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# Potential barriers when considering Machine Learning technologies in healthcare

- A quantitative survey research about barriers considered by Oncologists, Pathologists and Radiologists operating at Central Hospitals

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# Abstract

Artificial Intelligence (AI) is arising across many disciplines worldwide and is expected to rapidly grow in the coming years. AI is said to have great contribution to improvements of the operational efficiency and the delivery of care for patients as well as the accessibility of healthcare services for people. Therefore, such technology is said to have remarkable impact on the dilemma of aging population and the increasing lack of healthcare workers. These are essential aspects an organization like healthcare should aim to benefit from when considering implementing AI technologies into its organization. Such technology can manage a range of different tasks, from managing the supply chain to giving diagnostic support. A Machine Learning (ML) algorithm is able to process and analyse huge amounts of information, such as clinical notes, health records and diagnostic images and find insights and patterns in a much shorter time than human performed.

The aim for this thesis is to identify the possible barriers when considering implementing AI and ML technologies into clinical settings according to clinicians working within oncology, pathology and radiology. This work utilizes a literature review for collecting knowledge about how these technologies are currently being applied in the field and potential challenges as well as barriers a healthcare organization might face when considering such implementation. The second approach utilized in this thesis is a quantitative methodology consisting of structured interviews to identify potential barriers according to Oncologists, Pathologists and Radiologists operating at Central Hospitals in Finland.

The results from this thesis imply that AI and ML can support high quality, efficient and accurate diagnostics, but are still some steps away from implementation and further research within some topics is recommended. These topics are for instance evidence of achieved efficiency, quality and cost benefits of utilizing AI and ML technology within diagnostics as well as scientific proof of its realized benefits and values achieved within diagnostics. Other areas that can be considered as barriers are the pursued current state of regulation and ethical guidelines regarding in what extend such technology is accepted to be utilized within the workflows for clinicians. Furthermore, the results show that it could be implicated as a barrier if there would be suggestions about AI and ML technology making diagnostical decisions for clinicians without human input.

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# 1 Introduction

As time has contributed to advances in technology, so has the demand of systematic changes in health systems in order to improve quality, effectiveness and efficiency in the care of patients (Kaur & Mann 2018). In order to provide the precise disease treatment for a patient, an accurate diagnosis is required (Wong & Yip. 2018 p: 446). One of the most considered challenging tasks within medicine is the prediction of accurate disease outcomes. For such tasks, Machine Learning has become a convenient tool for research within medicine, due to its ability to recognize patterns and relationships from such complex data. Therefore, it is also an efficient tool for predicting future outcomes, such as what type of cancer a patient might have. (Kournou et al, 2015) By utilizing AI into medicine it is possible to increase the accuracy of diagnosis with greater efficiency while reducing clinicians load of work. (Zhou et al 2019)

Artificial Intelligence is arising across many disciplines, in healthcare within pathology and radiology perhaps most apparent within processing and interpreting complex medical images. Now also increasingly starting to reshape the specialty of oncology, such as radiation treatment planning for patients. (Thompson et al 2018) By implementing Machine learning, a subfield of Artificial Intelligence into healthcare systems will come to effect both on individual patient level and at system level (Panch et al, 2018, p:3). Machine learning technique is successfully increasing in the field of diagnostics based on images, risk assessments and the prognosis of diseases (De Bruijne 2016 p:94). With todays´ computational power it is possible together with the availability of Big data to do a lot of things that was not possible back in time within the healthcare sector, such as prevent diseases and identify health related trends.(Kao et al 2014, p:116) Machine learning has the potential to reveal such trends in the stored data, which has until now been hidden, this is due to its capability to improve hypothesis generation and tasks that will test the hypothesis within healthcare systems. (Panch et al 2018 p:3)

This thesis will aim to identify potential barriers when considering implementing machine learning technique into clinical workflows within diagnostics. Due to the lack of literature when applying machine learning into organizations like healthcare the thesis will consist of literature regarding considered challenges and barriers when applying AI technology into healthcare organizations. The research utilizes a quantitative approach whereas a questionnaire with structured questions are used for collecting data from the desired target groups operating at Central Hospitals in Finland.

## 1.1 Objective of the study

As the introduction section provided a cover about the potentials within utilizing Artificial Intelligence and Machine Learning solutions into such fields in diagnostics as oncology, pathology and radiology. Also realizing that there might be some barriers to address in order to benefit from the values of implementing such technologies into clinical settings within diagnostics. This thesis aims to identify potential challenges and barriers when considering implementing machine learning as a tool in the diagnostic work of oncology, pathology and radiology. This empirical question is scoped down to three main research questions, which this thesis aims to find out:

1. How is AI and Machine Learning being applied in clinical settings today
2. What could be the potential barriers when implementing AI and Machine learning into clinical workflows.
3. Are the identified barriers from the literature review possibly the same considered by clinicians within oncology, pathology and radiology when considering implementing machine learning into their clinical workflow.

The empirical questions 1 and 2 will be answered through the literature review and question 3 will be answered through the literature review and findings from the data collected through a survey.

## 1.2 Scope

This thesis aims to identify barriers within implementations of Artificial Intelligence and Machine Learning technology into clinical workflows such as within oncology, pathology and radiology. Due to the lack of literature and previous studies in this specific topic of barriers in implementing Machine Learning into clinical workflows, the literature review will consist of barriers in the field of healthcare sector when considering implementation of both Machine Learning and Artificial Intelligence. While conducting the literature review, it became obvious that there is more literature of both topics;" implementation" and "barriers" combining them with Artificial Intelligence than combing them with Machine Learning in the fields of healthcare.

The identified topics through this literature review from both AI and Machine Learning will be used as a framework for developing the questionnaire where the identified topics are tested if suited as barriers when considering implementing Machine Learning into clinical workflows pursued by clinicians. The targeted clinicians in this research are working within oncology, pathology and radiology operating at Central Hospitals in Finland.

The aim of this study, together with the literature review and the quantitative methodology is to identify possible challenges or barriers according to clinicians when considering implementing Machine Learning technologies as a tool in the clinical environment of oncologists, pathologists and radiologists.

## 1.3 Methodology

The research utilizes a literature review and a quantitative research method consisting of structure interviews in the form of a web- based questionnaire and results analysing.
Quantitative methods often consist of scope, quantities and strengths of things, processes and actions. This method focus on what purpose actions are given due to how these actions are expressed. Quantitative studies should use concepts and hypotheses as starting point and then trying to find correlations between measurable features in the desired unit of study. (Gran, 2012.p:122-123) A quantitative research approach is often used for mapping a situation or a field of interest by using this method finding a greater reason for things is not possible. With a quantitative approach it is possible to dig into a topic including questions about; What? Where? How much? How often? (Heikkilä 2014, p:13)

## 1.4 Structure of the study

In this study, a research methodological approach that encompasses nine phases was adopted and will serve as a structure for the thesis, as visualized in the figure below (Heikkilä, 2014 p:23). These nine phases will be more presented in more detail in chapter 3.

