. So it's really important that you calibrate it beforehand. If you use it more as, which we don't, but if you use it more as an concurrent assistant to the radiologists that the radiologists just get some help, you can look at colors, the numbers that is output by the algorithm, then kind of part of the calibration is like by the radiologist when they use it. Then it's... I don't know if it's easier or not, or harder. But I mean, it's a different type of implementation.	
2.30	**AS:** I see. And in terms of doing this binary decision that the algorithm does, the reliability of it, it's it depends on the data that it's trained off? Right?	
2.31	**R2:** Yeah, absolutely. So before we implemented it, we tested it in retrospective data. First of all, we tested it, which is also published, like a study, with the first author's *...*, and the last author is me. So you can find it, *...*. This one was the best one is from *...* in *...*.... Yeah, it's been trained, what was a bit surprising was that it was mainly trained on *...* women, and on GE equipment. While we have not so many *...* women in Sweden, and we at *...* we don't have GE-equipment, we have Hologic. And everybody that is a radiologist could probably tell you that the images look different. So a GE-image looks different from a Hologic-image of the same breast. So there is definitely something different in the images, so I think it's probably important. But it has also been trained on Hologic-images, just that the majority, or the largest proportion was from GE. So it was still kind of surprising, or interesting that he worked so well for us.	SC
2.32	**HK:** Right. So normally, when we talk about these kinds of systems, transparency always comes up. And my question, I guess is, are the people or the radiologists able to understand the logic behind some of these insights that the system is providing?	

2.33	**R2:** I mean, it's. So I mean this, like binary decision itself is very easy to understand, like, it's yes or no, basically. It's flagging something suspicious or not. But what it also does is that it kind of it makes mark... it marks up image areas that it has found to be, where the suspicious finding is located. And sometimes you really can't understand, like, why it... like, let's say paints a certain area of the image. And it doesn't... So for when you do screening, you take two images of each breast, so take one, like from the top to bottom, and one more or less from the side, to the side. So you get like two projections, because it's like the shadow, is a X-ray shadow that you see. So you need two projections to get a better idea of different structures that are overlapping, and so on. But the AI-algorithms that we are using and so far are implemented, they don't like take into account that those two images has a correlation, that they come from the same... it's two images of the same organ. So if you see something very suspicious in one image, it should probably also be seen in the other image. Otherwise, maybe it's not true. And therefore, for radiologists can be quite hard to understand why it paints up a big area in one of the views. And then in the other view, there is nothing, because I mean, it's not really realistic that there is a large thing in one and nothing. So sometimes it's hard to understand those things. And I think it's because it doesn't really... has included this perspective that it's two images of the same thing. And so then it's difficult to understand for the radiologist, another thing, even this binary decision, what can be difficult to understand or maybe at least important to understand is the way we calibrated it. So at first, we didn't really think about telling them exactly how it was calibrated. So they were expecting AI to find more cancer than it did. Because when we calibrated it we didn't give it the same sensitivity as a radiologist, but we gave it worse sensitivity, like lower sensitivity. So we intentionally made it find less cancer than a radiologist, because it finds different cancers than a radiologist. So as a compliment to one radiologist, it doesn't have to find as many cancers as another radiologist, because the cancers that two radiologists find are more like the same, they find the same ones. But AI finds different ones. So we didn't, and that we didn't really tell them. So in the beginning they were kind of disappointed at AI didn't find so many. And so, I guess that's something we learned also that it's very important to under... to let people know, I mean to calibrate also the expectations of the radiologists basically.'	T
2.34	**AS:** Nice. That's about it for our technical questions in regard to the new technology. So you mentioned the the project at *...*... So, in terms of these projects, or when you're trying to introduce these systems, to what extent... it may be hard for you to answer, but I think you can give it the best of your knowledge. But when it comes to the top management support, how involved are they in this process and driving these kinds of initiatives, essentially, or is it solely based on the need and research from that perspective?	
2.35	**R2:** So, yeah, it's been quite. I mean, it's been quite driven by me and others in the research group. And it's pretty, I think, when you drive things from the other way,	TMS

	it's very slow. And sometimes it doesn't really come true. You know, it doesn't realize.	
2.36	**AS:** I see.	
2.37	**R2:** It's easy to have like visions and PowerPoints as, like management, top management but I mean, it's not. And I think it's not… For the *...* study, we were felt quite supported by the head of Radiology and the management of radiology. But then there was not, I don't think, we didn't need like commitment much higher up. But now, when the study has been going on, and we're close to finishing it now in *...*, they have told their owners and everybody's got a little bit more interested. So now they're really interested. Because maybe they didn't really, you know, maybe it took them like a year or so to fully understand how interesting it is with AI. I guess it could be something like that, or I have no idea. But they're more interested now, even higher up.	TMS
2.38	**AS:** All right. And the these projects and research initiatives, are they are funded through external... externally. You...	
2.39	**R2:** Yeah. So the project at *...* is funded directly like the incremental costs or the, yeah, cost increase costs to the hospital... by this research study, is like reimbursed by the company that has the AI algorithm. So they pay it directly, I don't get any money. But I mean, the hospital gets money for it. The additional cost, because it does create a little bit more workload and so on. But for the research parts, I mean, what I'm doing, I don't get money from that. And the study at *...* we have funding from mainly from *...*, which is a collaboration in *...* between the *...*.	FR
2.40	**AS:** I see.	
2.41	**HK:** So in terms of regulations, when we're reading about some literature, we found that there were a couple of regulations in terms of data privacy and all that had been cited, we just wanted to touch upon, we just want you to sort of touch upon that and see which sort of regulations did you consider, were you impacted by them and all?	
2.42	**R2:** Yeah. Oh... Yeah, there's a lot of regulations. So you have the "Patientdatalagen", and you have "GDPR", and you have the "Offentlighets- och Sekretesslagen", and... what else? Those might be the most important ones. And then you have, of course, you have "Etikprövningsmyndigheten", the ethical review authority that	REG

	has to approve the studies and whatever law they abides by. So I guess those are probably the most important ones.	
2.43	**AS:** I see. That's a good insight, because we previously we only touched upon "Etikmyndigheten"... So that's good, useful insights. But as you said, that the company that provided the algorithm, they were sort of part of this funding. In terms of market trends, I guess they are also part of driving this process. There is like a demand for this. And what we're thinking is, like research projects initially are the company's reaching out to researchers, or is it a matter of the opposite? Like, the dynamic between those two actors? Meaning you and, maybe the company, how does that work?	
2.44	**R2:** Yeah, so I don't know for I mean, like... I don't know about all different projects everybody's having in the world. But I mean, for me, there has been... well one company, they reached out, they wanted us to conduct a certain study. We didn't do that, because I felt it was like a bit of a waste of time. But after *...*, and this *...* company was the best one, then I didn't want to go for... I mean, we wanted the best ones, because it's for the patient's sake. So I mean, then I asked them if they would like to they provide the AI algorithm for this study... I think it can go both ways. Sometimes it's the researcher reaching out, I mean, for *...*. So it goes both ways, but I think it's... Yeah... But I think there is some reason to be a little bit skeptical when the companies have too much influence over the research. Especially when, like, a lot of the authors of a research article, actually work at a certain company, then you might want to be extra careful, and the reader shouldn't have to be, I mean, you can always be a little bit skeptical to everything, but the journal should do the job. I don't know to what extent they do that, for example, they could require that if it's too much company involvement, every protocol, and everything should be published before you start the study. So that you don't like, tweak the study protocol afterwards, to what suits you, and so on. I mean, I think they could do a little bit more there.	MT
2.45	**HK:** Right. We've touched upon so many very insightful elements, and we are very grateful. And looking at the time, we probably need to... So I'll ask one of my concluding remarks is, from your opinion, what are some of those factors that have influenced your decision to adopt or take on some of the initiatives that you've taken on?	
2.46	**R2:** Well, almost, I don't know. I guess it's, for me, personally, I guess it's a combination of curiosity, wanting to contribute, and especially, I mean, contribute to the development and especially what I see can be of most like value to the patients and their lives.	
2.47	**HK:** Okay. And from an organizational perspective?	

2.48	**R2:** Eh… I don't have my main motivation coming from that perspective.	
2.49	**HK:** Okay I get you....	
2.50	**R2:** I can't say.	
2.51	**HK:** Well, then I'll probably ask if you have anything else you would want to add or any particular feedback you want to give to us in regards to this?	
2.52	**R2:** Eh, no, not right now. But I mean, I will tell you, if I come to think about something.	
2.53	**AS:** Great. We would like to thank you for your time. We'll make sure to send you the transcript. It's also part of the information in the consent form.	
2.54	**R2:** Yeah I saw that now.	
2.55	**AS:** Yeah, great. So once again, thank you for your time. And have a lovely last day of Easter. [Laughter]	
2.56	**R2:** [Laughter] You too. Okay, good luck with your work.	
2.57	**HK:** Thank you.	
2.58	**AS:** Bye bye.	
2.59	**R2:** Bye bye.	
2.60	**HK:** Bye.	

Appendix 5 – Transcript Respondent 3

Speakers:

HK = Herman Joseph Kambugu

AS = Axel Svansson

R3 = Respondent 3

Date: 19th of April 2022 Length: 45 min.

Row	Transcription	Code
3.1	**R3:** How are you guys?	
3.2	**AS:** Hello, we're good. How are you?	
3.3	**R3:** Oh, you know, I'm getting along. First day back from long weekend is always tricky [Laughter].	
3.4	**AS:** We'd just like to introduce ourselves first. I'm Axel and this is...	
3.5	**HK:** Herman.	
3.6	**AS:** And we're from the Department of Informatics at Lund University. So that's about it, about us. So, we're doing our master thesis, and we're going to interview you. And did you have the opportunity to see the consent form?	
3.7	**R3:** No, did not actually, see here.	
3.8	**AS**: **[Information of consent form, asking if it is okay to record the interview]**	
3.9	**R3:** Yeah, that's not a problem.	

3.10	**AS:** Good. Then we officially start recording here at zoom, and you will hear a notification.	
3.11	[Zoom: Recording in progress]	
3.12	**AS:** Great. So then we're officially started. I'm just going to quickly, like give a summarization of our topic and what we're going to talk about today. So I'm going to read here in my notes. So this research study is focusing on the factors that influence the adoption of machine learning enabled clinical decision support systems. So for us, this entailed looking into the factors that are or were being considered when adopting this new technology. And we're thinking that these factors are technological, environmental, and as well from an organizational perspective. So that's a little bit how we divided our questions. Some questions might feel a bit repetitive, but it's in terms of this protocol guide that we created. And yeah, so this will act as a foundation for our conversation. But when we started this inquiry, we needed to find people to talk to and you came up. So I guess we start there. So it would be nice if you could tell briefly about your background, what role you have at your current organization and sort of how you're connected to this topic.	
3.13	**R3:** Yeah, can I just ask, how did you find out about me? I'm kind of curious.	
3.14	**AS:** It was from *...*, where you talked with your colleague, *...*, I think.	
3.15	**R3:** Ah, okay.	
3.16	**AS:** And then we also found your paper as well, that you have written about *...*.	
3.17	**R3:** Cool. Excellent. Yeah. So my name is *...*. I guess, the term would be like business developer like "verksamhetsutvecklare" at the *...*. In addition to that, I'm a PhD student as well. So I'm doing my thesis on machine learning based risk assessment tools in *...* with a focus on low acuity patients. So patients who tend to be ruled out for having a high acuity condition that needs an ambulance, like right away. The kind of lower acuity patients who maybe need an ambulance, maybe need primary care, maybe need something else. Those kinds of less, extremely emergent patients. I guess, in addition to that, I'm also an EMT, "ambulanssjukvårdare" and I work clinically now and then during the summers. Yeah, I guess that's kind of my role at my organization. Was there another question in there?	UC

3.18	**AS:** Maybe if you're related to any projects or initiatives, you sort of touched upon it with *...*?	
3.19	**R3:** Yeah, So we have, I guess we did a project, like a *...* project. That I guess was, where we kind of got the start for the machine learning kind of stuff. So we got a little bit of project money. We had a project that ran for maybe two or three years that led us to develop a software, like all the software that kind of enables the AI and machine learning based risk prediction stuff. So we kind of developed those tools during those two or three years. Project is over now. And now it's just kind of internally funded. So I do a bunch of quality development work as part of my regular job. And then the kind of AI stuff has gotten folded into that, along with my doctoral thesis. So yeah.	UC, FR
3.20	**AS:** That sounds super interesting actually. Do you enjoy your job?	
3.21	**R3:** Yeah, yeah., it's a lot of fun. And I think there's a lot of overlap with the research that I do and the job that I do. I mean, you got my PhD, like a clinical PhD student. So, I'm a PhD student on 50%-time. And generally, they say that, you know, like half of that time 25% is funded by your workplace. And then 25% is just kind of like magical time that you create for yourself [Laughter]. And I find that there's a lot of overlap between the kind of business development that I do and just data analysis type stuff that I do in my regular day job and the research that I do. So it's a lot of synergy there. So that's pretty handy to have this kind of data analysis heavy work, and then doing research in kind of quantitative data analysis also. So there's a lot of overlap there that helps things run smoothly, so to speak.	
3.22	**HK:** Yeah, nice. So you talked about the project that you've been working on, you worked on *...*, could you tell us just a little bit more of how that is being utilized?	
3.23	**R3:** Sure. So, this was maybe in 2017, I think that we got funding for this project. So there's been kind of like, even before then, there's been a lot of work at the ambulance service by our "verksamhetschef", I guess Operations Manager, to kind of create a combined dataset between our dispatch center, our ambulance service, and then some hospital data that we collect and combine into a quality development database, I guess you can say that we're used to follow up decisions and these kinds of things. So if we make changes to our current Decision Support System, which is not AI based, it's just kind of rule based. So they have, generally, when you call 911, you say to the nurse, like, "Oh, help me help me, I am sick". And then they ask you a bunch of questions about you know, okay, well, "Are you sweaty?", "Are you pale?" And these kinds of things, they enter that information into a digital kind of decision support system.	UC, SC, DA, TMS