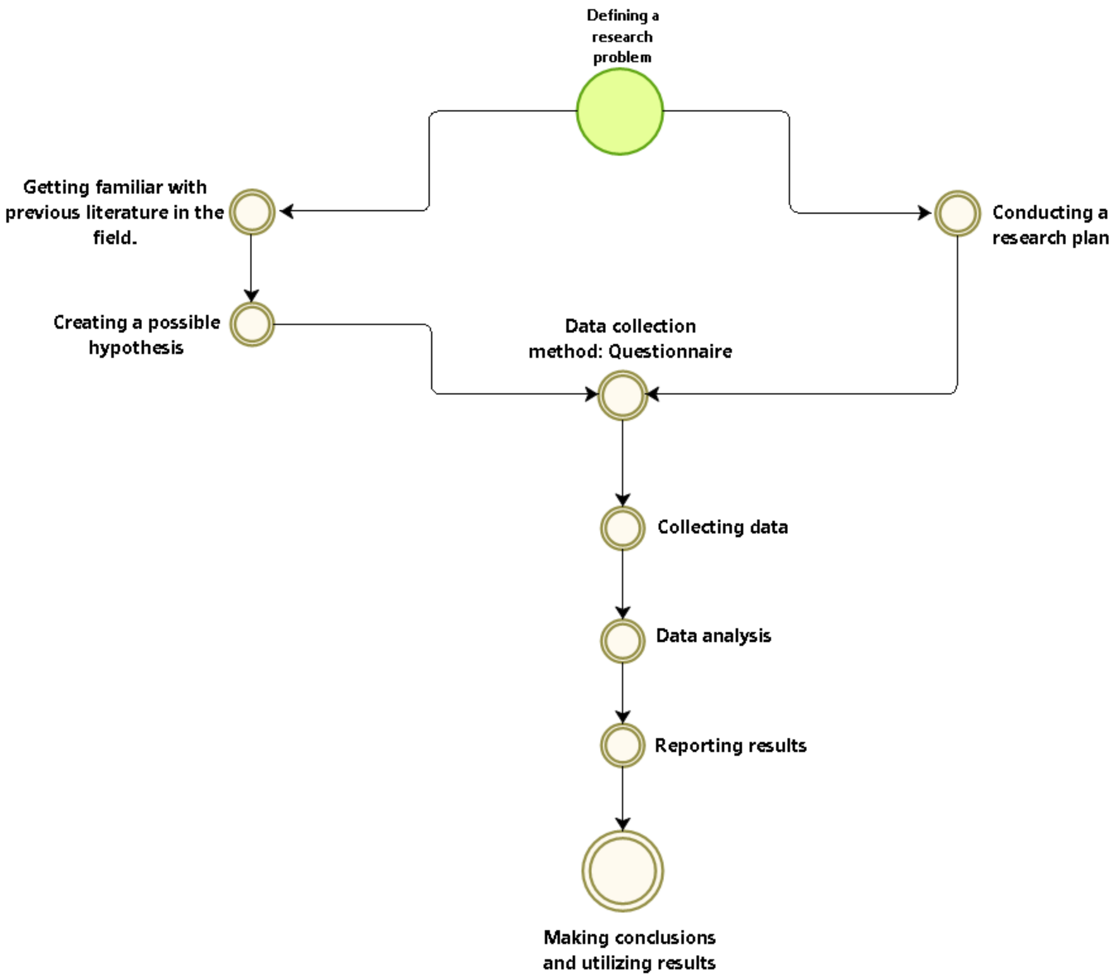


*Figure 1 - The Research Process*

In the first phase “Defining a research problem” is to identify and clarify which areas and topics are considered as interesting for the writer which led to a clear scoping of fields into Artificial intelligence and diagnostics. The second phase consisted of a comprehensive literature review of articles containing ‘” Machine learning” and “AI”-related topics in the healthcare sector including diagnostics was conducted. This was done by the purpose of getting an understanding of what kind of solutions with this type of technology in this sector is currently available and what are considered being developed. These findings will be introduced in chapter 2, the “Literature Review” chapter.

In the third phase, “Creating a possible hypothesis” took place whereas identifying topics related to barriers for implementing such technologies into the healthcare sector and more specific, to the field of diagnostics within oncology, pathology and radiology took place. During the fourth phase “Conducting the research plan” started.

The fifth phase will take place in chapter 3 the “Research” and is based on the findings from the previous phase. A quantitative approach was conducted to establish a questionnaire as a method for collecting the data, a web-based questionnaire. The questionnaire consists of

statements, which are aiming to seek if the potential barriers when considering implementing Artificial Intelligence and Machine Learning into clinical workflow according to available literature can be considered as barriers according to clinicians within oncology, pathology and radiology at 5 Finnish Central hospitals.
The sixth phase will consist of "Collecting the data", which as mentioned will be utilized using a web- based survey tool, a tool called "Survey Monkey". This will also be presented in the 3rd chapter the "Research" chapter.
The seventh phase will consist of "Data analysis" and will also be as the phase before, presented in the 3rd chapter consisting of information about how the captured data from the questionnaire will be analysed.
The eight phase "Reporting results" will consist of presenting the results gained from the data collection part, the web-based questionnaire. This will be presented in chapter 4, "Results", which will be a chapter that is divided into two main sections. The first section will consist of a total results review and the second section will consist of analysing the findings correlated to the findings from the literature review going through each question one by one from the questionnaire.
The ninth phase will consist of conclusion making for the research and will be presented in the 5th chapter "Conclusion" consisting evaluation of the research and suggestions for further research.

After this introduction about the structure for this thesis, the next chapter will as according to this structure be phase 2, getting familiar with the field and will therefore be the literature review. In the literature review will provide a brief background and an insight to the topic of Artificial Intelligence, an introduction about the subfields of Artificial Intelligence including Artificial Intelligence in healthcare, after this a chapter about Machine Learning and Machine Learning in healthcare. Since the aim of this thesis is to identify possible challenges or barriers when considering Machine Learning as a tool in the diagnostic process among clinicians in the field of oncology, pathology and radiology the literature review will also provide a chapter about some considered challenges and barriers when applying Artificial Intelligence technologies into organizations like healthcare, this will be introduced in the end of chapter 2.

# 2 Literature Review

Chapter 2, the literature review will begin with a brief introduction to the topic of AI with a section about the definition of Artificial Intelligence, which technologies are perceived to belong to the field of AI. Followed with a section about AI in healthcare including what kinds of technologies are in use and the potentials with AI technology within healthcare sector.

After this there will be presented a section about the chosen AI technology in healthcare, an introduction about Machine Learning. How this technology is currently being utilized and its potentials within diagnostics such as oncology, pathology and radiology. When approaching the end of this chapter, the “Literature Review “a section about the considered challenges and barriers for implementing Artificial Intelligence technologies into healthcare organizations will be introduced. The whole chapter 2 will serve as a framework for development of the questionnaire, which will be introduced in chapter 3 and in chapter 4 analysing the findings from the questionnaire will be introduced.

## 2.1 AI

Artificial Intelligence (AI) can be defined as an intelligence that is artificial and which has the capability to solve complex problems, such system is generally assumed to be a computer or a machine (Borana, 2016). The buzzword AI was in early phase introduced as a concept to mimic human brain that could with a holistic human approach explore the real-world problems. Researcher and scientists worldwide are excited about developing better and new technologies that could ease humans to widen beyond their own physical capability. AI enables the capacity for processing and storing huge amounts of data in an intelligent way and has the ability to translate that information into functional tools. (Kannan, 2017)

AI have many suggestions what it is and where it belongs, though according to Potember (2017) in the academic world research of AI is located largely in the department of computer science together with many other sub-disciplines of computer science, examples of such are: Natural Language processing (NLP), Robotics (incl. human-robot interactions), Computer vision, Social Media Analysis, Multi-agent system, Knowledge Representation and Reasoning (KRR) but such as Machine learning (ML) is considered to be the fundamental basis for AI. Though the list above over fields is not complete, it is considered to cover a large scale of AI researchers. The one´s doing research within AI traditionally align themselves with research from other areas that could desirable be to aligned with. (Potember, 2017)

### 2.1.1 The definition of AI

The term Artificial Intelligence (AI), whereas the term intelligence refers to the perception of intelligence, still the concept of both human and machine intelligence is diaphanous, which has been studied for a long-term by biologists, neuroscientists and psychologists. However, researches within AI usually uses the perception of rationality, which sincerely is not the only element the concept intelligence includes but an essential one. The perception of rationality in this context refers to the capability to choose the best action for a specific purpose, given criteria and available resources to be maximum efficient. (European Commission, 2019) I Gisslén (2014) explains that the definition of AI is considered to be difficult, but a popular definition is to define it as human like intelligence. To mention some included aspects considered as human intelligence are abilities such as creativity, logic and reactive thinking, self-learning and so on.

AI is considered to be a broad scientific discipline with roots from mathematics, philosophy and computer science aiming to develop and understand such systems that presents attributes of intelligence (Panch et al, 2018). AI is a combination of physiologic intelligence and technology which can be used in reaching goals by calculation. Intelligence is an ability of thinking by creating memory and understanding, recognizing models, adapting to change and learning from experience. AI enables machines to behave as humans, this though in a shorter time than humans when solving a specific task (Borana, 2016) AI can be described as currently the most widely used term that provides computers the possibility to imitate the intelligence of humans by using logic, If-Then rules, machine and deep learning and decision tree (Parloff, 2016). The key factor for AI to make great success is about the large amount of data available. This is because AI itself, does not have the capability as we humans does to reason and deduce. What AI does, is to learn thorough error and trial based on the data. (Datamer, 2018)

Machine learning (ML) is one of the subareas of AI (Panch et al, 2018; Starr, 2018; Parloff, 2016) using statistical technologies which enables machines to learn from their experiences. (Parloff, 2016) According to Henglin et al (2017) ML belongs to computer science discipline and a subfield from both statistics and AI. (Henglin et al, 2017) ML can be explained as a sub-specialty of AI that is providing the developing methods for the software so it can learn from experience or use the information needed for a task from the database (Coiera, 2015, p:581) and make predictive associations from examples in the data (Panch et al, 2018) without explicitly programmed rules to perform the specific task (Henglin et al, 2017). Another description by Shai & Shai (2014) is that ML is a term meaning to find automatically important patterns in the data. The term Machine Learning refers to automated detection of meaningful patterns in data. In Such developing methods mathematical and statistical algorithms are commonly used in the application areas of AI (Potember, 2017). According to Lee et al (2017) speech recognition is an area whereas both research and knowledge from other sciences can be embodied with, such as computer science, linguistics, electrical engineering, healthcare including radiology. Speech recognition systems are available in corporations, such as Apple, Microsoft and Google. A more detailed description about ML will be introduced in the chapter about Machine Learning.