	So you'll say okay, they're pale and sweaty, yes, that means that you get an ambulance with lights and sirens basically. And then there's a bunch of different questions, right, 1000s of questions that they can fill in. All that data is connected to what happens on the ambulance. So what kinds of medications do you get? What kind of prioritization decisions made by the ambulance nurses? What kind of interventions, all these kinds of things? And then that's also connected to what happens in the hospital. So once you get to the hospital, do you get admitted? Do you get, you know, is there like a triage, is there like a... what we call it? Like a trauma... alert... activation, all these kinds of things so that we can use these things as outcomes in machine learning models, based on the earlier data. So all that information about, if you're pale and sweaty, that increases the risks of you know, you getting a high priority transport to the hospital, for example. And we can use that as the outcomes in machine learning models based on earlier data from earlier parts of like the care chain, right? So we take information from the dispatch center, or predict what happens on the ambulance, we can take information from the ambulance and predict what happens in the hospital, basically. So having this kind of longitudinal data kind of, lets us do these cool, like risk prediction type things.	
3.24	**HK:** Right, it sounds like it's so many interconnections. How complicated was it to sort of implement this machine learning model that touches upon so many elements of that critical clinical care?	
3.25	**R3:** Yeah, I mean, I think what takes up the vast majority of time. There's really like data management and cleaning data and doing all these things, handling missing data, like how do you do all these like just practical, like data cleaning tasks, right? Maybe like 80% is of the time is just getting the data into a format that you can actually use, right? And then yeah, sure, you can use like a fancy neural network model or whatever, your decision tree or regression model or whatever, that matters less really than actually the practical, like issues of handling the data, I think. At least in terms of, you know, kind of the amount of work that get put into it. And then also, how do you how even operationalize what you're interested in, right? So if you want to say, okay, a patient, how much does a patient... a patient calls 911? And we want to know, how much do they need an ambulance? We need to actually define, like ambulances need in terms of something we can measure, right? And there's no real like, how do you measure that? [Laughter] There's no consensus really, on what you're supposed to measure. So that's also like maybe like, theoretically, that's probably the most difficult problem is, how do you define what we're interested in? In terms, the decision that we need to make in the dispatch center, how do we define that in terms of something we can measure, is probably the most difficult theoretical problem. And then kind of data management and data cleaning is probably the most difficult, practical problem. And then, you know, we can use a fancy model, that's not actually that difficult, like all of these, like neural network models and stuff, are all implemented in relatively high level API's in Python, or R or whatever. And that doesn't actually take that much time or effort to really do. It's this kind of theoretical issue of how do we define what we're going	DA, SC

	to measure, and how do we get data that we can actually put into one of these models and get good results.	
3.26	**AS:** So it seems that the reliability of the data is solely, or it's your role of managing it, is a critical part before even like assessing the reliability of what you have from the first go? Because that's your raw data, right?	
3.27	**R3:** Yeah, and I mean, it's garbage in, garbage out, right? Like, if you, the model is really just a function of the data you put into it, and what you're trying to predict, really. Sure, maybe you can increase the accuracy by you know, a few percent or something by using some different model or another model. But in the big scheme of things, that doesn't matter that much, really, it's much more, you know, how good is the data? And what's the quality of the data? And what's the quality of your operationalization of the outcome? Right? How well does that align with, it's like an AI safety term, right, alignment. Like, how do you align the outcomes that you're like, measuring with the decision that you actually want to make?	DA, SC
3.28	**HK**: Alright. When we talk about machine learning and AI, and you've touched upon some of these things, one of the other key terms that comes up outside reliability of data is transparency. How important was that when you're implementing the project, the transparency, the way, do the people understand how these insights are derived? And how important was that for the project?	
3.29	**R3:** Yeah, I mean, I think there's, there's two ways that you can think about transparency, at least. I think that one is kind of, like transparency and a process that you're using to generate the models, right. And I think that's, you know, quite important, I think that there's a lot of kind of commercial interests in the field, that are kind of competing to make like "buy our AI model", or whatever. And they have a lot of strong incentives to, you know, make things look like they work better than what they actually work, or like how they actually work, right. And one thing that I'm trying to do is be very transparent in the methods. So I'm a big open source guy. Actually, the tools that we're using at our dispatch center right now, you can go on GitHub, and you can download the source code and see exactly what we're doing. The models themselves aren't available, because the dispatch system is there's some like intellectual property stuff going on with like, what what questions are we asking when, but in theory, you can get the methods that we're using, you know, download them and apply them on your own dataset, and basically reproduce our results. That's one kind of transparency. In terms of the processes that we're employing, the methods that we're using to get our results. The other one is kind of, I guess, like user-"facing" transparency, which maybe is what you're talking about more like interpretability of the models, right. And that's something that we do also, we use something called like Shapley values, to kind of assign an effect size and the direction of each variable, right. So you can look at the Shapley values super	UC, T

	cool. We use a package called treeSHAP, to generate these kinds of things where you can see, okay, the patient's age was 75 years old, and that had a marginal impact of you know, plus 0.8, or whatever, in terms of the model prediction, the model risk, and then you can see how each of the questions kind of moved the needle, so to speak, in terms of the patient risk. Actually, like, I think you read in the literature that that's like, really important and stuff, but when I talk to the users of the system, they don't really ever look at it. Because the phase is, like it's a dispatch center, right. So usually when... let me take a step back. And the kind of intervention that we're doing at the dispatch center is basically, in cases where we have like too few ambulances, right, we have several people calling 911. And they all need an ambulance, but at a low priority, right, so we send an ambulance right away. If it's something like high emergency, like they need lights and sirens ambulance, like they're, you know, "my arms chopped off", or whatever, just send an ambulance. But for patients who like don't need an acute ambulance, right, like a priority "two" so no lights and sirens, they just drive normally. A lot of the times, actually, we have more patients, we have patients just waiting for an ambulance, we don't have enough ambulances sent to everybody. So when we have two or more patients who both need an ambulance with, like as a priority two, then we basically use, we let the users select the patients who want they want to compare, and then the risk assessment tool. So we feed all of this kind of dispatch information into models, and then we generate a risk for each of the patients, right? And then it'll kind of the system will indicate which patient has a higher risk score, right? So it's a randomized trial. So when 50% of the cases, they'll show that so I can get from like red one in their user interface, right. And then if 50% of the cases, it'll just say, Okay, this is a control-case. So just make your decision about which patient needs to ambulance more, based on, you know, the current process. So, you know, they talk to the nurses and say, Oh, well, this person probably needs it more. And then in 50% of the cases, they'll have this kind of little red indication about the model saying that this patient needs the ambulance more. And then they can take that into account when they make their decision. And we have a functionality so that they can press on that button and get some more information about how the model is thinking right, about what they need about like, okay, what factors influenced the decision? They don't use it that much.	
3.30	**AS:** But I find it really interesting, because it's something they can use concurrently to the decision process. It's not that, like... there is bound to be some kind of intervention at one point if they like at least. So that's something positive, at least how I view it without being into it that much.	
3.31	**R3:** Yeah, exactly. And like, we were pretty clear that like, this is a suggestion. Like if the nurse says like, we have nurses at the dispatch center, right. So these people have gone through like, five or six years of education [Laughter]. And I don't think like a little statistical model is going to be able to, like, make really like... maybe even make better predictions, but probably, it can work faster, right? It can make like, especially in these kinds of situations where we have a lot of patients calling in usually, like the most stressful situations really, for the nurses, the most stressful times. And they just don't have time right there on the	

	telephone taking calls. And then we have a dispatcher who needs to make a decision. So it's much faster just to make the make a comparison rather than you know, especially rather than, like go and talk to each of the nurses and make some kind of like really good in-depth kind of determination as to who needs an ambulance. Really it's a question of like scaling this thing, right. So we have a relatively small region in *...*. We have two nurses who are sitting and making decisions. So it's feasible kind of to sit there and for the dispatcher to say, "Okay, I have two patients, I can just talk to the nurses and see who needs it more". But in another situation, like I know, and probably where you're in Lund you said?	
3.32	**HK:** Yeah, Lund.	
3.33	**R3:** So, Skåne, I'm sure they have a much bigger dispatch center, they probably have like, six or 10, like nurses all sitting there or not even nurses, they have dispatchers in Lund and Skåne, taking calls and making decisions, and they just don't have time. They don't have the ability even to talk to each of the relevant nurses who are involved in the call taking and making decision, they need something more automated than this kind of human process of evaluating each patient individually and comparing the risks, it's just not really feasible. So these kinds of tools are going to be I think, even more useful in situations where we have a larger region than *...* where it's just not even possible to make a human determination as to which patient needs the ambulance more. I think it's a question of scalability too in terms of using the tool.	
3.34	**AS:** Nice. ... That was actually our set of the more technical questions. We're going to sort of alter as we go in order to fit the time schedule as well. It feels like we're going to nag about this project that you've been doing but of course it is of interest, you could try to reflect upon other stuff as well. But in regard to some organizational aspects, your supervisors during this process like did they encourage or drive this process? Or was it something that came from another? Another angle?	
3.35	**R3:** Yeah, like I mentioned that even before the project, they were working on developing this dataset, right, that the machine learning based system is based on. So we have the data from dispatch center, ambulance and hospital. And really, the reason we started with a project was that we needed to use this dataset for something in a way, like need to know why do we spend all this time making this combined data set? Well... Yeah, machine learning is a great application. And the fact that we have the preconditions for doing this kind of motivated the project rather than the project, motivating the preconditions in a way. So I think that's kind of one interesting aspect of this is kind of if you build it, they will come [Laugther] kind of thing. Like, we have the data. So it was relatively easy to start the project, rather than okay, we're going to apply to *...* but we don't have any data, we're gonna like work to make a dataset, like that's a lot of work.	DA

	And, yeah, having that stuff already done, made the project a lot easier, and a lot more kind of feasible to do in kind of timeframe, of a *...* project, right, like two years or whatever.	
3.36	**AS:** And that maybe goes hand-in-hand, like if you have these opportunities and preconditions that sort of makes it easier. The organization itself, then is sort of ready for this kind of next step. I don't know how it is, in terms of the user, the nurses, you said that they don't really care about the suggestions, maybe at some points but...	
3.37	**R3:** I think about 85% of the case, they go with the machine learning based recommendation. So reasonable	TR
3.38	**AS:** Yeah, definitely. So yeah, that's about it for the organizational context, then...	
3.39	**R3:** Yeah, I mean, I would say there's like, it's, um, I was pretty free, I'd say I have a lot of freedom to just kind of work on whatever I think is most interesting, in a way, which is kind of nice. Like, I have some tasks that I just need to do, but then a lot of my time is just kind of I spend it on whatever project, I think is most kind of important. And I think that machine learning is like, there might be stuff that gives more like immediate feedback, like, pay off, maybe like we have projects to deal with, like feedback to our staff and stuff. And that might be more like, immediately impactful. But I think that in the long term, you know, risk assessment tools are going to be going towards machine learning based systems, and kind of getting our foot in the door and kind of driving that development in a way that's like, kind of good, for lack of a better term. It will have a lot of payoff, like using open source software, right, instead of like buying some commercial solution, I think, can produce a lot of value for the healthcare system by avoiding having to pay private companies a bunch of money to do it for us, is pretty useful.	TMS
3.40	**HK:** Right. You talked about open source software and a couple of things. I just want to touch upon regulations, for example, are these impacting you or your project in any way in which kind of regulations could be impacting you or influencing your speed of implementation?	
3.41	**R3:** I'd say there's two main pieces of regulation that we need to think about. The first is GDPR, obviously, I mean, everybody thinks about GDPR these days, and you need to, you know, be very sure that you're not using data in some way that's going to be against GDPR. Right. So you need to make sure that you're kind of taking appropriate technical safeguards to secure your data. So you know, we do a lot of work to ensure that the data analysis all occurs on hardware that's, you know, physically owned and secured by our IT department. So I	

	think the public sector in Sweden is very skeptical of these kind of like cloud solutions like that, Microsoft, and all these different companies are offering. Probably... it's, I mean, it's maybe more theater than real security, I don't know. But that's kind of what the lawyers are saying that and we need to use like internal systems as much as possible. And if we do use cloud solutions, they need to be based on hardware that's, you know, physically within at least the EU if not within Sweden. So I think in terms of the kind of like I do all my training models, right, I bought a laptop that I'm talking to you guys on now with like a graphics card to be able to train the models that we use, as opposed to you know, doing it on Azure, like AWS or something like that. Mostly for reasons of GDPR, like patient integrity, securing our data based on you know, the region's own data. So we don't need to hand it off to a third party and get all these kind of legal agreements, especially if its "biträdesavtal" and these kinds of things. There's a lot of kind of legal overhead and bureaucracy that goes on to enable third parties to use, especially like identifiable patient data is a very high kind of threshold to get out. So GDPR, and these kinds of things kind of drive us towards using local hardware as opposed to cloud solutions to do the model development and do the model cleaning and all these kinds of things, that's what I'm talking about.	
3.42	**HK:** Right.	
3.43	**R3:** And I guess the other one is MDR. Like, what do we even call it in English... like the medical device law, I guess you call it?	REG
3.44	**AS:** What do you call it in Swedish?	
3.45	**R3:** Yeah, what's it called? I guess it's the medical device regulations must be for MDR. Yes it is actually [Laugther].	
3.46	**HK:** Yes it is.	
3.47	**R3:** And I think those got updated pretty recently, actually, like maybe a couple of years ago, there is a new version of the MDR that came out and basically made things a little bit more strict in terms of what kind of classification and what kind of safeguards needs to be in place to use these kinds of risk assessment tools based on machine learning. Um, we actually have it CE marked. I think all like medical devices that gets sold in the marketplace need to be CE marked, as it's called, according to this new MDR law, so the medical device regulations, so it needs to go through "Läkemedelsverket" and all these things to get approval. There's a loophole to the MDR. And that's if you have an "egenutvecklad medicinsk teknisk produkt", so like medical device that you develop yourself, it needs to fulfill the same requirements as a CE marking, but	REG

	you don't need to go through all the legal kind of formalities to do it. So you don't need to send in your applications to the "Läkemedelsverket" and all that stuff. We still have to produce evidence that it's safe, and that it does what we say it does. But we don't need to go through all the formal kind of application processes to get things approved, the "Läkemedelsverket", CE marking, and all these things. So that's kind of I guess, those are the two major... yeah, legal kind of things that we need to take into account when we're doing this. So patient integrity, GDPR, and the kind of medical device legislation in the form of MDR.	
3.48	**AS:** Okay, so there is a complex landscape. But I was thinking like with current regulations, would you be enable to collaborate with other regions with ease, or would it also hinder you guys sort of making this more available?	
3.49	**R3:** Yeah, so that is going to... so this is a problem, right. So once we get beyond our region, then it's no longer a device that we've developed ourselves. So if Skåne wants to implement this, then they haven't developed it. So it's not going to be a self developed device. So it's gotta get a CE marking, and then you gotta go do all these legal things. So well, as long as it's just us using it, then it's not really an issue. But once we start trying to spread it to other regions, then we're gonna need to figure out a way to accommodate the quite of more formal benchmarking processes that you need to do and see, to get a CE mark and all these things. There may be some loopholes around this. Like, okay, at what point is it a self developed medical device? If I get a Python developer or something who works for Region Skåne to, you know, make some commits to my repository. Is that also a self developed product? And if they have developers who work on it, like, how many hours do you need to spend developing a product to be developed by yourself, right? So I think that's kind of an interesting kind of thing that there is no legal answer to, like this is not like anything that's been tried in a court of law to determine. So we'll see, we'll see the answer to that soon. I know we are working on kind of at least getting data for like a study to evaluate, to like validate these kind of machine learning models and ambulance data, and we've gotten data from like, a few different regions, for the purposes of doing a scientific study. That's a little bit easier than using like using something in clinical practice, though, and like, evaluating it there, rather using it line in clinical practice outside the context of like an ethically approved scientific study is more difficult. But that's a problem for future me [Laughter].	REG, COL
3.50	**HK:** [Laughter] Nice. So there have been events that have happened like the COVID-19 pandemic, and the other market trends that we may not be able to get into because of time. Is there any market trend or event that triggered your initiative basically, or that influenced you implementing it?	
3.51	**R3:** Well, I mean, I think in terms of the model, like the actual, like the validity of	SC, MT

	the model, the COVID pandemic is kind of a good example of something that can really screw with the model predictions, right. Like if you get a major change in the population of your patient population, that can impact the accuracy of a machine learning model for example. So you need to make sure... that so, that's also one of the things that we're going to be looking at, in the study that I mentioned with multiple regions, is okay if we have data from a machine learning model, based on data from like, before the pandemic, how well does it actually predict outcomes during the pandemic, right? Does the accuracy go down, because of the changes in the patient population owing to COVID, for example, we need to make sure that our model is robust, even if the patient population changes somewhat. So that's something that we're going to be looking at in kind of future studies that are going to be coming out,	
3.52	**HK:** Right. I see that we actually out of time. So I think I'll ask my final question, which is, in your own opinion, which factors do you think influenced your decision or to adopt or to start this kind of initiatives?	
3.53	**R3:** Yeah, so like just the fact that the data was there, right. And it was really just crying out for us to use it, I think, kind of one of the major things. It just seemed like a really kind of low hanging fruit. Given that all the data was there, turned out to be a lot of work [Laughter]. But you know, it would have been a lot more work without the kind of preconditions. And, yeah, I don't know, I mean, I think I'm kind of a data nerd. And I think it's pretty cool. All these kinds of like, the possibilities that are opened up by machine learning, to move away from the kind of rule based decision support tools that we use a lot in medicine now. So the idea is right, like a lot of the decsions for tools that we use now are basically, a doctor sat down and said, Oh, well, if a patient says that, then we should do that, for example, right. And we can move away from that now that we have enough data to kind of characterize patient outcomes, we can start doing things empirically, instead of based on kind of expert opinion, which is how decision support tools have been developed traditionally. Yeah, I think that'd be pretty good. I don't have like, anything directly after this. So if you guys have more questions, that's fine.	DA
3.54	**AS:** No, but I was just thinking we have sort of had the same epiphany as well, maybe not in a more practical context as you, but the possibilities of data. So we just had a recently a course in machine learning as well and you sort of discovered the the possibilities. And I guess, when you're when you're more into it, and have more more experience it gets, really interesting, really fast I guess. And we were just thinking, like, also one of our concluding questions is like, is there anything you think we might have missed? Like, we there's tons of factors when you look into literature of decisions to adopt something, but we tried to make our our best to include stuff that we thought were important. But you're always bound to not to make mistakes, but to maybe disregard something that maybe someone else would have included? But like, it could just maybe	

	from a technical perspective, I think you would have... if you would have something it would be in that area.	
3.55	**R3:** Yeah, I mean.... I don't know, I mean, I think it would be nice to a have I guess, I don't have like a super mathy background. I mean, I'm like a public health guy with a master's in public health. And I think it'd be really nice to have more kind of cooperation with like, an IT department, for example, right? Like I've kind of, I didn't know any Python before this project started, right. I just like picked it up because I realized, like, kind of the machine learning type skills that you need to build this stuff is so rare to find people who kind of know what they're doing. That just felt it was just easier to just learn and learn all myself and do it instead of trying to you know, find a good cooperation. So I think having a tighter kind of cooperation between different departments, like people with medical expertise and people with, like, machine learning expertise would be a big enabler of this. Like, if I had somebody, I could just like offload all the technical programming stuff to, I would be super happy. But I also think that part's kind of fun. So I	COL
3.56	**AS:** I can imagine it's been a lot of quite a trial and error, especially when you're learning something new.	
3.57	**R3:** Yeah, it was good. I usually do most of my programming in R like both my data analysis and that kind of stuff. And that's what we were using originally implemented at all. But I realized, you know, in the end, Python, probably the better language, and we just kind of rewrote everything, or I just kind of rewrote everything in Python in the end, and then implemented it. So yeah, there's a lot of kind of trial, trying your way forward, figuring out like, what kind of processes are needed to implement things working with, like third party, the dispatch system, for example, we needed to figure out a way to work with our developers of the dispatch system in order to implement, integrate this kind of machine learning system with the with the dispatch system, right. So there's a lot of kind of drawing up specs like and mock ups and stuff, to see how that would look and kind of refining what the actual use cases, right? Like, how do we figure out an intervention that is kind of can produce some kind of benefit for our patients, but also doesn't result in a huge amount of risk. Because it's a new technology. So we can't like... for example, our original intent was to use machine learning to identify patients who don't need an ambulance at all right? But the problem is, if you miss a patient who actually needs an ambulance, and don't send an ambulance that can cause a lot of damage, right? And what we landed in is kind of this resource constrained thing, where we have multiple patients who are all going to get an ambulance eventually. But it's a question of, do they wait 10 minutes? Or do they wait half an hour? And that's kind of less risky. And so we needed to kind of calibrate the level of risk that we were taking in a project with kind of performance of the models, basically, to make sure that we're not like, even if the model is wrong, we're not causing too much damage.	SC

3.58	**AS:** And I guess also, that also reflects to what you said earlier, the part of like making, like understanding the theoretical use of the data, you could use for multiple ends or perspectives? And I guess that's a very quite evident one, like, "do you need an ambulance", or "should we send an ambulance" or the way you phrased it.	
3.59	**R3:** Yeah, exactly. And how do you measure that, again, like, we need to, what we ended up doing is kind of making a composite score, kind of right. So we actually, we actually look at four different things. So for different outcomes, we have four different models that each that can generate, like a weighted average prediction, to define ambulance need, instead of just saying, okay, patients who, like, get an ambulance or get transported to the hospital with priority one. That's our gold standard definition of an ambulance need. Like, that's part of it, but it's probably not everything, right? We also want to look at a what was the status of the patient when the ambulance got there? Like, did they have like an abnormal airway or breathing or circulation condition? Or did they get any interventions like they did to get it again? Did they get medicine or like oxygen administration? And then what happens at the hospital, right? Do they get admitted? Did they die within 30 days, all of these things are important. None of them are everything, like they none of them completely describe ambulance need, but maybe together. They can kind of approximate it, they can serve as a reasonably valid proxy measure of ambulance need.	SC
3.60	**AS:** So does the individual algorithm measure different aspects, as you said, it's not that all of the four do the same measurement, but they ended up with the same measurement that you then average?	
3.61	**R3:** Well, I mean, they all measure different things, right. So one of the measures, like the priority that the ambulance that the patient gets transported to hospital, one measure is hospital outcomes, one measures, interventions in the ambulance, and then they get kind of there's like a weighted average, we kind of decide, okay, so the initial assessment is the most important so it gets the highest weight in this kind of averaging process. And then what gets finally... all these things and get weighted together into a single number that can be compared between two patients, and that we feel is like a reasonable proxy, and also needs to be generalizable between different types of patients, right, like a patient with a with like a trauma patient and a breathing difficulty patient are very, very different, right? And and you need to get find outcomes that are relevant to both types of patients or to all types of patients really. And that's kind of challenging to just find like a single measure that's valid for all of our patients. And so we decided that, you know, combining these model predictions will probably be more robust in a way than using any single one of them.	SC
3.62	**AS:** All right. Also, just reflecting back, you said you wrote the entire script, or the	

	program from R to Python, was it based on accessibility criterias, or opensource?	
3.63	**R3:** Mostly it's like, a lot of this, it's pretty comfortable to write, like, API's in Python, like, [Inaudible] stand up a server, and all this stuff is really more appropriate to do it in Python, than in R just feels more kind of... Yeah, I think like, especially like server administration type people are more comfortable with Python, and kind of using that than they are with R you need. Kind of more, I guess, architecture is just kind of like more heavyweight with R, like, you need to have like an R server running and everything. Python is a little bit more lightweight. And there's good like API libraries and stuff for Python. Also, my kind of normal workflow is kind of I do like research and stuff, do all that in R, and then when I put stuff into production, I'll rewrite everything in Python, right? Because a lot of times, you can do a typo, that like mess everything up in ways that you may not even notice, right? So just figuring out these kinds of stupid errors, human errors, it can be helpful to just rewrite everything, before you put it into a production environment where you don't want errors that can wind up killing people, right? So that's not... I can sleep a little bit better at night, knowing that I've at least looked through all my code twice.	
3.64	**AS:** Yeah and I guess you also see, you also see possibilities of improvement as well?	
3.65	**R3:** Yeah, exactly. When you put stuff into production you'll, yeah figure out different ways. Like why did I think this way, maybe that's not right at all. At the more theoretical level as well, yeah. I think that's good.	SC
3.66	**AS:** All right. Like, we're still in the hunt, of interesting people to talk to. So we are, we have tried to at least identify three different groups. So we want to talk about from user perspective, so we have talked to some doctors, or planning on doing that. And then some sort of business developer/project manager as you are here. And then also, like, this is also I guess, an expert perspective. But do you have like any particular leads? Maybe a direction?	
3.67	**R3:** You mean, like, you want to talk to like our user of the system?	
3.68	**AS:** Yeah, that would be nice. Yeah,	
3.69	**R3:** Sure, I mean, either that or you can talk to, I guess we have our medical director here is also like, if you want to get more of like, a clinical perspective on it, that might be a good choice.	

3.70	**AS:** You could at least ask if they were they would be interested. Like, there's no... we don't want to force anyone.	
3.71	**R3:** Yeah, no, I'm sure my medical director would be happy to talk to you guys and give you some input from that direction. And I can see if there was like and again, like I don't know how much how involved they are like the users just kind of clicking buttons [Laughter].	
3.72	**AS**: Yeah I guess we could just...	
3.73	**R3:** That might be interesting perspective. I can take a look.	
3.74	**AS:** Yeah, that would be super kind. And also, you will have some time now after to read the consent form. But we will make a transcript out of this and we will send it out to you, so you can validate it, if you don't want to spend too much time on it you don't. But you have some time to review, see that nothing is sketchy. And then yeah... that's about it. We're super grateful for having a conversation with you.	
3.75	**R3:** Yeah, absolutely.	
3.76	**HK:** Thank you very much.	
3.77	**R3:** Good luck with your project. Yeah, feel free to if... I guess this is gonna go out to, you get this stuck on some like school server or something?	
3.78	**AS:** Yeah.	
3.79	**R3:** Yeah, send me a link when you're done.	
3.80	**AS:** Yeah, we'll do so. Nice.	
3.81	**R3:** Cool.	

3.82	**AS:** Have a good day.	
3.83	**R3:** Cool beans, take care.	
3.84	**HK:** Bye	

Appendix 6 – Transcript Respondent 4

Speakers:

HK = Herman Joseph Kambugu

AS = Axel Svansson

R4 = Respondent 4

Date: 25th of April 2022 Length: 30 min.