Deep learning (DL) is then considered as a subarea to ML, which consist of algorithms that allows the systems to complete self-learning tasks, such as speech- and image recognition by using Neural Networks (NNs) when processing big amounts of data (Parloff, 2016). When feeding a system huge amounts of raw data DL methods makes it possible to discover the needed representations for classification detection (Panch et al, 2018). Another description of DL is that it is a system of probability, a ML that is based on a set of algorithms which is attempted to model high-level abstractions in data (Wisskirchen et al. 2017, p:10). DL can also be described as a type of ML including a class of algorithms with the purpose to model high-level abstractions based on data from stacked layers of processing, both linear and nonlinear transformations, this class of such algorithms are called Neural Networks (NN). Another type of NN is Convolutional Neural Network (CNN), a type of Deep Neural Network (DNN) which is used in imaging for making predictions from the image data. CNNs are at most effective in large data sets, which for instance in medical image setting is suitable since their suitable size of databases. CNNs can learn automatically how to combine for instance an edge and a color contrast (local image features). DNNs can consists up to hundreds of layers stacked up on top of one another, which is the reason for great potentials in the areas of speech, image and text processing. (Henglin et al, 2017) According to Lee et al (2017) thanks to advances during the past years within DL and big data has contributed to great progress in the field of speech recognition.

To summarize DL, basically the system works as followed: a human feed the system with a large dataset, based on this the system can make decisions, predictions and statements with a degree of certainty. While machines are connected to each other all the time, thus if one machine makes a mistake, all autonomous systems that are connected will learn from this mistake, which enables the system to avoid and not making the same mistake again. This is an action that differs from human behaviour and is one of the reasons there are speculations about intelligent machines will win against human experts. (Wisskirchen et al. 2017, p:10) The earlier mentioned CNN in this chapter, is also addressed to be very useful when looking at the manual measuring and capturing complicated relationships. CNNs come with great use in managing complicated relationships between an input and output, for instance image data and the outcomes. (Henglin et al, 2017) The impact of DL and many sub-fields of AI started to accelerate for a few years ago, for instance, by using DNNs between 2011 and 2015 the error rate for image recognition dropped from 25% to 3%, which is a lower rate than human performed, which is approximately at 5 %. Other examples where DNNs have exceeded tasks performed by humans are object detection, speech recognition, face recognition etc. (Potember, 2017) The figure below will visualize the development of AI, ML and DL:

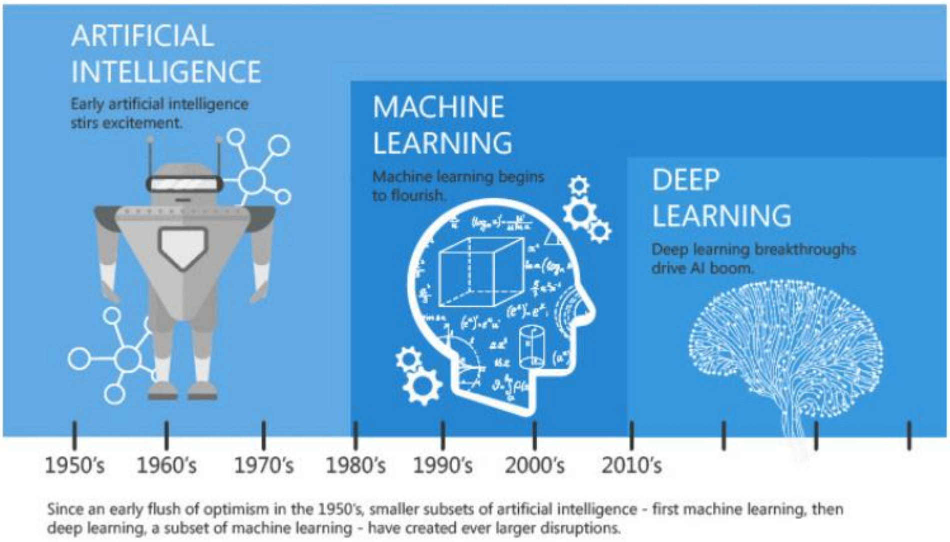


*Figure 2 - Development path, from AI to deep learning (Tandon, 2016)*

AI is being and will be applied in many disciplines, as presented earlier in this chapter, but it all started in 1950 by Alan Turing in his paper Computing Machinery and Intelligence. He discovered a test, called “Turing test” and the original question for this test was “Can machines think?”. In this test, he tested the machine´s ability to exhibit intelligent behavior. (Borana 2016)

But until around 2010 the field of AI had been standing quite at the same place regarding a decade of old technology, such as multi-layer NNs, but at this time, something evolutionary in this field started to happen. The development of fast hardware Graphics Processor Units (GPUs) allowing training of much larger and deeper networks and large labeled data sets, such as images, social media etc., which could be used for training testbeds. The description above, is development of what is behind the “data-driven paradigm” Deep Learning on deep neural networks and Convolutional Neural Network. (Potember, 2017)

These two chapters above provided a brief introduction about the definition of AI and what AI is considered to be and some insight about what kind of types of AI there are to be considered. The following chapter will be an introduction to what kind of applications of AI could be considered in healthcare.

### 2.1.2 AI in healthcare

A doctor´s ability to diagnose and to treat patients is something that increases by experience, due to being exposed to treating many patients of different kind. Essential is also to stay updated on progress within the field of medicine, such as updates about published studies and scientific articles within the field of medicine a doctor is performing in. Though, it is limited how many patients a doctor can treat during a day, even during a lifetime, same goes for the amount of going through articles and studies. Here is where an AI system has great potentials of serving as a valuable decision support tool for doctors, due to its ability to process big amounts of both patient data, studies and articles in one hour. (Ahlén & Bravo, 2017)

Realizing the value from applying AI into organizations like healthcare is essential. Some identified benefits are for instance to collect, store, normalize and enabling to trace the data are possible with such technology (Mesko, 2017). AI in healthcare aims to determine the relationships between treatment techniques or prevention of care and patient outcomes by using algorithms that brings closer the human cognition in the analysis of complex medical data (Krishna, 2017). AI techniques in the field of healthcare and medicine is being used to support diagnosis and to avoid false diagnosis. Due to the rapid progress of technology it is possible to improve treatments, making the right therapeutic decisions and being able to predict the outcomes for clinical scenarios. Healthcare and medicine are facing the challenges of solving complex problems by obtaining, analyzing and applying the existing large amount of knowledge (Siuly et al, 2018).

Examples of such system that is in use in the healthcare sector is the well known IBM Watson. IBM Watson is a system that supports doctors in diagnostical decisions, providing evidence-based management plans and doing this in a shorter timeframe than before. This intelligent system interface is based on cloud-based Big data and is capable of comparing millions of anonymous types of similarities in diagnosis, diseases or illnesses and is also comparing this data with medical studies around the world. (Weber, 2015) Jiang et al (2017) are stating that this described IBM Watson system is considered to be a pioneer within this field and has in the field of oncology made promising advantages. This system utilizes both modules of NLP and ML. Another big IT company which is entering the healthcare field is Microsoft, who according to Richman (2018) are announcing an initiative where ML applications are being used in order to increase patients´ awareness regarding their treatment plans.

The great increasement in recent decades about applying AI into medicine and healthcare has led to the growth of interest for research within this field, even such as scholarships within medicine has truly increased in recent years which has contributed to the transformation within AI in medicine (AIM) (Tran et al, 2019) Artificial Intelligence in Medicine (AIM) is an application of AI methods for solving problems in the field of medicine. Such methods could for instance be developing expert systems for treatment planning or assisting in diagnostics (Coiera.2017p:572). Expert systems again, is a computer program consisting of knowledge about a specific problem and has the capability of solving the problem equivalent or greater than humans. These systems often consist of sets of if-then rules (Coiera.2017p: 577).

For AI to be successfully deployed into applications in healthcare, the AI should be trained through the data generated from the organization where it is supposed to be interpreted in order to learn and associate between the subjects. Such data can be data from clinical activities, diagnosis, screening, treatments and these types of data exists for instance in medical notes, EHR´s (electronic health record), medical devices, clinical images etc. (Jiang et al, 2017) Thompson et al (2018) are also saying that sources of available data plays a significant role for AI application methods. For instance, in radiation oncology there are huge amounts of available data such as laboratory, radiotherapy planning data, imaging, pathological data and data from electronical medical records. These all different sources of available data provides opportunities for applications of AI contributing to improve such as the overall safety and quality of cancer care delivery. Tiina Ihme (2018) is also saying that AI can be used to improve image reconstructions, it could allow more accurate automatic image analysis. For instance, by todays practices tomographic images are still being reconstructed by old methods using high dosage of radiation. For such process a reconstructive algorithm using AI could significantly reduce the radiation load for the patient and also improve the quality of the image.