Row	Transcription	Code
4.1	**R4:** Hello.	
4.2	**AS:** Hallå.	
4.3	**HK:** Hi.	
4.4	**AS:** How are you?	
4.5	**R4:** I have a big cold. ... probably even some fever. So, but I can still sit up.	
4.6	**HK:** Oh no.	
4.7	**AS:** That's very kind of you, very kind.	
4.8	**R4:** Just fire away.	
4.9	**AS:** Thank you for being here and especially during these conditions. But just a quick check, did you manage to see the consent form?	
4.10	**R4:** I haven't looked at it very carefully yet, but I'm sure it's okay.	

4.11	**AS:** Yeah, but I guess for the interview, the most important thing is that we get consent to record.	
4.12	**R4:** Yeah, that's okay. Go ahead and record.	
4.13	**AS:** Perfect. So then we started like, officially here. So you will hear Zoom announced.	
4.14	**[Zoom: Recording in progress]**	
4.15	**AS:** All right, so we're officially started. So I will just briefly summarize what our study is about. And then we're gonna get into some questions. So, our research is focusing on the factors that influence adoption of machine learning-enabled clinical decision support systems. So for us, this entailed looking into the factors that were or are being considered in the initial phases of getting to use and create the systems. So we're thinking they're both technical, they're organizational and environmental. So it's quite a wide topic. So when we started our research inquiry, you were one of the first to come up, actually, when we looked at *...*, and seeing that you seem to be into this, at least in terms of research, but who knows, it might be in a more clinical setting as well. So I guess we could just start there. So we would just like to know a bit more about your background and what roles you have currently. And then we sort of a base off from there.	
4.16	**R4:** Okay, I am a consultant in Emergency medicine at the Emergency Department of *...*. I am a professor of Emergency Medicine at *...*. So I have basically three jobs, I treat patients, I teach at *...* and I do research.	UC
4.17	**AS:** All right, cool. So as we've seen in your research profile as well, you are looking into the use or the potential of these machine learning or AI-based decision support.	
4.18	**R4:** Yeah.	
4.19	**AS:** So in what current ways are you planning on utilizing, or what's the main takeaway, with these kinds of systems?	
4.20	**R4:** So, in my research I am interested in all kinds of decision support systems. And we have implemented some decision support systems based on the sort of simple rule-based systems and we're now moving into AI and machine learning-based	UC

	decision support systems. These systems are intended to... well they are intended to be used in emergency medicine, in the emergency department basically.	
4.21	**AS:** All right, I see.	
4.22	**R4:** And they deal with triage, the initial risk assessment that we do for all patients that come in and also specific patient groups, for instance, chest pain patients, or patients with breathing problems and so on. So, both the general risk assessment that we do for all patients when they come in and then in specific patient groups after the initial risk assessment.	UC
4.23	**AS:** All right. So, when looking into the technical aspects of these kinds of systems, with this new methodology, how do they currently relate with other systems? Is it a hard challenge to integrate them?	
4.24	**R4:** Yes, it is. The simple rule-based decision support systems are easy. I mean, we just use paper. It's an algorithm on paper. But when we try to implement the machine learning-based and AI-based decision support systems we need to get the IT department to be..., I mean we need their help. Because these decision support systems need to be fully integrated in the patient record systems. So, data has to be sent from the different databases, for example ECG databases, biochemistry databases, patient record databases, and they had to be sent in real-time to the decision support program, the model. And then the model has to create a recommendation of course, and then that recommendation has to be displayed in some form to the user, which is the doctor on the floor of the emergency department. So this is a big thing. And we are currently working together with the IT department to set up such a solution. And it's difficult, takes a lot of time and first and foremost, it takes a lot of money. To get the IT people to... I mean, to get time for this, and we have to pay these people to do it.	SC, FR
4.25	**AS:** I see. And then also in terms of that, like you said that it's in real-time, does that add an extra dimension of complexity compared to maybe something that's done without the intervention of a human? I'm thinking maybe these classical rule-based, they are more like, you have your input, and then you get your output concurrently, or as a result, but this is something you have to call for, you need to call for the information in this journal or this database.	
4.26	**R4:** Yes, and that has to be done automatically. I want the decision support to pop up in the face of the user. I don't want the user to have to sort of start something or call on specific information. I want the recommendation just to pop up in the face of the user. Because in that way, it will be used much, much more than if	SC

	the user needs to do something cumbersome, perhaps even to get the decision support.	
4.27	**HK:** Well, so when it comes to these kinds of systems. Data availability is another key issue that normally comes up. Would you say you have data available? And is it reliable for the systems?	
4.28	**R4:** Yes, it is. We have lots of data. But the problem is, as you say, I mean, we have huge databases, that are practically a goldmine. But the availability is the problem, we need to have the data sent in real-time to the decision support model and that requires a lot of IT work. For each patient that comes in, let's say with chest pain. There should be automatic prompts, to make the data be exported from the databases to the decision support model, and the model's recommendations should then be automatically displayed to the user.	REL, DA
4.29	**HK:** Right. You mentioned that you're a doctor and you're involved in treating patients as well. My next question is twofold, number one, from a doctor's perspective, in terms of transparency, how important is it for you to understand the reasoning or the logic behind some of the decisions or recommendations that the system will be able to give you? Maybe I'll start from there. And then I can ask from another perspective.	
4.30	**R4:** Okay, that's a very difficult question to answer. Because it depends. It depends on how established the decision support is. If I know, for example, that it has been used for three years, by my colleagues, all over the country, then I don't need to really understand what happens. But if it's new, and if it looks complicated, if I knew it's AI or machine learning or something then I will feel the need to understand what's happening. So, it depends. And we are working with that with the user interface in these decision support systems. You need to give the user enough information so that it makes the decision support to look trustworthy. I mean, we need to give them information, like what are the basis for this recommendation? This is the results of the blood samples. This is the results of the ECG. This is the patient, the age and the sex. So that is the thing that we think really hard and long about, "How do you present the results?", "How do you present the recommendation?", to optimize the trust. And I use the word optimize because you don't want the doctor to trust the decision support system too much. Because there will always be cases where you shouldn't trust the decision support system. So 100% Trust is not good, I want it to be like 95 or something [Laughter].	T
4.31	**AS:** Right? Yeah, I see. And doctors of course, they have gone through, like extensive education.	

4.32	**R4:** Yes, and in the foreseeable future, the doctor will be the one who makes the decision, not the computer, not the model. The doctor will be responsible for any mistakes.	
4.33	**HK:** You've actually pretty much answered my second question, because it's going to ask it from a setup-perspective, that you have answered.	
4.34	**R4:** Just hold on a second, I need a tissue.	
4.35	**AS:** Yeah. [Brief pause]	
4.36	**R4:** All right, sorry.	
4.37	**AS:** No worries. Ready?	
4.38	**R4:** Yeah.	
4.39	**AS:** So that was... we touched upon the technical aspects. But you also mentioned in terms of like organizational, it takes time, it's hard to organize. So we're thinking in these initiatives, or projects or research projects that you have been involved with. To what extent do you feel that there's a need... like do you need support from your managers or supervisors? Or is it something that you can drive on your own?	
4.40	**R4:** We need support from the entire system, from the clinical managers, from the IT department, to some extent, from the *...*, but mostly from the clinical side of the clinical leadership, the IT clinical people. So we need a lot of support.	TMS, COL
4.41	**AS:** Yes. And I see, I guess that each of the managers in each branch or division, the department wherever you're in have to coordinate this in order to make it feasible, I guess?	
4.42	**R4:** Yes, but mostly they have to say "yes, go ahead".	TMS
4.43	**AS:** Okay.	

4.44	**R4:** So we in the project do the coordination, mostly.	
4.45	**AS:** Alright. Would say you guys have the curiosity from that end like you want to develop and...	
4.46	**R4:** Yes.	
4.47	**AS:** Yeah, okay I see... And you also mentioned money, it's expensive, both in terms of resources, but in terms of technology, is it expensive?	
4.48	**R4:** I wouldn't say that it costs. I mean, the hardware is cheap, the people are expensive and there are no specific budgets for this and in the *...* IT department. So, we have to get the money.	FR
4.49	**AS:** And do you get it from external founders?	
4.50	**R4:** There is a special grant that you can apply for from around the *...*, whatever it's called. So that's where we have gotten money so far. There are special specific grants that you get from *...* and you have to apply for them and you have to compete for them.	FR
4.51	**AS:** I see.	
4.52	**HK:** So in terms of technology readiness, how ready are the doctors or the people that you're working with for this kind of new technologies that you are working on?	
4.53	**R4:** Oh, they're ready. They're ready. And we are very computerized in the clinical work.	TR
4.54	**AS:** And it was sort of like... you maybe hinted it a bit without knowing, but you said you needed just the "Go ahead" from the managers. So I guess that indicates also to some extent...	
4.55	**R4:** Yeah, and we use decision support systems all the time, but they are very simple. Like scores, where you add up like you get one point for this, you get one point for that, you get one point for that, and then your total score is three. Okay, so	TR

	then that means that you have a risk of so and so much. And that means that this is the way to treat this patient. So we're used to decision support systems. We use them all the time but we just haven't used decision support systems based on AI or machine learning.	
4.56	**AS:** All right, I see. So you mentioned that, okay, so the first traditional type of system that are ruled-based are quite simple.	
4.57	**R4:** Yeah, most of them can be used on paper.	
4.58	**AS:** Yes, okay. So I guess, in terms of regulations, healthcare is quite heavily regulated space in terms of introducing new technology, new devices. So we're thinking, is there a difference? Or there should be a difference, but when you're doing these projects, or initiatives, how restricted are you in terms of regulations? And are they up to date? Is it easy for you guys to understand what rules to follow?	
4.59	**R4:** Yeah, this is a funny thing. Because if we want to use a simple rule-based decision support system, there are no rules, no rules whatsoever. We can use whatever we want. But if we are going to use a machine learning-based or an AI-based decision support system, that will be classified as a medical device. And that will be governed then, or it will fall under the MDR from the European Union, the medical device regulation. So then, we will probably after testing these things and before we want to use them, we probably will have to get them CE-marked, perhaps. But when we talk to the people who are supposed to know this, this is fairly unknown. Because they haven't been working so much with these things so far. So it's sort of... it's a white spot on the map. I mean, the law people and the regulators within *...* they have to find out what is really... what are the rules in *...* and in Sweden. This MDR, this medical device regulation, is fairly new. I think it's about two years old or something. So I think there are a few prior cases where this legislation has been really tested.	REG
4.60	**AS:** All right.	
4.61	**R4:** Yeah. So it's hard to know, we are sort of moving slowly forward. And everything is happening simultaneously, the law of things, the legal questions, the technology development, and everything is happening simultaneously.	REG
4.62	**AS:** I see. Yeah. So that may be something exciting that you will like discover as you go, and then you have to be ...	

4.63	**R4:** We discover as we go, the legal people discover us they go and they look at prior cases in the EU and what is allowed and what is not. And how do we go about this? There are even local regulations in *...*, like, is this a project or not? Lots of things are unclear at this time.	REG
4.64	**AS:** And I guess if it's not evident how to proceed, I guess it's it becomes harder to make the use of these new systems more readily available in other regions, maybe here in Sweden, but like the bigger picture is hopefully you could spread a new device across the entire world.	
4.65	**R4:** Absolutely and there are many things, many issues with trying to spread these things to other regions or countries or other parts of the world, because the IT systems they will be different in all the places. The populations, the patient populations will be different in all the places. So if we come up with a good AI-based or machine learning-based decision support system and we would like to spread it to other parts of Sweden, to other parts of Europe, to North America, this decision support system has to be retooled. It has to be reset, readjusted and validated at the new site.	SC
4.66	**AS:** Yeah...	
4.67	**R4:** So the model will work probably be somewhat different in other countries. The IT systems will definitely be different. So the export of data and import of data will be different at each site.	SC
4.68	**AS:** I see. So also, in terms of that this is quite, it's new, but at least many seems to have come to the stage to develop and try out and like... would you say that it's driven by market trends? This is maybe hard to speculate around. But is it like only internally? Or is it that you have, okay, there is a lot of research and you want to adapt it to your setting. Or is it maybe driven more by the curiosity that you expressed earlier?	
4.69	**R4:** I would say, I would say it's driven mostly by curiosity. At least for us. We've talked a bit about maybe, to commercialize it, but it's going to be difficult, for the reasons I just mentioned. So I think it's driven mostly by curiosity at this point.	MT
4.70	**AS:** And then, we were also like, when we were looking into this topic from the beginning, we had a perspective that market trends could also be large happenings in the world, right? So we had a pandemic, could that be a potential	

	driver at least? But in terms of initiatives, you seem to have started these kinds of projects before that?	
4.71	**R4:** Absolutely, yes. I think the pandemic has... maybe sort of increased the incentive a bit. But I mean, these ideas were... have been present for a long time. For at least 25 to 30 years, the development has been slow, and it comes and goes. They sort of, sometimes it's more fashionable, and then it goes away for a couple of years and then becomes more fashionable again. There's a sudden breakthrough in one area of medicine and people are getting inspired by that. And start projects in other areas of medicine. So it's been a long time development, that's been around for a long time. But it's come and gone over time. Now. I think it's more fashionable yet again.	MT
4.72	**HK:** All right. So we have touched upon so many factors that could influence machine learning-enabled clinical decision support systems. But we want to hear from you, like in your opinion, what are some of those factors that have influenced your decision to take these initiative on, in your own opinion and doesn't have to be anything we've discussed prior	
4.73	**R4:** The factors that have worked? Can you repeat that?	
4.74	**HK:** Yeah, factors that have influenced your decision to go ahead with these initiatives for machine learning clinical decision support systems.	
4.75	**R4:** Ooh, interest, curiosity. Availability of great databases. That's basically it. I'm interested in decision-making in emergency medicine. How do we make decisions? What do we base our decisions on? Because that is at the core of what we do as emergency physicians. We are a very decision intense specialty. We make decisions all the time, all the time.	UC, DA
4.76	**AS:** Nice, we actually managed to get through our set of questions, and we're super happy with this conversation.	
4.77	**R4:** Okay, good. Thank you!	
4.78	**AS:** Did you find it, any particular things that, was curious for you? Or is this just the old same-same?	
4.79	**R4:** Some of the things I've heard before, but it's always interesting to get to hear other people from other fields of academics talk about these things because often	SC