Within Pharmacology AI has been for instance used for the development of drugs and algorithms in order to find new and more accurate drug combinations, such as finding suitable combination within cancer treatments (Neittaanmäki & Lehto, 2017, p:28). Regarding this, Dr. Oliver Elemento mentions that AI has shown some great potentials in finding new effective drug combinations among cancer treatments. Elemento gives an example about the complexity of an issue where the point of view where a researcher might consume a lot of time for such treatments that turns out to be ineffective treatments. There are about 100 drugs which can be used in order to create combinations for two-drug treatments, then this amount can arise up to 5 000 possible combinations. But how about when some wishes to research more combinations, such as combinations of four drugs. This will lead to rapidly growing amounts of grouping which will be extremely difficult to experimentally test each combination while researching. By using AI in such research environment this amount is possible to narrow down and get a more specific grouping on which drug combinations are good candidates for being experimentally tested. (Elemento, 2017)

AI tools will become more accurate, due to researchers bring all the time more data to the algorithms, which will therefore become more useful for healthcare professionals. AI has not only affected the clinicians´ practices, other areas in hospital organization, such as becoming a more individual-centric medicine and improving operational and predictive cost management. (13D Research, 2017) For instance, lower back pain is one of the most common reasons in Finland to seek for medical advice and is one of the most health related problems that reduces the ability to function. Magnetic imaging is needed when a patient is experiencing pain without a particular reason for this pain. These images of a spinal structure can be difficult to interpret. According to Tiina Ihme (2018) an AI solution could enable to bring more systematic, effective and quantitative methods for evaluating the spinal structures. (Ihme, 2018)

Jing et al (2018) are saying that, though AI techniques may be as powerful as they can be, they need to be adapted into clinical practice aiming to solve clinical problems. AI technology in today´s healthcare are considered to be categorized into two main categories, Machine Learning and Natural Language Processing (NLP). Machine learning and its subfield Deep Learning are considered to be the core of many recent advances regarding artificial intelligence applications. (Bughin et al 2017, p:10) Such fields where AI is currently within medicine being applied to, except from previous mentioned oncology and pharmacology are for instance pulmonology, cardiology and insomnia.  Insomnia is a sleeping disorder disease that more often affects the elderly population and in fact a disease increasing among the population. The aim is to discover a combination of treatments from both drugs and other solutions. Here AI is being used for finding such personalized treatments whereas drugs and other solutions are combined. As mentioned cardiology as a field where AI applications are being utilized, which is the medical field of heart diseases. (Neittaanmäki & Lehto, 2017, p:28) To mention an example of such application is from Finland, whereas AI was developed as a risk assessment tool for such disease detection. This tool is called the “FINRISKI”- tool, which is determined to calculate the possibility for a person to fall ill in an artery disease. It is utilized to help healthcare professionals to decide what medication a patient should have in order to avoid the artery disease. This FINRISKI-tool is based on a research on risk factors for the disease from the 1980`s and data collected from 10 years of surveillance of mortality and morbidity for artery disease in Finland. (Ruokoniemi & Rannanheimo, 2018)

In the Western countries cardiology is, as many fields of medicine considered as a very important field, however heart diseases can have significant consequences for patients and is one of leading cause of death. AI has enabled to monitor, to predict and to diagnose heart failure for patients. By taking advantage of AI it has also became possible to predict patients remaining time of life. (Neittaanmäki & Lehto, 2017, p:28)

Deep learning has also showed some great potentials in the field of medical image analysis. Oakden-Rayner et al (2017) are saying that there are experiments of proof of concept for such system that enables prediction of 5-year mortality in people who have undergone chest CT and have passed the age of 60 years. The promising results resulted in great prediction accuracy from the routinely based chest CT images which were similar in this study for both the "human made" approach and for the deep learning approach. In this study the obtained predictive accuracy appeared very similar to clinical risk scores published by humans. (Oakden-Rayner et al, 2017)

NLP methods are used for turning unstructured data to machine-readable structured data which then again can be processed by a ML technique. Such unstructured data that needs to be converted into structured data can be text from medical journals and clinical notes (Jing et al, 2018). ML is a technique that has the capability of analyzing structured data, which in clinical settings can be such as electrophysical data, genetic data and imaging, which often are used for recognizing patient features and to predict patient disease outcomes. (Jing et al, 2018)

Oncology departments are adopting AI technologies for early recognition of cancer. Radiology is another department where AI is also being utilized and where it is said that the performance is in line with humans. (Eubanks, 2017). The impact of AI in radiology has started to appear in the international community of radiology, big focus at international radiology meetings and more and more dominating in both academical and industrial headlines (Liew, 2018).

The future holds great promises for improving patient care by applying AI into healthcare processes, such as recommending the suitable diagnostic test at the accurate time, individual treatments in order to maximize the efficiency, while minimizing the side effects. Further, which should not be excluded is the impact on the field of medicine, the potentials of discovering new medical knowledge will in the end will come to have impact on the quality of patient care. (Neill, 2013)

In this chapter some examples of how AI can be utilized in healthcare was introduced, it is though also important to highlight that AI also have considerable serious limitations within healthcare. Such as forecasting and prediction are often made from a presence case or an example, which the AI model keeps building on, this means that it is not possible to build on cases where no prior example is available. Tacit knowledge is difficult to code and are therefore hard to imagine that AI would replace this kind of knowledge. (Mesko, 2017)

Another interesting highlight made by Bahadori et al (2016), who suggested a AI Doctor using recurrent neural network (RNN) to predict future events for patients based on patient records. In their study they realized a clear limitation regarding limitations of AI. Namely that some incorrect predictions within medicine can sometimes be even more important than correct predictions, since such can make patients even more sick.

The following chapter will consist of an introduction of the chosen technology of AI for this thesis, namely Machine Learning. After the introduction about what ML is the text will continue with how ML techniques are being utilized in diagnostics, particularly in the fields of oncology, pathology and radiology, since these specializations within diagnostics are the chosen fields of this work.

## 2.2 Machine Learning

During the past centuries, statistical methods for automating decision making and modelling has been numerous times both invented and reinvented. Problems regarding regression, control, prediction, system identification and pattern recognition has led to recognizing the potential of Machine Learning methods to address these problems. (Wernick et al, 2010) The primary approach with ML techniques is the segmentation of data into both learning and validation of data sets for development of precise classification algorithms, after this algorithmic development phase is done the algorithms are applied to the full data set where the prediction is being done. (Crown, 2015) This can also be described that the ML consist of two main concepts, the first is its capability of developing algorithms that quantifies the relationships in data and second, to identify patterns in order to make predictions based on new data. (Wernick et al, 2010)

As earlier introduced Machine learning is considered to be a subfield of AI (Panch et al, 2018; Starr, 2018). ML is according to Motwani et al (2016) a field belonging to computer science where algorithms are used to identify patterns through big amounts of datasets. Including many different variables which enables the prediction of different outcomes based on the data (Deo, 2015). Since the ML algorithm is required to have high amounts of data healthcare would be a sufficient field since it possesses high amounts of different types of health data within health systems. Health systems are used in various healthcare settings, such as clinics and different physician offices and hospitals. Examples of such systems consisting of healthcare data is EHR, clinical decision support systems (CDSS), picture archiving communications system (PACS), computerised physician order entry (CPOE) and various laboratory information systems. (Kuo et al, 2014)

Due to its ability of seeking and learning from patterns and relationships from the data it will be contributing to more efficient algorithms from both computer science and statistics. This tight bond between mathematics and computer science will lead to building remarkable statistical models from huge data sets, including up to billions, even trillions of data points. (Deo, 2015) ML can be described as a rapidly growing field resulted from both AI and statistics. This growing field of ML focuses on building such systems that based on data makes accurate predictions, a visualized figure from Henglin et al (2017) below:

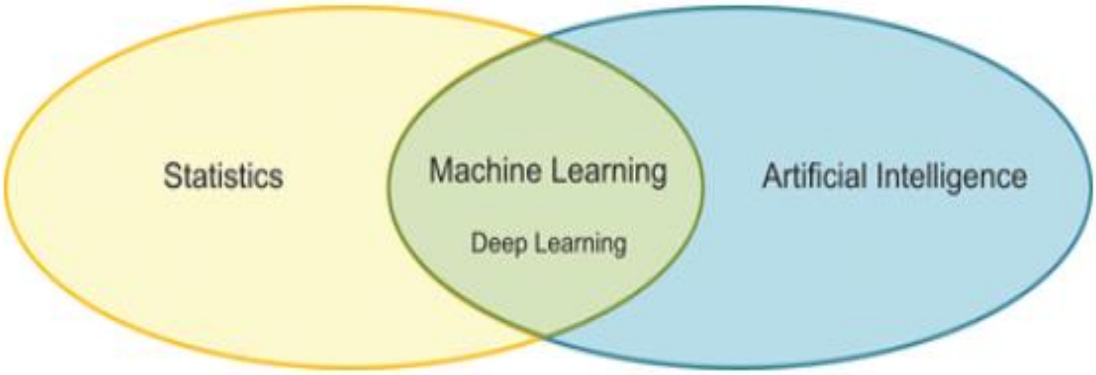


*Figure 3 - The fields of ML (Henglin et al, 2017)*

A similar description of ML, according to Kang et al (2015) ML is described as a part of computer science where predictions are made from complex data through statistical models. ML can also be described as a model which consist of so called learning algorithms, these learning algorithms needs to be fed with data in order to learn, this phenomena can be described as the data being the fuel for the algorithm (Starr, 2018). The main goal with a ML technique is the development of a model that can be applied in tasks such as, prediction, estimation, classification and similar tasks to those. This learning function with a ML technique is to classify the data sets into one consisting of several predefined classes. (Kourou et al, 2015) ML can be identified of such intelligence that could be performed by a human such as speech recognition, decision making, visual perception and for instance translation between languages (Starr, 2018). ML techniques have been successfully implemented in many different fields such as finance, entertainment, pattern recognition, biomedicine, computational biology and medical applications. (Naqa et al, 2015, p:3) These fields have become suitable for such approach due to the techniques capability of developing

such algorithms that quantifies the relationships in data and to identify patterns in order to make predictions based on new data (Wernick et al, 2010). Further, Deo (2015) is highlighting the central role of features for ML. In order to develop successful ML techniques, with efficient algorithms, it is crucial to consider the feature selections. This is due to the ML ability to progress, but with insufficient features or predictors the ML is very unlikely to make progress. Henglin et al (2017) are saying that due to advanced technology in this field, where programs automatically can learn rules from accessible examples of data, notable these systems are not distinctly programmed on large sets of rules into a computer. Many industry domains that are completely dependent on ML techniques are for instance text translation, speech and image recognition and email spam filters.
Since the ML has the potential to learn and improve from its experiences, it can be a convenient technology for complex problems or where adaptivity is required (Shai & Shai, 2014p:3). This is a type of capability that is especially suitable in medical settings and particularly in those settings that are dependent on measurements from such complex as genomics and proteomics (Cruz & Wishart, 2006). Other problems that are considered complex to program are tasks that we humans perform quite by routine, such as speech recognition, image interpretation and car driving. These are examples of tasks that can be considered as complex, but if a ML program is sufficiently being exposed to such complex tasks, it has the possibility to learn and improve. Another example of complex tasks is the capability to find “hidden” patterns in large and complex data, based on analytical methods, such as genomic data, astronomical data and turning medical data in to medical knowledge. (Shai & Shai, 2014, p:3) The ML manages to analyse and interpret the data due to the algorithm, which performs the classification, prediction and the segmentation about the data, which are not easily interpreted by the human eye. (Rabbani, et al. 2018, p: 2) When a ML based classification model is developed, it is then possible to start producing the training and generalization errors. The training errors means misclassification errors on the training data and generalization errors means the errors that are expected on the training data. (Kourou et al, 2017)

Within ML there are two types of learning techniques, supervised and unsupervised learning (Coiera. 2015, p:529). According to MeSh (Medical Subject Headings) a supervised machine learning algorithm, makes the predictions for future instances based on a given set of examples, labelled paired input-output training data (Finto, MeSh). The labelled training data are used for the purpose of estimating or mapping the input data in order to get the wanted output (Kourou et al, 2017). These set of examples, which are used for training are chosen and can be called labelled value of interests, depending on what the purpose of the algorithm is (Starr, D, 2018). This means that each type of data is needed to be assigned before applying this type of learning technique (Coiera, 2015, p: 529). When this is being done and the learning technique is being applied, the algorithm looks for patterns in those chosen value labels (Starr, D, 2018). This type of ML learning is a convenient method for instance in radiology, since the data is being labelled before the model is being trained (Kohli et al, 2017). This can also be explained as followed, the algorithm utilizes the input to define logics and correlations, which then can be used to predict the answer (Nevala, 2017 p:15). According to Erickson et al (2017) supervised learning technique is the most utilized within medical image analysis.

One example of how supervised learning could look like in the field of medicine is for instance where a set of variables could be microarrayed measured genes that are mostly utilized on categorized data that belongs to a specific class of interest, such as a class of a given disease. (Coiera, 2015: p: 529) Other techniques considered similar to this type of learning, such as; Neural Networks, Forecasting, Decision Trees, Bayesian statistics. Other alternative methods to ML such as random forests are often used for developing predictive models and classification trees are related to such method (Crown, 2015). Decision trees are commonly known by it typically answering to yes or no question, such as if a numeric value is lower than a given value, but what applies to ML is its ability to quickly search for as many as possible combinations of such decision points resulting in the simplest tree consisting the most precise results (Erickson et al, 2017)

The unsupervised machine learning works the other way. The data patterns with this technique needs to be analyzed without labels (Coiera, 2015: p: 529). Using this method, the examples of labelled data are not given and there is no idea about the output for this type of learning process (Kourou et al, 2017). Opposite to the supervised learning technique, unsupervised technique makes predictions about instances for the future based on a set of examples that are unpaired input-output training data, the supervised used paired input-output data (Finto, MeSh). In other word, the result from this kind of learning process is that the learning model gets the key role in finding patterns and grouping based on the input data (Kourou et al, 2017). The most common application with this unsupervised technique is to "data mine", where the goal is either to discover for instance a totally new cluster of genes with a hypothesized common function or to maintain a cluster of genes that appears to have patterns of expressions that are alike an already known gene, the latter is more commonly used (Coiera, 2015: p: 529). Kohli et al (2017) highlights that this type of learning is also convenient to use when there is a need for identifying meaningful clustering labels. After such identifying step is done, it is possible to use them in a supervised training model when aiming for development of a useful ML algorithm, this mix of both learning techniques can be called "semi-supervised" learning technique. The semi-supervised learning combines both labelled and unlabelled data, more often used in cases where there are more unlabelled data, aiming to develop a proper learning model. (Kourou et al, 2017)

Earlier in this chapter an example of how a supervised technique is determined to have assigned data before applying the learning technique on a set of variables (for instance the genes) and the algorithms looks for patterns in a class of interest (for instance a disease) was presented. The unsupervised technique could allow us for instance to search for genes that are commonly regulated in any kinds of tissue samples. Such features can be of many kinds, such as gene expression, measures of clinical outcome, proteomic measurements, drug exposure, gene sequence and much more in order to find out whether there exists a functional relationship between every possible pair of genes. This technique often includes such as dendrograms and self-organizing maps for analysing the possible relationships. (Coiera, 2015: p: 529)

In medicine, most computer based algorithms are called “expert systems”, which are in a given topic, rule encoded knowledge in a specific clinical scenario, such as drug detection (Obermeyer et al 2016). Expert system is according to Coiera (2015, p:577) a computer program consisting of expert knowledge in a specific given problem, commonly with a set of if-then rules in order to solve problems at such level that are considered as equal or greater than human experts. Contrary to these “expert systems” ML approaches the problems by learning rules from data, for instance; Starting from patient-level observations, the algorithm transfers through a large amount´s of variables looking for combinations that reliably predict the outcomes. This can be interpreted as a tradition regression model, but the difference between traditional regression models and ML is its capability to manage huge numbers of predictions. In some situation´s even more predictors than observations in combination of highly interactive and nonlinear ways. This capacity is the reason for what allows us to suddenly use new kinds of data, whose complexity or its volume would have previously been unimaginable to analyze. (Obermeyer et al, 2016)

In this chapter a brief introduction to what can be considered to be called Machine Learning, including techniques, common terms and how this technique can be applied. In the following section an introduction to how Machine Learning could be or is applied within diagnostics and especially within oncology, pathology and radiology.

### 2.2.1 Machine learning in diagnostics

There are suggestions ML systems will be contributing to changes in the sector of healthcare in the near future, especially in medical fields where there is desired with more accurate prognostic models, such as within oncology. Even in such fields in medicine which are considered to be based on pattern recognition, such as pathology and radiology (Cabitza et al, 2017) ML techniques has the ability to detect key features from complex datasets and has therefore led to many different research development teams who has started to utilize ML into their fields. Such as bioinformatics is a field that has started to study ML application methods for their field, where the goal for instance is to develop cancerous progression treatment models. (Kourou et al, 2015) Imaging plays a significant role in both diagnosis and the treatment of many diseases. The number of medical images has increased due to population ages and therefore are also the total amount of medical images increasing. The research is becoming more complex and the increasing volume of information is therefore also getting more complex (Ihme, T, 2018). When analysing digital pathological images, general image recognition is often utilized, such as facial recognition. Digital pathological images require special processing techniques, due to special characterization of the images, machine learning algorithms are considered as possible solutions for such task (Komura & Ishikawa, 2018, p:35).

According to Wernick et al (2010) the standard for measuring the image quality is based on an observers diagnostical skills while measuring a given set of images, this observer can for instance be a radiologist. Such studies, due to its complexity impedes the possibility of routine use of such studies. Which is one of the reasons such numerical observation could be very suitable for an algorithm to replace or to assist the human performance of such skills. Liew (2018) are saying that since radiologists possesses capabilities to make clinical assessments based on data and they are therefore potentially going to exceed diagnostic algorithms in this field, which will make radiologists suitable in a role between AI and radiologists. Seeing that the profession of a Radiologist is considered to be a profession rich of data interpretation, since the work consists a lot of extracting information and features from images and then applying a large base of knowledge in order to make some interpretation from those features being discovered from the images. (Kohli et al, 2017, p: 754) Jha & Topol (2016) regarding this aspect, considers the main purpose for both radiologists and pathologists to interpret and extract information from medical images are therefore considered as “information specialists”. Many of such tasks could be performed by an AI. Such as going through hundreds of images searching for a specific cause. What these “information specialties” could instead focus on is to interpret important data and advising on value added from other diagnostical test, such as laboratory test, anatomical pathology and then integrate this information that could help guide clinicians. With this type of change in workflows and allowing AI to assist parts of the diagnostic processes, radiologists and pathologists would still be physician´s physician.

There are promising potential to gain from analysis from both typical measurement data and image-based raw data. The image-based raw data has the potential to generate new measures based on its data. Let´s imagine a task that is determined to predict clinical outcomes, at first the analysis starts from the raw pixel level. A conventional data analysis approach starts already at this level where large amounts of possible combinations from these pixels are available Then there is possible combinations of filters and other image processing techniques which aims to discover relationships between an image and an outcome. Here comes the success of a technique to be utilized in such situation, namely ML. Deep learning, as a modern type of ML could also vi utilized in such task, which could automatically discover the relationships already at the pixel level. (Henglin et al, 2017)

A variety of ML techniques, including Bayesian networks (BNs) Support Vector Machines (SVMs), Artificial Neural Networks (ANNs) and Decision Trees (DTs) have been quite widely applied in research within cancer. This have been done in order to develop predictive models and has resulted in both precise and effective decision making. (Kourou et al, 2015) Image features that can be automatically extracted, such as features based on geometry, texture, morphology and image contrast are examples of information located in images ready to be extracted. ML techniques that has been employed for such task is a range from fuzzy logic techniques, linear discriminant analysis, committee machines, neural networks and more recently to kernel-based methods, such as relevance vector machine (RVM) and support vector machine (SVM). Additional to the diagnostic process based on images, there are other types of information available about patients in healthcare systems. (Wernick et al, 2010) Lee et al (2017) are saying that though there are studies showing promising results within object matching in medical image registration using ML methods, there are also some problems identified. The model is capable of recover the objects location but matching the accuracy requirements for images of 2D and 3D registration tasks is not sufficient, which are due to diagnostics and surgical purposes needed to be of high accuracy.

A ML model has the potential in a clinical workflow setting to reduce the effort that is required when analyzing large amounts of data from medical journals (Yala et al, 2017). ML in healthcare systems shows great potentials in predicting disease models. One examples of this is predicting chronic diseases where an algorithm can be trained and applied for healthcare systems to identify patients who are misdiagnosed or undiagnosed with a chronic disease. It is also possible to develop models that are able to predict which patients has the likelihood of developing a chronic disease. Further, with this kind knowledge it is then possible to suggest patient-specific preventive interventions for these patients. (Wang et al 2015) This is due to the ML algorithms capability of making so called “knowledge bases” that are used by predictive analytics from data and expert systems (Kaur & Mann 2017). Ross et al (2016) developed ML algorithms with the aim to identify peripheral artery disease (PAD) and its prognosis of mortality risk, another aim with this study was also to determine whether the model achieved better performance than traditional statistical analyses. This study resulted in excellent discrimination and calibration performance with the prediction model. Even significantly better than the logistic regression model, especially when trying to identify undiagnosed patients.

A radiologist is a medical doctor who is specialized in interpreting medical images in order to guide treatments of diseases in patients. Such images are for instance CT scans, Digital radiographs, MRIs and Ultrasounds. (Liew, C.2018). While considering the work of a diagnostic radiologist, these physicians spend much time in analysing images in order to find anomalies in patients and much more. In many cases this is often seen as a critical phase while diagnosing patients because the diagnosis is based on the physicians´ findings, for instance identifying a tumor. (Starr, D. 2018) Another considered use case could be for instance a radiologist whose features might predict an important outcome, such as death. With a standard statistical model in this case, the radiograph’s interpretation could be like this — “normal,” “atelectasis,” “effusion” — as a variable. But instead, it is possible with a ML model to let the data speak for itself. Due to advances in computation power, these digital pixels matrices behind radiographs become millions of individual variables. Here is where the algorithms clusters pixels into shapes and lines and ultimately learning contours of fracture lines, parenchymal opacities and more. (Obermeyer et al 2016)

As earlier mentioned in the chapter about ML techniques about how the imaging aspect within radiology, a convenient type of ML learning technique would be the supervised learning, since the data being labeled before the model being trained. An example of such case could be for instance where the goal is to identify a specific tumor. The labelled data, which can be as general or specific as required for this tumor or it could for instance be genomic information and pathologic results. After this the ML algorithm needs to be exposed as much as possible to the labeled data and will then be converted into a designed model which should serve the purpose behind designing the model. (Kohli et al, 2017) Within medical imaging a field called “Radiomics” can be defined as when using high-throughput computational techniques in order to analyse the high-dimensional data of medical images. Contrary to the traditional way of treating medical images as pictures intending exclusively for visual interpretation the radiomic data consists of first-, second-, and higher-order statistics. Such data is combined with other patient data and are mined with bioinformatics tools in order to develop such models that eventually could improve the predictive, prognostic and diagnostic accuracy. (Gillies et al, 2015) By adopting new technological methods, such as ML into image diagnostics it might provide new capabilities in patient outcome, disease appearance and the prediction of diseases. This is due to that these images contains a lot of prognostic data embedded, which may not visually be as noticeable for a pathologist that it might be for a computer. (Madabhusi & Lee. 2016). For instance, a ML model can be trained on pathology reports in order to extract information about pertinent tumor characteristics which then makes it possible to create a large database of attributes searchable in pathology reports. This large database can provide identifying cohorts of patients with characteristics of interest. (Yala et al. 2017)

Within todays techniques for diagnosing brain tumor, analyzing both histological and molecular features are essential parts of this type of diagnostics. (Wong & Yin. 2018 p:446) According to Finnish medical dictionary (Duodecim, 2018) histology means tissue doctrine, which contains learning about the structure and function of tissues. The study of tissues is mostly made by microscope and chemical methods. When diagnosing a brain tumor, samples of the tumor are placed on glass sliders and then being microscope analyzed. This process requires skills in evaluation of sensitive cellular transformation, which makes it possible to execute different classifications for such samples, depending on the person analyzing the piece of sample. In this presented diagnostic process of brain tumor, the molecular features are by today possible to advantage from ML technology. This method enables the ML to classify brain tumors based on the molecular patterns. When it comes to the histological part of the diagnosis of brain tumors, it would be essential for further development of computational tools which could allow the ML to analyze histological data. (Wong & Yin. 2018, p:446)

According to de Bruijne (2016) the probably most expanded diagnosis based on ML applications appearing in publications is within the field of neurodegenerative diseases, whereas researchers aim to diagnose Alzheimer's disease and other types of dementia based on brain magnetic resonance imaging (MRI) images. Analyzing fMRI (functional Magnetic Resonance Imaging) data has shown some increased interest in using ML classifiers. The fMRI is a medical image technique for studying brain activity. According to Pereira et al (2009) there are several studies that shows great potential of the possibility to extract new information from neuroimaging data by using ML classifiers. (Pereira et al, 2009) A Classifier is the so called function that takes the values from different features, such as independent variables or predictors in regression. When these values of features are taken into an example, which is a set of values of independent variable and then predicts which class this example may belong to, which is the dependent variable. Within neuroimaging regression is mostly used based on General Linear Model, by this method predicting the time series of each voxel from many columns in the design matrix is being done. When utilizing ML classifiers, these are used in the reversed way, which means that the prediction parts of the design matrix are from many voxels, not from each voxel at time. A number of parameters are needed to be learned or trained from training data for a classifier. This means that a classifier needs a set of examples to be reserved for this purpose. The learned classifier will become the model of the relationship between features and the class label in this training set, which is similar to how parameters in regression are measured using last squares. (Pereira et al 2009)