	you don't understand.... you don't have the entire picture of what it's like to work with these things in other fields. It's like me asking questions about economics and marketing or whatever, I don't understand it. And oftentimes, you don't understand the complexity at the local level. Because all these ideas, they look so nice. They are so attractive, but when you get down to the details, you understand that it's not so easy [Laughter]. I mean, ideas are great. I'm not sure who said this, it might have been Mark Zuckerberg or something. "Ideas are great, but execution is everything". A lot of people can have ideas, that's easy. But to execute it, to get it through, to make something of it that really works in the real world. That's the thing. That's the thing you need to do to succeed.	
4.80	**AS:** Nice, nice insights.	
4.81	**R4:** [Laughter] They say that there were a lot of "Facebook's", and like a lot of digital students registers all over the universities in the United States, but only one grew into Facebook, the one at Harvard.	
4.82	**AS:** All right, so we're not going to occupy your time more. And hopefully, you will get better soon as well with the cold. So just the consent form...	
4.83	**R4:** Yes! I'll print it and sign it and send it	
4.84	**AS:** Yeah, but as long as we got your mutual agreement here, so you don't have to print it.	
4.85	**R4:** It's okay, you have it on tape.	
4.86	**AS:** Great. So what we're going to do is we know that you have a busy schedule, but as a formality, we will give you the opportunity to review the transcript that we create.	
4.87	**R4:** Okay.	
4.88	**AS:** So it's up to you how much time you want to spend on it. We have like full	
4.89	**R4:** Probably not a lot of time.	

4.90	**AS:** Exactly, but it's part of the process. So you the email will pop up in your inbox, so you know. But once again, thanks for your time and have a nice day.	
4.91	**R4:** Yes. you to! Did you have any more questions? Just email me.	
4.92	**HK:** Great, we'll do that. Thank you.	
4.93	**R4:** Okay, bye bye.	
4.94	**AS:** Bye.	

Appendix 7 – Transcript Respondent 5

Speakers:

HK = Herman Joseph Kambugu

AS = Axel Svansson

R5 = Respondent 5

Date: 25th of April 2022 Length: 30 min.

Row	Transcription	Code
5.1	**R5:** Hello.	
5.2	**AS:** Hello!	
5.3	**HK:** Hello.	
5.4	**AS:** How are you?	
5.5	**R5:** I'm fine.	
5.6	**AS:** Good. Thanks for being able to put up with an interview with such a short notice.	
5.7	**R5:** Of course!	
5.8	**AS:** So, I'm Axel, you spoke to my mom on the phone [Laughter].	
5.9	**HK:** And I'm Herman.	
5.10	**AS:** So we're from the Department of Informatics at Lund University. And we're doing our master thesis. We looked for appropriate people to interview and we found you at *...*.	

5.11	**R5:** Yes.	
5.12	**AS:** So yeah, that's sort of how we got to know about you, and what you do in your day-to-day work and some of your research. So did you have an opportunity to view the consent form?	
5.13	**R5:** I got it here, yeah.	
5.14	**AS:** Good. So just for the sake of this interview, we just need an okay, on tape, that it's good to record and so on. So, as long as that is okay, we will then proceed with pressing "Record" on Zoom. So just the formalities.	
5.15	**R5:** Of course, I'm fine.	
5.16	**AS:** Good. So that will start...	
5.17	**[Zoom: Recording in progress].**	
5.18	**AS:** So I will just begin with to give a brief description of our topic once again, even though maybe you read it in an email. But just to give some context, and then we'll go into some questions. So to begin with our research is about machine learning-enabled clinical decision support systems. More specific, the factors that influence the adoption of these kinds of systems. So for us, from an informatics perspective, this entails looking into different kinds of factors. And we sort of divided it between technological, organizational, and environmental. So we're trying to get the perspectives from doctors, researchers, experts, and so on. So that's sort of about it. But then we came about you. So we would just like to begin with maybe you telling us a bit briefly about yourself and your role, and sort of how you're related to this, these kind of new systems, essentially.	
5.19	**R5:** Okay. So I'm a specialist doctor in infectious diseases. And I'm also a PhD student. And as part of my PhD I've worked with looking at prediction models based on machine learning to predict onset of sepsis. Sepsis is a severe kind of manifestation of infection, so it's not one kind of infection, it's like a syndrome. So it can develop as a response to many kinds of infections. But it's severe, it happens usually in hospital and it is associated with a high mortality. So that's why we looked at models to see if we could use data readily available from the electronic healthcare records to predict this syndrome called sepsis. So it's part of my PhD thesis. That's how I work.	UC

5.20	**AS:** Okay, so you sort of answered straightaway our follow up questions in what way you're planning to utilize this, but it's about predicting...	
5.21	**R5:** Yes.	
5.22	**AS:** ...I guess, how prone you are to this sepsis infection?	
5.23	**R5:** Yeah, basically, I mean, when it comes to prediction models, and their utility in healthcare I'm not sure if it's mature enough, or the data is good enough to predict individual patients' onset of disease. But maybe you could somehow stratify patients based on risk. So basically, you could have a low risk, or medium risk, or high risk or something like that. And I think that's more feasible in terms of what kind of data is readily available today to do that kind of prediction. So that's basically what I'm working with to see if I can find a model good enough to stratify patients based on this kind of "traffic light", kind of decision support. And then you can somehow use this stratification and connect it to other kinds of interventions, such as increased surveillance or checklists, or more hands on clinical kind of workflows.	
5.24	**AS:** I see. So there's, at least at the current state, it seems that it has the possibility to have a lot of interventions. Since it's in such an initial stage, it may be hard to talk about the complexity of the systems, or the I guess... it would rather be a matter of fact you trying envisioning the complexity of trying to implement a system like this. Since this is not, I guess, this is what you're researching about. It's not that it's a tool that it's developed and an application that is ready to use, right?	
5.25	**R5:** No, no, not yet. Not my kind of research, but I've been involved in other projects, in collaboration with a Danish company called *...*, and they have developed a tool, which is actually in use in several hospitals in Israel and also maybe in Italy. And that is a clinical decision support tool to aid in choosing the correct antibiotics for acute infections. That's also one kind of clinical decision support tool or model I've been working with. So these two, ones, the prediction model but also this clinical decision support for selecting correct antibiotics.	UC, COL
5.26	**HK:** Well, that sounds interesting, actually. Because it looks like one, you're working on your PhD, but then you've also worked with other projects that are already implemented. So are there any others? Or was it just the antibiotics?	
5.27	**R5:** No, I mean, they have a product they're selling basically, it's a software which has a quite wide... I mean, it's very common when patients enter the hospital that	SC

	they have a suspected infection of any kind. It's a very common kind of reason to be admitted to the emergency room. We have data that approximately 1/5 or 1/3 of all patients in the hospital have some kind of suspected infection. So it's a common issue when you enter the hospital. Basically, when you suspect an infection, you draw a culture. And if you're lucky, you grow a bacteria, which explains the kind of infection the patient has or what's causing the infection. In many cases, there never grow a bacteria, so you have to rely on previous knowledge, what kind of bacteria causes pneumonia, what kind of bacteria causes urinary tract infections, but basically, this information is not available when you're giving the patient's antibiotics. So you don't know what kind of pathogen is causing the infection. And you have a range of antibiotics to use more than 20 and you have a range of pathogens, bacterias, and you need to match correct antibiotics to the correct pathogen. So then, this company has developed a system that uses kind of previous knowledge about what kind of pathogen is common in your setting and what kind of source of infection you have and they try to match. So they give you a suggestion, you should probably use this kind of antibiotics because it will most likely cover the pathogen that will most probably grow. So that's the kind of system and they have involved other aspects of giving antibiotics because you have also cost both economic, but also ecological costs in terms of antibiotic microbial resistance. So they, involve that kind of things in the model as well. **So, yeah, it's quite a complex kind of system.**	
5.28	**AS:** So in terms of this, I don't know if you're very well versed with it. But when it comes to this system, and it suggests what type of antibiotics to use in combination to the bacteria. Do you know, if it provides something additional to why it came up with the suggestion, like, is there a logic behind it that a user could try to understand?	
5.29	**R5:** Basically, their system is based on a Bayesian network, causal probabilistic network model. How they sell their system is that they say that it's transparent, it's not a black box, you can always follow the reasoning behind the model. It works with probabilities, so it's very much like how a doctor or physician would think. It gives you like, kind of suggestions, and you could click yourself further and see kind of why it suggested this and it's based on a probability. So they give you "it's a 60% probability that it's this pathogen and the pathogens, in your setting looks like this, in terms of antimicrobial resistance. So we, we give this kind of advice." So it's quite transparent but only for the interested user, in the first kind of view of the system, you just get to suggestion. But it also includes variables like how severely ill the patient is, so if it's a more severely ill patient, you will get the kind of broader suggestion of a broader spectrum antibiotic, because you want to really cover all the possible pathogens if the patient is really severely ill. And if the patient is not severely ill you will get the narrow recurrent spectrum antimicrobials suggested. So it also gives you this kind of like score of how severely ill is your patient, it has several aspects of it.	

5.30	**AS:** So it's, like you mentioned the complexity and dynamic it's quite high for this particular system.	
5.31	**R5:** Yes, definitely. Perhaps too high, I don't know... because they have had problems selling it. Mainly, I don't know... because the system is really nice if you're interested. But if you're doctor under high kind of workload and stress, and not really interested in infections, you just want to solve problems, then it's maybe too much information.	
5.32	**AS:** Since your PhD is something that's a work in progress as of now, and maybe it's more related to the other projects. But it's, we understand that it's on, like in different hospitals where they utilize this system, or that was developed by a company. But how involved were you in these kinds of projects, or to what extent, or what angle did you have?	
5.33	**R5:** So my angle has always been the clinical side, since I'm a clinical doctor, I'm working clinically. So I'm the intended user in some ways. So that's always been my role in these projects. For the company, their model it was developed before I entered the project. So it has been in use for several years, but now they're working on an update of their model, to simplify it, to make it more user friendly. I'm one of many kind of partners that work. So firstly, we are giving inputs to how their model is working and how it's used. But also, we're providing a clinical data set to validate the model, so it actually gives results that are valid. So that's how I'm part in that and for the PhD project with the sepsis algorithm, I've been developing it together with one civil engineer/programmer, basically. So he's been coding the algorithm, and I've been kind of designing it, like "I want this and we want to evaluate it in this way."	COL
5.34	**AS:** I see, so in terms of this project how driven or engaged are the supervisors of the project? Like the managers, in terms of an organizational context? Are they part of driving it? Or is it mainly that they, they get a...	
5.35	**R5:** I would say that they're very much part of the process. So I mean, for the company, their model I'm very often in contact with the CEO of that company. He's really into the details of their model, their decision support. For the other projects, where my PhD supervisor, he has been part of all the discussions and decisions when it comes to developing. So I would say that the manager has something really.	TMS
5.36	**AS:** I see and maybe it's also in alignment with, at least when you buy a product, it's, I can imagine that it's a large investment as well.	