Dolgin Ellie (2018) explains in an online article "The First Frontier for Medical AI Is the Pathology Lab" how a recent start-up company "PathAI" are working with pathological AI solutions. According to this article, where the founder of the company Andrew H. Beck was interviewed explains how such solutions could work. This company provides a software where the ML algorithms is trained on digitized slides combined with clinical data performing statistical analyses beyond the ability of a human. This clinical data can be such as treatment plans, patient outcomes or aggressiveness of a tumor. The differences in the current pathological workflow versus the "new" digital workflow can be explained as followed: A pathologist examines a biopsied and sliced tissue sample under a microscope. The "new" digital approach, consisting ML the slides are being scanned and imported into a software program. This program, using ML for training in order to spot capillary patterns and then provides this information to the pathologist. (Dolgin, 2018)

ML technology can be applied in a wide range of work situations, such as radiation oncology, for instance from localization of the tumors movements to image processing (Kang et al 2015). Since the goal for the ML algorithms is to learn and train from the available data in order to produce patterns and enabling informed decisions are reasons for such field as radiation therapy to recognize the potential by starting to apply this technique. This is due to its availability on data and its' so called "data-driven" nature which are therefor considered to have great potentials in discovering such as cancer management. (Kang et al 2015) ML technique, even more specific a supervised learning technique, could be for instance utilized in a diagnostic case where the tissue coming from acute lymphoblastic leukemia or acute myeloid leukemia aims for predictions of such diagnosis. Learning systems such as decision trees and NNs are included in this category. For this method to be applied, these tissues in these types of leukemia needs at first be labelled. After the leukemia tissues being labelled the learning of which possible combinations of variables could predict the disease can begin. (Coiera, 2015, p: 529) Other cases where ML technology has been utilized in are cases where the aim was to build a model for predicting asthma outcomes and the risk for type 2 diabetes (Luo, 2016). Macyszyn et al (2015) conducted a study where they used ML techniques together with image patterns in order to predict patient survival and molecular subtypes in glioblastoma. Glioblastoma is according to Finnish medical dictionary (Duodecim, 2019) a malignant tumor, mostly appearing in brains and the first step of diagnosis is to conduct an MRI. The steps in this study was used as followed: At first, the MRI from 105 patients with the diagnosis glioblastoma (GB) were used for extracting about 60 various features which were recognized from the preoperative multiparametric MRIs. After this, the features from the images were applied by a ML algorithm to conduct predictors from imaging of patient survival and molecular subtype. Based on this a cross-validation was made and ensured generalizability of the predictors to new patients and after this, the predictors were evaluated in a prospective cohort consisting of 29 new patients. (Macyszyn et al, 2015)

The medical field has some clear benefits from the development of technologies, one to mention in the field of oncology research is the high availability of the amount of data about cancer (Kourou et al, 2015). By utilizing ML methods into the field of oncology it is possible to improve the understanding about cancer progression, its recurrence, sensitivity and even predictions about the survival is possible. (Kourou et al, 2015) According to Rabbani et al (2018) while diagnosing cancer, different types of detailed imaging technique is required in order to evaluate both the presence and the dimension of the cancer. Such imaging types are computed tomography (CT), MRI, single-photon emission computed tomography (SPECT) and18F-fluorodeoxyglucose positron emission tomography-computed tomography (18-F-FDG PET-CT).

Interpreting mammography images is considered being demanding and one big challenge within this is to reduce the number of false positive findings. Currently, about 3% of the screened people get a false positive finding, this means that patients are wrongly diagnosed. This contributes to stressful and unnecessary concerns regarding a possible cancer for patients. A ML method is possible to help reduce the number of false positive findings and assist doctors in making the right diagnosis. (Ihme, 2018) The time of computation is a critical issue when it comes to mammography, an image can contain up to 3000 x 5 000 pixels that needs to be evaluated. Wernick et al (2010) developed an approach based on relevance vector machine (RVM), which emphasizes sparsity and perform very well in many medical imaging applications, often with lower computational cost. RVM uses a Bayesian approach. RVM is an important successor of support vector machine (SVM), which briefly explained is about defining the boundaries of the training examples that are dangerously close to a class they don't belong to, in other words, two classes are separated with a linear decision boundary, this approach is automatically concentrated on the examples that are difficult to classify. However, the developed RVM approach for the mammography showed 35 times less computational cost. SVM and RVM base their decision completely on a subset of the training data, the subsets thought most often different. The relevance vectors are usually spread and near the decision boundary in the distribution, these are motivations for why such approach is considered to be suitable in mammography. (Wernick et al, 2010) The small bright spots that are appearing on mammograms are deposits of calcium and are called Microcalifications (MCs). These are very essential while diagnosing, clustered MCs are indicators for breast cancer, which also appears in 30-50% of cases. It can, in some cases be difficult to find individual MCs, due to their size, brightness, shape variations and orientations. The texture of surrounding breast tissue can also prevent or harden the detection of MCs. These are all reasons why breast cancer has been and still is a field where investigation is highly targeted. ML approaches has shown some great effective applications in the field of breast cancer diagnostics. (Wernick et al, 2010) Thus, many types of AI have shown some effective and accurate decision making within cancer research, such as Bayesian Networks and ANNs but there are still some validation that needs to be determined before these models can be taken into daily clinical workflows. (Kourou et al, 2015).

Madabhusi & Lee (2016) are saying that there are big research opportunities in the field of image computing due to the new availabilities of big data. Further, Rabbani et al (2018) are saying that since radiologists, oncologists and surgeons analyse big amounts of data which can be complex, adopting ML tools into clinical care can help these clinicians receiving a greater understanding about their patients is something that should be a motivator for continuing integrating such technology. Within the same topic according to Krishna (2017), a healthcare expert within consultancy claims that AI have great potential of solving today´s challenges in the healthcare sector, thus technologies have a lot to improve until the obstacles are defeated until we can state that the care delivery systems are being improved due to AI.

This chapter provided some insight to the topic of ML and how such techniques could be utilized and are currently utilized within the field of diagnostics, mostly examples and use cases from oncology, pathology and radiology. As the chapter provided some insight to possibilities and how the future with ML tools could impact the field of medicine. The next chapter will provide some identified challenges and obstacles a sector like healthcare might face when considering implementing AI and ML technology into their organization.

## 2.3 Challenges and barriers within the healthcare sector when considering implementing ML and AI technology

When a healthcare organization are ready and willing to adopt AI technologies to their organization, they face some challenges that needs to be taken into consideration and gain a broader understanding about. An understanding about the limitations and risks regarding the technology is crucial. It is also important to demonstrate the successes achieved with the technology and a strong governance model. Implementation of workflows and protocols are also important. All these are actions that need to be taken into great consideration when AI technology is going to be utilized in hospital setting. By processing this in an early phase, the organization will also gain improvement to the adaption phase. (Krishna, 2017)

This chapter 2.3 will provide an insight to some considered topics regarding what could be considered as challenges or barriers a healthcare organization might face when considering implementing AI or ML technologies into their organization.

The first topic will introduce some “Professional aspects” that could be considered as challenges or obstacles when considering such technology implementation. The second topic will consist of potential challenges within the “Ethical and legal aspects” and the third “Economical and organizational aspects” when considering implementing AI or ML technology into a healthcare organization. This whole chapter 2 will serve as a framework for the development of the questionnaire, which will be presented in the following chapter, in chapter 3.

### 2.3.1 Professional aspects

According to the World Health Organization (WHO) the lack of global healthcare workers at year 2013 was up to 7,2 million and is estimated to be in 2035 up to 12,3 million, which is expected to have serious impact on peoples´ availability for receiving healthcare services around the world. It is implicated that AI technologies will have a remarkable impact on this dilemma. AI technologies could namely come to have an impact on the availability, delivery, also in such areas that are already being underserved and lower the cost of accessing these kinds of services. The adoption of such technology is already on the forefront, approximately by the year of 2013 600 million US dollars was spent on AI technologies and is expected to grow up to ten times more by the year of 2021. (Infosys, 2017) To improve the operational efficiency and the delivery of care it is a high and important priority when considering adopting AI technology into an organization like healthcare. Such technology can manage a range of different tasks, from managing the supply chain to giving diagnostic support. From a physician´s point of view, by adopting such technology physicians could focus on more critical activities by letting the technology take over such as clinical and outpatient services. An example is for instance a ML algorithm that is able to process and analyse huge amounts of information, such as clinical notes, health records and diagnostic images and then find insights and patterns which for a human would have taken extremely long time. (Infosys, 2017)

According to Krishna (2017) there is a need for cultural shift among institutions, governments, healthcare providers and patients for AI to become a part of the healthcare field. Organizations attitudes for AI should also be transformed to a direction where they see AI technology as a supplement and for a better care for patients.