5.37	**R5:** Yeah, of course, and the customer in this case would be a hospital or electronic health record vendor or something like that. And, yeah, so it's really... would be a big deal and very expensive to implement it.	FR
5.38	**HK:** Yes. So coming back to your research that you're doing right now, in terms of financial resources? How is that working out?	
5.39	**R5:** So these projects are financed by grants, research grants.	FR
5.40	**HK:** Okay, so it's founded externally?	
5.41	**R5:** External funding with the research grants, and it's not kind of coming from the clinical hospital side, they are not financing it. I mean that, they don't have a problem that they want to be solved. It's more that this is more research-wise. So it's more of could this be done to somehow innovate or develop the clinical work.	FR
5.42	**AS:** I see. So from the perspective, just from your perspective in this from your infection and sepsis angle, in terms of technology readiness, would you say that doctors within your field of area are the ready for a new kind of decision support? That's not really based on rules?	
5.43	**R5:** I'm not sure. Medical doctors are usually, to some extent, quite conservative. I would say the medical field, but on the other hand, it's really a field where things develop quite rapidly in terms of new medications and new treatment opportunities and things like that. But when it comes to these kinds of decisions supports, I'm not sure how mature already the clinicians are to trust or reuse these kinds of systems.	TR
5.44	**HK:** Right. And in terms of regulations, of course, when we talk about healthcare records and medical data, there's quite some heavy regulations, at least, what we've read in literature, but from your perspective, you could talk about it from the angle of your research that you're working on now, or the other project that you worked with. Regulations, which kind of regulations are impacting you?	
5.45	**R5:** I would say it's two kind of main issues. The first is the project, you need to have a quality mark, the CE marking, you have all the documentation, all the validations, everything like that. That is really cumbersome work. It takes a lot of time and resources, both financially and human resources. So that is something I would say that is an obstacle in some ways. The other one is to really implement it in the hospital, and you need to somehow have something that is marking, but	REG

	then you need to sell it to the hospital. And in terms of regulation in Sweden, you need to have... I don't know the English word for it, but "upphandling". So that makes everything very complicated as well. So, yeah, in terms of regulation is quite complex.	
5.46	**AS:** It's impactful, at least?	
5.47	**R5:** Definitely and you need quite a lot of financial support, I think to move a product from the research phase to the market and actually being implemented.	FR
5.48	**AS:** I see. And these kinds of initiatives that drives this research, would you say that it's based on current market trends, as you said, like, at least with infections that you said that the new medicines are coming up? Or is it based on the, solely the research academic side to it, that people are curious to innovate?	
5.49	**R5:** I would say from my perspective, it's solely the research perspective to see if it's possible to improve the kind of clinical environment. I mean, we collect a lot of data, but we make very little use of it. So I mean, it's driven by some kind of mission to use the data in a more efficient way... I mean, we collect a lot of data but we only store it and we never use it for any intelligent kind of models or machines.	MT
5.50	**AS:** So in your collaboration, in your PhD with this civil engineer, or programmer, have your discussions regarding the data available is it... I guess there's a lot of work that goes into that as well, like, conceptualizing what you have, and make it usable. But that's maybe part of his process?	
5.51	**R5:** Yeah, it's part of both our processes, because he needs to somehow understand the data, and I can help him with that. Because in all of these models, you need to somehow pre-process the data, find variables that are relevant, filter them and just clean them because we're working with quite messy raw data. In some of the projects, we are more looking at research questions like, do we add anything to the prediction if we add this kind of variables or not, and stuff like that. So it doesn't add anything to prediction, it will make the model more complex by adding these and none of these things. So this is some of our research questions, basically.	REL, COL
5.52	**AS:** I guess it again ties into the dynamics and the complexity of these systems. It just goes hand in hand to some extent.	
5.53	**R5:** Yeah., you could have a complex model. Or you could have a more complex...	SC

	the back end can be very complex. But what you see as a user could be quite simple. And the other way around, and I would say the sepsis prediction tool is more complex in the backend. But the thing that the user will see it's very simple, more like a traffic light kind of system. But the other thing I talked about the company, they have more complex user interface where you really have to interact with... it's basically like another application to work with.	
5.54	**AS:** I see.	
5.55	**HK:** Right. So in your research, and this you could answer from your research perspective, also the other projects that you've worked on. What are some of the factors that you think have influenced one, your decision to pick up the research to go into sepsis? Or what are some of the factors that influence the decision for the project that you worked on to be adopted? In your own opinion. I know, we've touched upon so many, like reliability and transparency, we've touched upon the regulations, but in your opinion, what are some of those factors that you would consider important?	
5.56	**R5:** I mean, it's basically comes from interest, personal interest. For one thing, but the other thing is that there's some kind of unmet need. And also it's situations or diseases where it's possible to somehow both in terms of frequency, it's quite frequent. And it's possible also in terms of the kind of data you have access to. So it's somehow, what you call it? It's feasible to work with these kinds of problems.	MT, DA
5.57	**HK:** So feasibility is...	
5.58	**R5:** Yeah, feasibility I would say. I mean, you need to start somewhere, you need to pick the low-hanging fruits. And I would say, these two are.	
5.59	**HK:** Right, I see that we're actually out of time, but maybe any closing remarks from your side or anything you think we haven't touched upon that you could add some tips or information, or feedback, basically?	
5.60	**R5:** No? No, I think it's...	
5.61	**AS:** Oh good. The thing that we find interesting, it's just that we have the opportunity to talk with people from a completely different field. And there's always bound to be some sort of, not overlap, but sometimes we try, or we think that we understand some part of the clinical side, but there's so much more to it.	

5.62	**R5:** I agree and I would say that this company, for example, I think the problem maybe with their product is that they were underestimating how important it is to have the clinical side of it. To have clinicians or the users involved, I mean, they had doctors involved. But they should probably have been more doctors, because if you only use like one pair, or they used maybe one or two doctors, and they had really strong opinions about things and were quite old. So their product was somehow really tweaked to their kind of opinions, and maybe not applicable to other settings. I don't know if you understand what I mean. But I would say that the involvement of several different clinicians really work with usability and these kinds of things is really important.	SC
5.63	**AS:** I see. But we would just like to thank you again, once more, for taking time to talk to us, have a brief conversation.	
5.64	**R5:** No worries.	
5.65	**AS:** So just to conclude, the information is in the consent form but we will create a transcript. And as a formality, we also give you the opportunity to read it through, make sure that nothing is sketchy. You decide completely how much time you would like to devote on it. We understand that you have more important stuff to attend, such as your work, your PhD, and stuff like that. But it's part of our process, so it will pop up an email in your inbox, just for your knowledge. But once again, thanks for the conversation.	
5.66	**HK:** Thank you.	
5.67	**R5:** Thank you.	
5.68	**AS:** And have a good day.	
5.69	**R5:** You to guys and an interesting project! Good luck with your thesis.	
5.70	**AS:** Thank you. Bye bye.	
5.71	**R5:** Bye	

Appendix 8 – Transcript Respondent 6

Speakers:

HK = Herman Joseph Kambugu

AS = Axel Svansson

R6 = Respondent 6

Date: 26th of April 2022 Length: 30 min.

Row	Transcription	Code
6.1	**R6:** Hello guys.	
6.2	**AS:** Hello, how are you?	
6.3	**R6:** I'm good. How are you doing?	
6.4	**AS:** Nice. A bit of early morning, we had to rush to school to get a meeting room. All right, but thank you for allocating time to talk to us. So just to start with, my name is Axel, and this is...	
6.5	**HK:** Herman.	
6.6	**AS:** So we're from the Department of Informatics at Lund University. It's not the engineers section, but rather under the business school rather, that the informatics departments so to speak. That's a little bit about us and we're writing our master's thesis. And you've seen our topic, but I will brief you on that in a second. But just to start with, did you see the consent form that we sent?	
6.7	**R6:** Yes, yes. I skimmed through it.	
6.8	**AS:** Good. And there's no issues with recording the interview?	
6.9	**R6:** No, no problem.	

6.10	**AS:** Good, then we will press record here and you will hear Zoom shout.	
6.11	**[Zoom: Recording in progress]**	
6.12	**AS:** All right, we're officially started. I will just begin with to summarize our topic, and then we will go into the questions and a little bit about you. So just to begin with our studies is about the factors that influence the adoption of machine learning enabled clinical decision support systems. And for us, from the informatics perspective, this entails looking into factors that are or were considered in the initial stages of these kinds of new technologies. We sort of divided them between technological, which maybe you have some good insights of, and then also organizational and environmental. So we needed to find people to talk to, you came up. We could maybe start off there with you telling us briefly what you do, what your role is, your day-to-day role and how you're sort of related to this topic.	
6.13	**R6:** Okay, I'm a PhD student, I have been for four years now almost. Before that I was a research assistant in *...*. So as an engineer, I was taking care of data and making sure that we could carry out projects that involve data from the monitors, from the patient monitors. I studied at *...*, and I've done all my studies in the engineering part of things. Then I was dropped into *...*, which is very much different environment, it's the medical environment. Over there, actually it’s why I was a bit interested in what you're asking, because I really experienced these differences in both the technological problems and the practical problems that emerge when you want to implement these kind of machine learning algorithms into the world. So my role in the project has been to gather data, organize the data, talk to the people to get access to the data, and then analyze them. So design models and report scores and argue that our models are useful for future use.	UC
6.14	**AS:** Okay, nice. These projects that you've been involved in so far, the one that we stumbled across was about prediction of neonatal sepsis *...*. Are there any other projects that utilize machine learning that you've been involved with?	
6.15	**R6:** I was involved in a project about detecting the drops in blood pressure during operations. That's a project I was involved with at the start of it, but not at the end. That means I have access to the data and that I can download data that some other groups are actually interested in. I was responsible for delivering the data. But I was not involved in the analysis part.	UC
6.16	**AS:** All right, I see. And are these projects... I guess they are in the research-phase, or is it something that's planned on being utilized in practice in recent future? Or is it in an initial stage?	

6.17	**R6:** It's a bit of both. They of course already have algorithms today that they use, very simple things. Like you calculate a few quantities and then you see if one is too high, then you say "Okay, there's more risk for a certain disease" or something. They have already algorithms implemented, but they are very simple. What they want is to apply machine learning, have a more complex algorithms that we can rely on. So it's in the research phase in the sense that some reason doesn't exist, but they very much want to use it in practice. But in reality, this doesn't happen very often. It means that the these kinds of research often stay in a theoretical stage.	
6.18	**AS:** All right, I see.	
6.19	**R6:** Very rarely, that machine learning algorithms are translated into actual clinical use.	
6.20	**AS:** That's also sort of part of what we're trying to investigate, like what's the next step in this process, and both from a technical perspective, but also other aspects, such as an organization, and that to some extent, you may have experienced in these projects. So it seems like you should, or hopefully, can be able to elaborate on the questions that we planned out. So we can just start with the technical aspects, regarding the system complexity that these new machine learning algorithms introduce, compared maybe to the traditional rule based simple ones. In these stages are they hard to comprehend from the perspective the ones you collaborate with, the clinicians, are they finding it hard to comprehend these models? Like from a large, holistic perspective?	
6.21	**R6:** Yes, the main problems technically for the models it's their complexity and the fact that you cannot predict what what the model is going to output given any input support. When the model is simple, it's clear that a certain quantity will be for example multiplied by two and other one divided by three, and then at the end, you get a score. That's very simple to understand for a doctor. But when the model is nonlinear, and even the engineers don't know how the model is going to behave, it's very difficult to prove that the model is going to be useful, and it's going to be reliable. This issue with interpretability is actually a big one.	SC, T
6.22	**HK:** So you talked about reliable, and I want to pose the next question that regards data reliability. Do you have data in place and is it reliable at the moment?	
6.23	**R6:** Do I have, sorry. Data?	
6.24	**HK:** Is the data available? Because machine learning models require a lot of data to	

	be able to make these kind of predictions and decisions. Is that data available and would you say it's reliable at the moment?	
6.25	**R6:** Yes. So it's a good question. So is the data available? Yes and no. At the level of one hospital, it's possible to build datasets that are large enough to include every possible patient, or every possible case that you will encounter in the future. The problem arises when you have to interact within different hospitals, because the IT systems are very much developed internally by hospitals. Often it's not easy to interact with hospitals and that creates a problem where the model that one hospital develops, might actually not translated to another hospital, to other patients. That's the case within Sweden, for example, but even more so within Europe. When you try to interact with different European countries it's often difficult to get enough data so that your model is actually generalizable. I'd say it's both available and not available. It's available on small scales, but when you want to do larger scales, which are required to test your models, then the data is not available, or you have to build bridges.	REL, SC
6.26	**AS:** As you mentioned, if hospitals have different self-developed IT systems as a foundation, the integration part and the complexity increases, the dynamics of the system, it increases even further. So it maybe goes hand in hand, like in terms of being stuck in this theoretical phase.	
6.27	**R6:** Very much so, most of the models that we see in the research literature, they are tested internally, that means maybe one hospital will make a score and test it on itself, and then say it's relatively good. In a few cases where one score has been taken to another hospital, so to another empirical context, doesn't work anymore. Because there are many reasons for that, the main one is that the patients are actually handled completely differently within two hospitals, depending on the culture of the country, depending on the past main professor or whatever. So it's very important to test things on two different sides. But the IT systems that are developing currently are the problem,	SC
6.28	**AS:** I don't know if it contradicts like one of the strengths with machine learning algorithms, but they're supposed to be able to adapt as they get new data, right? But they can't even reach that phase because it's not compatible. Is that the situation to some extent?	
6.29	**R6:** Yes. Basically, when you do machine learning you're supposed to, from the data that you see, you're supposed to determine the underlying factors or the underlying predictive signs of the outcome that you want. If your dataset is too small then there is a chance that in this dataset, there are artifacts that are also predictive of the outcome that you want. So if you test only internally, you might actually report a high score, but based on these artifacts not of the true underlying mechanisms. So then, when you transfer it onto another hospital, then you using	REL

	your artifacts, you will not get anywhere, because you haven't learned the underlying processes.	
6.30	**AS:** I see and the last aspect regarding the technical questions that we had, it's sort of in terms with interpretability, but this is maybe also a "next step". Interpretability and transparency might be related, in that the sense. But when you have been part of these projects and initiatives is transparency a key step in the process of maybe you managing data, or the prediction outcome, how important is it to derive how it came up with a certain conclusion?	
6.31	**R6:** So, I'm not doctor. I used to argue that... I used to argue this way, now I don't. If you get two scores, one is very interpretable but let's say has a prediction ability of 0.8. You can interpret everything that the model does. And you test it in the classical way, you do like a randomized control trial, and you see if it works with accuracy of 0.8. Now you take another algorithm, that's not transparent, not interpretable but that predicts at 0.9. Not 0.8 but 0.9 and you test it exactly in the same way, randomized control trials and so on. Then you ask the doctor "What will you use?" You know, that, based on the same criteria, one of the scores is better than the other, but it's not interpretable. If this better score, the score that scores the best raises an alarm for a patient, would you actually consider it or would you rely on the poorer score? In my mind, the answer is you would use the, one although you don't understand it but because you have tested it enough, you would use the one that's not interpretable. So that's what I think. But in practice, I don't think that will happen [Laughter].	T
6.32	**AS:** I see, and doctors they have their education as well.	
6.33	**R6:** Exactly.	
6.34	**AS:** Then that's a completely another dimension to consider in such a setting.	
6.35	**R6:** I think it's very important actually, extremely important.	T
6.36	**AS:** All right. So in regards to a more organizational context, like in the ways you work in these projects. How are they driven in the sense, because when we talked to previous respondents, they talk a lot about their curiosity for the topic and wanting to develop. We also seen instances where people have been supported to a great extent by their managers and supervisors, would you say that this aids or helps in this process of getting the support to take on further projects or keep on going.	

6.37	**R6:** Ehm, so you want... Let me see... I think it's at the start, it's a very personal choice that you do, because it's a very different engineering approach when you want to work within engineering, or if you want to apply your stuff to medical problems. So I would say at the start it's a personal choice to really be willing to discover something completely new. Then depending on your supervisor, they might be a bit critical towards other ways to do science. Because of course the medical way to do science is completely different than the traditional engineering way. You just have to agree with yourself to take whatever you can take from your engineer, supervisor and take whatever you can take from the medical supervisor. Because on the other hand, the medical doctors, they care not too much about details of the math and the engineering and so on, so you won't get any support from them. They just want something that works, they want to report to score, they want them to be able to integrate, and so on. When you want to translate from one domain, from one world into another, you have to be the one to take all the informations at the different places. And I would say not count too much on your supervisors [Laughter].	TMS
6.38	**AS:** Okay...	
6.39	**R6:** They have their own very personal ways to think about how things should be done. And it's not easy to convince them.	
6.40	**AS:** I think it's quite interesting, because I think you're the only one that have the clash between the fields.	
6.41	**R6:** Very much, yeah.	
6.42	**AS:** When you explain it, it sort of became very evident that they just want something that works and an engineer is more interested in like, "How does it really work?", "How do you solve problems?" All right... regarding your... it's not free to conduct any study, everything costs money. So how is this funded? Maybe your PhD for instance, or projects you've been part of.	
6.43	**R6:** So that's the kind of information I had to ask for my supervisors [Laughter]. It was funded at the start, because for a PhD, especially in *...*, you need to block a certain amount of money to make sure that the student has at least two or three years funded. That's a lot of money from the start, so when the project is just getting started it's kind of difficult to get this kind of money. At first, we were financed by small research grants 100,000 here and there, grants. And then after a while, I started to be funded by *...*.	FR

6.44	**AS:** All right. This is also maybe a question that you can relate from, like how you view it from the perspective of coming from the engineer's field and then you collaborate with doctors, when you discuss and collaborate with this other actor or stakeholder, which has some more clinical setting. Would you argue that they are interested in the process, I understand that the manager from the medical field, they just want something to work, but are they ready in terms of this new technology, of discussing and trying to get ways to navigate and coming up with solutions?	
6.45	**R6:** Yeah, they are often very interested in understanding how you do research when you use machine learning. So they often ask me questions about how things work and can I explain in simple terms, you know, how algorithms work. Basically, they are very much influenced by the general public information that you receive about AI and machine learning and deep learning and then they want to understand these keywords to be able to use them more personally. So yes, I would say they're interested in the process of understanding.	TR, COL
6.46	**HK:** Yeah, sorry? So would you say that they are sort of ready for these initiatives, from a technology perspective?	
6.47	**R6:** I mean, I think they are, but you need to convince them very strongly. But I think that they are, in the sense that in the medical world there's been a lot of breakthroughs. There's always new technologies, new vaccines, new things kind of. As a doctor, you need to be cold head, like, you need to just establish the facts does this work? Does this doesn't work? If it works, we use it. If it doesn't, we don't use it. I would say there are ready, but then you have some people that just refused to trust algorithms, or some people that refuse to trust certain technologies. But it's true for engineering thing, it's true for mathematical models, but it's also true for medicine. Like drugs, some doctors wouldn't trust certain drugs because they have heard certain things at certain conferences or something. So I think you have the same... these new technologies are one thing, but you have the same problems that you get with new things in general. I don't know if you understand what I mean?	TR
6.48	**AS:** I think I get the point.	
6.49	**R6:** Some people are really against it. But you will also find some people really against other types of technologies.	
6.50	**HK:** Right. In terms of regulations, and this is for both your research and some of the	

	projects that you worked on with *...*, how are those impacting you, or any specific regulations in mind that you think have been impacting your work?	
6.51	**R6:** Yes, impacting for the best and for the worst. Of course, the GDPR laws, they impose certain constraints about how you should handle your data and they make you feel like you're responsible for what you're doing. For real. If you leak data, it's going to be your fault. In the past, you wouldn't have this kind of pressure in a sense. But it's not a bad thing, it's good that you're able to build a system that's actually robust, that you can share data safely within the hospital and so on. For that aspect, it has impacted but I think positively rather than negatively.	REG
6.52	**AS:** And also, from the perspective that you manage data in these projects. ... In your initial stages of developing machine learning models, when you're just trying out you then you just toying around, you get what data you get from Kaggle or wherever. But it puts large constraints on you as you said. Is it a matter of establishing principles, like a checklist that you keep on checking on and on and on? Or is there ambiguity in what to do based on GDPR? Do you think there are loopholes or like that you could work around a certain issue? Or is it quite evident what to do and what not to do?	
6.53	**R6:** So for certain aspects, GDPR is crazy in a way that, it's always like "you should use a certain constraints whenever it's possible". For example, you should encrypt everything, whenever it's possible, you should deidentify whenever it's possible, then it's a matter of, can you argue that this case where you haven't was actually not possible? Or was it just because you didn't want to do it just to save time. So it's a matter of choosing when you think things are acceptable, but there is no hard constraints, since you should just be able to argue that what you're doing is acceptable.	REG
6.54	**AS:** All right.	
6.55	**HK:** And then, in terms of market trends, we have seen for example, COVID, and we've heard a lot of papers saying that a lot of initiatives have come up because of COVID. Would you say that there are some trends or market trends or events that triggered your interest in the research area that you're working on? Also the projects that you worked on with *...*.	
6.56	**R6:** Yes, yes, of course... COVID was in an infectious disease, we were working with the infections on a certain population at hospitals. Of course, for us it became evident, because we had our hands on the data from *...* it wouldn't be such a big gap to actually go ahead and download, or go ahead and gather data for adults that were infected by COVID. So yes, it became a very interesting topic, because there were a lot of research grants that could allocate money to projects like we're	MT

	looking at COVID-19 related issues. Yes, it was to our interest, we actually try... we got the authorizations and we were trying to like create algorithms that apply to COVID patients that could monitor COVID patients. Yes, definitely interesting.	
6.57	**HK:** And one of the last questions we have, we're actually closing up soon, in the research that you've been doing, plus also the projects that you handled. In your own opinion, what are some of those factors that you think have influenced your decision, one to pick up the research that you're doing? And two, for the adoption of the initiatives that have been handled in the projects that you handled?	
6.58	**R6:** Can you repeat the second part? The...	
6.59	**HK:** Okay, so you mentioned that you worked on some projects with *...*, but you're still working on your own PhD? What are some of those factors that have influenced your decision to take this up?	
6.60	**R6:** Okay. So the main, the main factor is that other projects, other researchers came to me because they needed the data that I could give them. Then when I was involved, because I had the technical solution, provide what they need. For me of course it's just a continuation, so once you translate from the engineering to the medical then you're there. Then we can actually be involved in more research and more projects. So for me, it was natural to assist them to…	
6.61	**AS:** Alright, we find it very interesting, because when we've been talking to people that are from the clinical side, like we usually mentioned that it's interesting to just talk to someone from a different field. But you actually have gone to the extent that you're in there, even though you have a different background. You can see that it's more complex than you might imagine from the get go. Is it a lot more that goes into this clinical aspects that you don't really see from...	
6.62	**R6:** So what do you mean? Because of my background, am I like missing some of the...	
6.63	**AS:** We've been trying to at least get our respondents to think about if there's something that's missing in our discussion, in our sort of protocol. They think "You touched upon some stuff that we heard of before, some new stuff, but the bigger picture is sometimes left out." Because it's so more complex than you imagine when you're actually executing the clinical care, but I don't know how it would relate to you. I guess that it's still interesting to have this collaboration between fields, when it actually becomes practical.	

6.64	**R6:** So, I can answer that rapidly. From my perspective, I will be involved in the whole flow, so like getting the data, analyzing, grouping data and so on. I will make algorithms, but I will not test them, I will actually not be involved in randomized control trials, were actually things are evaluated, because that's yet another issue. The reason is that it involves companies, so it involves the company that sells monitors. In our case, we'll have to be the one to take our model and make something to actually display it to the wards and then test it. You start with the company, the data, you analyze, you make a model and then you have to go back to the company, so that the company can display the scores to the wards and to the monitors for the doctors. That aspect, I completely missed out, the interface between the public and the private sector. Because I try to stay away from it because completely... because then you have money involved, like "Who owns the IP?", "Who sells the solution to the hospital?", "Who buys?" and so on. And that's another complicated aspect that I'm not a part of.	
6.65	**AS:** All right, good. That's some nice concluding remarks actually. But once again, thank you for allocating time. As part of our research process, it's also in the consent form, we will create a transcript, send it out to you where you have the opportunity to look it over. Depending on the time you have, we understand that like it's not a matter of checking for spelling and stuff like that, but just to make sure that it seems okay and decent.	
6.66	**R6:** Yeah.	
6.67	**AS:** But yeah, so thanks again...	
6.68	**R6:** No problem.	
6.69	**AS:** Interesting conversation at least from my end, how I experienced it.	
6.70	**R6:** [Laughter] Looking forward to see the final results. Will you send me your thesis when it's finished?	
6.71	**HK:** Yeah, sure.	
6.72	**R6:** Cool.	
6.73	**AS:** Thank you.	

6.74	**R6:** Great.	
6.75	**HK:** Thank you very much.	
6.76	**R6:** Thank you guys, you too, have a nice day.	
6.77	**AS:** Have a nice day!	

Appendix 9 – Transcript Respondent 7

Speakers:

HK = Herman Joseph Kambugu

AS = Axel Svansson

R7 = Respondent 7

Date: 27th of April 2022 Length: 35 min.

Row	Transcription	Code
7.1	**R7:** Hello!	
7.2	**AS:** Hello *...*	
7.3	**R7:** Now! I'm sorry, I was in another... Oh, yeah, I'm ready.	
7.4	**AS:** No worries. We want to thank you again for taking time to talk to us. We can just introduce ourselves first, even though you talked to us on email, it's good to see a face here. So I'm Axel...	
7.5	**HK:** And I'm Herman.	
7.6	**AS:** We're part of the Department of Informatics at Lund University and we are writing our master thesis about AI and machine learning in clinical decision support systems.	
7.7	**R7:** Very important, yeah.	
7.8	**AS:** We sent the consent form, have you managed to skim through it?	
7.9	**R7:** Actually not, no. I've been working on applications, it's so many applications being done these days now.	

7.10	**AS:** I see. But I guess the only thing we would like to get permission to, is to record the interview.	
7.11	**R7:** Yeah, you're welcome. You can record.	
7.12	**AS:** Good. So I will press it here now on Zoom, so you'll hear it.	
7.13	**R7:** Yeah, sure.	
7.14	**[Zoom: Recording in progress]**	
7.15	**AS:** Right. So then we're officially started. So I'll just briefly talk about our topic, what it's about maybe in more detail, and then we will go into some questions.	
7.16	**R7:** Sure.	
7.17	**AS:** So the topic is about machine learning-enabled clinical decision support systems, and the adoption of these systems in healthcare. So from an informatics perspective, this entails looking into factors that were or are being considered when adopting these new technologies. We sort of divided them into technological, organizational and environmental, so that's sort of where we base our questions. But when we started this process, we needed to find the right people to talk to and then we came about you.	
7.18	**R7:** How did you do that?	
7.19	**AS:** We've been looking through plenty of research profiles, to be honest, we've sent plenty of emails as well. We came about your, the *...* clinical decision support system application that you've been working on.	
7.20	**R7:** Okay.	
7.21	**AS:** Or we don't know the progress of it, but that's maybe something that you could give some insights to. But before we do that, maybe we could maybe just learn a bit more about you. What role you have, what you do in your day-to-day work	

	and how it relates to machine learning and decision support systems for clinical care.	
7.22	**R7:** Okay, should I answer now?	
7.23	**AS:** Yeah.	
7.24	**R7:** Well, I am a research leader at the *...* and the *...* there specifically, and I've been doing most of my research in the field of unspecific pain, which is the most common problem together with flu and the infections. But unspecific pain is so much more debilitating and costly for the society. There is some measurements, they say that all other health care problems amount to the same as unspecific pain. So unspecific pain stands for half of the budget in the world of healthcare. Nothing compares to it and that's why I'm interested in it. It's such a large problem.	
7.25	**AS:** I see.	
7.26	**R7:** It's still also at the same time a very low prioritized problem in healthcare. It's actually considered one of the most, or it's the most unpopular field of interest among clinicians, physicians specifically. Many physiotherapists and other professionals they kind of live on this but among physicians, unspecific pain there are several papers publications showing that unspecific pain, Fibromyalgia, ME and other unspecific pain is the least interesting. So there is a huge need for help to diagnose people with unspecific pain and not only pain, but dysfunctions. A huge need because no one in the field wants them. They are just so difficult, they are considered difficult to diagnose and problematic to treat. "There is no treatment better than no treatment”, that’s a terrible thing. But it's been said several times in large conferences, we still don't have any treatment that is better than no treatment on these patients. If you look at the Swedish health, you see this, this the last health report from 2019. It's about "What are the health problems in this society?" according to large inquiries they do. Well, of course we have diabetes, it's announced to about 5% of the population, you have rheumatic diseases, they are 0.5% of the population, you have chronic obstructive lung problems, this is a few percent of the population. Then you have COVID, very small it's 0.018%. But these diseases receive a lot of attention and a lot of research money. It's because, well you may discuss this of course, but they are kind of easy to diagnose. It's a blood test or a lung test or something like that and there are simple treatment options. So they are very popular, every healthcare center in Sweden almost has a specialized nurse and maybe also a specialized physician. All hospitals or larger units, university units have their own diabetes knowledge centers and rheumatological knowledge centers and they have their COVID centers. I just take as examples but if you compare those diseases or diagnosis with the big ones... You may want to guess, "What do you	FR

	think are the big problems according to this, and to many others?" Can you guess?	
7.27	**AS:** Maybe it relates to the unspecific pains that you've talked about?	
7.28	**R7:** Yeah, of course. 50% of the population walk around with unspecific pain in their neck, 40% have unspecific pain in their spinal, in the lower back. And 30% has unspecific headache pain. All the symptoms that goes with that, it's not just the pain it's of course many other symptoms. 20% has unspecific stomach pain, IBS. So here's a great need to help the medical society to diagnose this. That's why I'm using this pain drawing, I actually call it discomfort drawing, and also made some research on that, if it can be used as an AI tool. And it can. Because if you learn to recognize patterns, it's a matter of pattern recognition, of course you know that, and it's very easy. I personally have seen now about, I haven't counted exact, but it's somewhere about 100 thousands of these drawings and also made the clinical exams and many of them have been radiologically examined and laboratory exams. So I follow these plus 100,000 patients to the end of the line, and it's no problem it's just a matter of recognizing the pattern. And you can do that if you just put these observations on an AI-algorithm. It's very easy, very easy, but it's possible.	
7.29	**AS:** I see. So in terms of this project with the pain drawings that you've been working on, has it been a long process getting that started?	
7.30	**R7:** Yeah, it has. I started in, I think the late 90s. Work with, I found a *...* fellow who was interested in developing a digital discomfort drawing. But somehow that fell out, it didn't work. Then in some way around 2005, *...* was interested in developing... They knew me, I was very much used as a *...* speaker and teacher and they financed development of digital pain or discomfort drawing app. But then I can say, they wanted me to confer the whole, my head [Laughter], they wanted me to sign a contract that all my AI interests was to be conferred to them and then *...* said "No, never, don't ever do that". So I didn't, we stopped that. Then of course, I didn't give up, so we started somewhere in 2015 again, a small group where we have developed a new app. Now there are many apps where you can actually map your discomfort, also in somewhere 2015, we started with *...*. I found an interested PhD student who was very interested in this. *...* was very smart. So *...* and her companions, they're actually the main first author of these papers on AI development of pain drawings.	UC, FR
7.31	**AS:** Alright, so these pain drawings, the application is something that could be integrated to work with healthcare systems, I guess that's the goal?	

7.32	**R7:** Yeah, that's the main goal. But you know that has been, I tried more than 15 years to make the authorities, at least in *...* area, understand that this is not only a problem, but it is a possibility to make it. But it's been... there are so many different persons that you need to contact and they change positions, and they... Well, I haven't reached that goal yet.	REG, COL
7.33	**AS:** I see.	
7.34	**HK:** So, in terms of data, so machine learning and AI require a lot of data to try and come up with this product. How reliable is the data that you have collected so far?	
7.35	**R7:** Well, I don't know, because we have not used the digital application. We haven't tried that in a research project yet, it's the paper version that is actually the basis for the AI development. The papers you've seen, or may have seen?	
7.36	**AS:** I've seen them. It's something that maybe could be used as an image that you just feed?	
7.37	**R7:** Yeah, exactly. It should be, if you have this good application where the patient can draw their own discomfort, pain included. Then we can use the same algorithms as used on the paper version so it should be about the same sensitivity, specificity, and etc. But I cannot say that because we haven't done it.	SC
7.38	**AS:** I understand. So then, some technical aspects is it's hard to speculate around, but when you as a doctor are using clinical decision support systems that are based on this machine learning models, would you find it important that it's transparent, in the way that you could understand how it reached its conclusion?	
7.39	**R7:** Yeah. If you asked me about the normal clinician, I think they will not have time to really go into depth understanding of how the algorithm is built. If they are assigned to learn it of course they will. But most clinicians will not use time to or will not have time to go into depth. So they will use it if it's told by their head or by someone dependable that say "Use this", then they will.	T
7.40	**AS:** Okay, I see. But maybe in terms of the project, that's maybe more interesting in terms of how far you progress, rather than speaking of the technical characteristics of a potential application or where you are as of now like it's in	

	the initial stages. But this project, I understand it as it's been quite driven by you and your curiosity. But do you have any sort of support from a mentor...?	
7.41	**R7:** Yeah, I didn't mention it. But I do have three colleagues, it's one physiotherapist, one manager and one technical, well not AI specialist, but good at building an app. So we are a little team that has developed this, the latest pain drawing, it's called *...*. ... Sorry, I'm having a little bit of a sore throat. ... Yeah, so it's, I'm not alone. No.	UC
7.42	**HK:** And then in terms of financial resources, how are you funding this project?	
7.43	**R7:** So far, as I said, in 2005, and then a couple of years there *...*, but we broke that so we started all new in 2015. And we've been financing this on our own, just private money.	FR
7.44	**HK:** Okay and then still on the organizational perspective, in terms of technology readiness, do you feel that the clinicians or doctors, or the target users of this system feel like they are ready for this new technology?	
7.45	**R7:** Yeah, that's a good question. I think clinicians are getting more and more ready and interested in AI. Because now it's kind of obvious that if you have an AI... It's been used in, the most well-known is the electrocardiographic assessment, it's been used for 40 years. You put an ECG on the patient in the home and there is an AI function to tell if it's normal or something wrong. Of course, we have been using it in cancer diagnostics, and in a radiology it's coming, so I think the clinicians are ready. But it's still a problem with the technical aspects of getting it into the journal systems. This app that we have developed it's supposed to be used by the patient in their own home or on the bus or wherever, before they even come to the clinician, before they meet a nurse, physician or physiotherapist. They should be able to fill it out, fill it in, so when they come to the care unit, they should be able to have this decision support. Like these are the three or four main options that this pattern indicates... The problem may be there, there, or there and these could be the main things you should check.	UC, TR, SC
7.46	**HK:** Well, that actually brings me to my next question, which is in terms of regulations, as you work on this app and the project in general? Are there any specific regulations or laws that you feel have impacted?	
7.47	**R7:** Yeah of course, the GDPR. It's a huge thing to get all the laws in right place. To have the right writing in the app. So that the patients know what they sign up and how to be used... We have actually, I think we spent, what was it 200,000 or	REG

	300,000 Swedish crowns on just having a legal authority view the writing on this to get it correct.	
7.48	**AS:** I see. And I know this project it started before something as big as a COVID pandemic. But would you say that there are any specific market trends that drives these kinds of initiatives? Or is it solely based on the curiosity from the clinician-side to find new solutions? How do you view it from your perspective?	
7.49	**R7:** Let me close the door, one moment.... I'm not sure I got the question, tell me once again.	
7.50	**AS:** These projects, especially the one that you've been working on, it's started quite long ago?	
7.51	**R7:** Yeah, more than 20 years ago. 25.	
7.52	**AS:** So at the time, were there any particular trends that made you feel that this is something that should be addressed? Or is it just based on the fact that you have the unspecific pain and that it's a huge problem and need to find out more about it?	
7.53	**R7:** Yeah, I would say it's the same thing. It hasn't changed. It's been the same problem. There are inquiries that's been done every 10th year in the medical society and among medical students. And you know, it doesn't change. In the top interest you find these... Well, let me say simple diagnosis, like heart infarction, and diabetes, cancer, broken bones, etc. The common denomination of those is that it's visible on a blood sample, a picture or a machine. someone just tells you "This is the problem". And all these diagnosis are well known, they are accepted by the society as problems, the insurance companies approved them. There is no problem if you write that a person has a heart attack or infarction, he will be accepted as having leave for a number of months and there is no one who will question that. It's very simple for any physician to write, you don't need to write a long story. You just write heart infarction and then it's done, so to say it's well accepted and it's supposed to be very problematic for any patient, with a broken bone or something like that. In the medical society, even in the primary care or in the hospital care you get kind of a priority line. Everyone knows what to do, it's simple. It's a machine who gives you the diagnosis and there are exact. Like if you get a heart infarction, you start with antithrombotic medicine and then you do this and this and this. But on the other hand of the interest line, you may guess what is the next to the least interesting diagnosis you can treat?	

7.54	**AS:** Could it be related to this unspecific pain, but is it maybe back pain, neck pain?	
7.55	**R7:** No, no, no, no... It's liver cirrhosis, meaning alcoholics.	
7.56	**AS:** All right.	
7.57	**R7:** Yeah, so alcoholics, because people say like "Whatever you do, they will keep drinking, and they will die by their own liver disease." But the least interesting persons in the medical society are those without unspecific pain, which represents about 90% of all pain. Whether it's from the stomach, the knee, the foot, the shoulder, the wherever, the head. So, it's such a huge problem. It's about at least half of the population in all the world has some kind of unspecific pain. It's called something, it's called "spänningshuvudvärk", it’s called migraine, it's called IBS, it's called patellofemoral pain, it's called tennis elbow, you put names on it. But the only thing you really know about these, by research, is that there is nothing wrong. If you take a sample from the tennis elbow, there will be no signs of inflammation or anything wrong with the elbow. Or the patellofemoral pain, which is the most common of all knee pain, it's about 50%, 52% in one study of all knee problems are patellofemoral pain. The only thing we know about that is that there is nothing wrong in the knee. You can look into the knee, you can take samples from the knee, fluid and etc., but there's nothing wrong in the knee but they still have pain in the knee. It's the same with Achilles tendon problem, they are unspecific to a very large extent, I don't have the exact numbers. Well I don't need to explain this, but this is a huge problem.	
7.58	**AS:** Mhm. So would you say for your specific project with this application, in your opinion, during this long timeframe that you've been working on it, what has impacted you the most or impeded you the most in terms of moving on?	
7.59	**R7:** It's a huge medical problem both for the patients and for the clinicians, because you don't know what to do with it. You treat it with the thing you have at hand, if you're a physiotherapist you try to treat with all massage and training. But the effect as said at different conferences "No treatment is better than no treatment". We spend billions of money on doing something that's not working, that's why 50% of people still walk around with neck pain, and 40% with back pain and 30% with headache. Because there's nothing helping and that's indirectly because you don't have the correct diagnosis, you have a symptom diagnosis not a pathophysiological diagnosis. That's because they are not examined in a thorough way... but many physicians don't understand that you can find a specific reason, you can do that if you just use a variety of diagnostic principles. But they are not used, so this AI pain drawing can help them, and can save... It's such a large saying that saving could be done, one of our professors *...* he is a Swedish professor. He said many years ago that the largest saving you can do in all	FR

	medicine is to put the correct diagnosis as soon as possible in the process of disease. The sooner you put it, the larger the gain, for not only the patient but for the society. So this is where this app comes in and what I want to help before I die.	
7.60	**AS:** Okay. I guess the financial side and the regulation side really puts an impact on how to proceed...	
7.61	**R7:** Yeah.	
7.62	**AS:** ... in addition to the clinical problematic of coming up with the right diagnosis. All right.	
7.63	**HK:** All right. So we've pretty much covered most of the questions we wanted to ask and I must say I've learned quite a bit about unspecific pain which you have talked about very passionately. I don't know if you have any feedback for us, anything you feel like we haven't covered?	
7.64	**R7:** I don't know what you will do with this, but if you can find a way that we can help each other to get this into the system, I would be so happy!	
7.65	**AS:** I see. What we find interesting, you're our final interview respondent for the thesis, we find it interesting to talk to people from a completely different field. Like the interaction between fields and how we can view it from different perspectives, because it's very obvious that we miss the clinical aspect of adopting a particular new technology into your practice. Therefore, we find it very helpful to get insight into what it's actually like. So hopefully, we could draw some nice findings and discussions in our paper.	
7.66	**R7:** I hope so, I look forward to have this thesis, a copy of it. Are you mailing me?	
7.67	**AS:** Yeah, we could, we can make sure to do that. But once again, thank you for taking time to talk to us.	
7.68	**R7:** Thank you!	
7.69	**AS:** And also to conclude, it's also in the consent form that we sent, but the transcription will be sent to you for validation, you have the opportunity to view	

	it. We know that you and other doctors and clinicians have a lot of time and duties to attend that are highly prioritized but it's part of our research process. So just for your information.	
7.70	**R7:** Mhm, okay. I know. Of course. Wonderful.	
7.71	**AS:** Nice. Again we wish you a great day and yeah, thank you!	
7.72	**R7:** Thank you. Good luck. Bye bye!	

Appendix 10 – Table 3.1

Search Keywords	Google Scholar	Web of science	Scopus	LUBsearch
(“AI” OR “Artificial Intelligence”) AND (“Healthcare”)	2 280 000	11 843	8 183	31 382
(“ML” OR “Machine learning”) AND (“Healthcare”)	3 550 000	28 815	13 378	45 283
(“ML” OR “Machine learning”) AND (“Clinical Decision Support Systems” OR CDSS)	28 800	400	1 195	1 049
(“Machine learning”) AND (“Adoption”) AND (“Clinical Decision Support Systems”)	3 230	13	38	34
(“Technology Adoption”) AND (“Machine learning”) AND (“Clinical Decision Support systems”)	289	0	0	0
(“TOE” OR “technology-organization-environment framework”) AND (“Machine learning”) AND (“Clinical Decision Support systems”)	121	0	0	0

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