The potentials for AI in domains like healthcare are seemingly high, due to the large amounts of data and the promises for AI is tightly connected to the availability for relevant data (Derrington, 2017, p: 43) Celi et al (2017) Implicates that the perhaps the most important element towards building a medical culture is to create such culture where there is great awareness and respect for the potential power of data. This data is namely going to have great impact on both supporting and impacting research and practice in the field of medicine. To mention, due to the increased availability of big data, it is possible to achieve many things that was previously impossible. Such as: identifying trends in healthcare, prevent diseases, meet the struggles regarding social inequalities and so forth (Kao et al 2014 p:114) In order for the AI technology that analyses big data to work at its highest potential it is required to be used and interpreted by a human who has the expert knowledge in the field, experts in the fields are considered to be the important big data provider to the AI, from which it will learn and produce new “problems” or “questions” from humans to interpret and learn from. (Ruokaniemi & Rannanheimo, 2018) Therefor it is of high importance to invest in the people and their skills at the unit. By starting to educate people in learning them to deploy, maintain and operate AI systems. A team of data analysists and technical staff is preferable, but also including people with skills in areas such as project management, problem-solving skills and team management. (Celi et al, 2017). Further, Erickson et al (2017) emphasizes the essentiality of understanding the properties of ML tools because it will help ensuring it being applied in the most effective and safest manner. One example of the need to reskill clinical professionals due to the aspect of safety is according to Macrae (2019) when in some situations an AI system could provide the clinicians with an AI tool that occasionally refrains from providing a prediction and hands a task back to a deskilled clinician is unlikely to constitute a safe clinical system

Inclusion should also be an important to prioritizing, meaning starting to include healthcare professionals, nurses, doctors and other medical professionals, which are the ones who are in the need of becoming accustomed to work with the support of machines and AI tools (Bughin et al 2017, p:66). Wisskirhen et al (2017, p: 24) are also highlighting that employees should be involved in early phases of development and also in the whole change process, this gives the employees and the organization possibility to grow together with the new technology. Furthermore, social resistance is said to be the biggest barrier when it comes to adopting AI to a healthcare organization. A high barrier is to ensure that the healthcare professionals, such as nurses and doctors are comfortable using the new technology. (Krishna, 2017)
Celi et al (2017) highlights that it is of high importance to start accepting that he next half century will only keep increasing with the need of hybrid skills within this field, which will lead to inclusion within the field of medicine and data science. Furthermore, the inclusion should already begin in the core of curriculum in medical schools and also during residency training. A Few big questions to be solved regarding this topic is who, when, what and how is the training going to be established. Such trainings should include both medical students and residents and students from the field of data science.

Ho et al (2019) then again, are saying that it is argued that radiologists are the ones who should be driving and thereby taking a more active role in the transformation of medicine towards into the digital age since there are considerable discussions about whether AI applications will replace clinicians in the future and especially then radiologists. Ho et al (2019) are also saying that applications of AI will in the near future be adapted into such clinical workflows as PACS. Lee et al (2017) is also pointing out some problems identified within object matching in medical registration using ML methods. Though studies show promising results of recover objects location using ML models, matching the requirements for accuracy at images of 2D and 3D registration is not yet complete, which is required to be of high accuracy due to diagnostical and surgical purposes. According to Liew (2018) when it comes to radiology, as promising it might appear to be, the successful implementation of current ML is still some steps away. Liew explains that this is due to failure of the potentials promised from the technology, already in the implementation phase. Example of such cases are the implementation with the hospitals current IT systems have turned out to work poorly such as radiology information systems (RIS), EHR, and (picture and archiving communication systems) PACS.

Bughin et al (2017, p:36) are saying that in many cases, when implementing an AI technology to an organization, the greatest challenges does not concern the technical part. It is the change-management challenges, by this meaning the transformation from what people do to what or how they will be doing their work within an organization. A concern among radiologists highlighted by Liew (2018) is that when it comes to the discussion about changing their practices is the definition of which tasks are such tasks that should for instance be automated and which would remain as radiologist tasks. Another concern in also the perspective of patient privacy and safety, maintaining the principles of data privacy and patient safety. Further, according to Park & Han (2018) adoption of AI tools into clinical practices will evolve many hierarchical steps but should in the end be based on the best interests of patients.  Neill (2013) is saying that AI have the potential to make great improvement in many aspects regarding the whole process of patient care, for instance monitoring both safety and health at population level, discovering new knowledge within medicine, AI enables a more personalized treatments which can minimize side effects while maximizing the efficiency of a treatment when it is more targeted. Yet another aspect is diagnostical tests, which can also get more targeted and suggest the right recommendations of what test to take and with what sequences.

Rabbani et al (2018) thinks that as time will pass, both doctors and patients will eventually benefit from adapting ML methods into clinical practices, but it will require that these tools are being validated through future studies. Further Park & Kressel (2018) the fundamental purpose of adopting AI tools into medicine is the aim to achieve efficient care for patients, including safety, which is reliable on systematic validation of the technology using sufficient clinically designed research studies before the technology is integrated into clinical practice in order to avoid unintentional harm and cause harm within the patient safety aspect while ensuring patient benefits. Park & Han (2018) are saying that the absolute verification of a clinical predictive or diagnostic AI model is required to demonstrate its value of effects in patient outcomes and are achievable through carefully designed observational outcome researches or clinical trials.

This section contained some insights to possible challenges that could be pursued as barriers related to the topic of professional aspects, such as demands on the organization and the challenges and changes from doctors´ perspective when considering implementing AI and ML technologies into their organization. A brief introduction also about how attitudes and social resistance can have impact when considering such implementation. Aspects regarding how the clinical workflows and how such applications will affect patients was provided a brief introduction to. The following section will introduce to some insights in what might be challenges regarding ethical and legal aspect concerning the same topic.

### 2.3.2 Ethical and legal aspects

The increasing use of AI applications raises some responsibility questions regarding social, ethical and legal aspects. Other issues that needs to be taken into account are the economical, safety and educational issues regarding implementation of such technology. (Finnish Ministry of Finance, 2017). Hospitals, as the largest and most complex entities of healthcare, are therefore required to respond to different policy reforms and technological innovations. In doing so, they are faced with challenges regarding operational efficiency, costs or quality in the provision of medical and care services. (Bohmer, 2009)

Legal, regulatory and ethical risks are considered to be one of the biggest concerns the healthcare sector phases when it comes to accepting and adopting AI solutions into its organization. This is due to the uncertainty of effectiveness of AI technologies and some procedures could have been performed more successfully by a physician. In order to navigate these challenges, it might require adopting new approach to legal arbitrage and governance (Krishna, 2017). Bughin et al (2017) are also highlighting, as mentioned in the section above the importance of an organization reskilling their people and the processes in order to exploit AI rather than to compete with it. Some suggested steps towards this direction is to face the ethical, legal and regulatory challenges, which are key elements holding AI tools back in organizations like healthcare. Decision making within regulatory and legislative solutions may come to assure that the public and their health data will not be put at risk. (Yang & Chen, 2018)

There are also many ethical challenges regarding adopting AI in to healthcare organizations when it comes to making clinical decisions and making life saving choices. How can a machine make ethical or “human-like” decisions? What are the ethical criteria that should be programmed into the machines in order for the machine to make decisions like choosing between two lives that are in equal conditions? And how will the legal aspect been taking into consideration, why did the machine choose that approach and not the other one? (Krishna, 2017)

Richman (2018) are highlighting the fact that current regulations were developed for traditional healthcare delivery system and are therefore not suitable for new technologies, in this time of digital age. Instead of trying to apply current regulations and laws to fit this digital age, it is required that this issue is recognized by policy makers, technologies, healthcare providers and services and start considering the option of starting from the beginning in this matter concerning regulations for AI technologies in healthcare. Due to no established regulation or standards regarding implementation of algorithms in to clinical workflows are at time considered as obstacles for such implementation in this field (Rabbani et al, 2018 p:5) Regarding the same topic, according to Jiang et al (2017) though the attractions of AI within medical research, there are still barriers when considering implementing such solutions and the first to mention is the regulation issue. No established regulation which should guarantee the safety and impact for such system is still lacking. Ho et al (2019) are also saying that in order for the governance of AI to manage to achieve its normative goals, there is a crucial need for closer integration of laws, ethics and vital practices.

Another considered ethical obstacle is the aspects regarding data ownership, which includes the anonymization and protection of patient health data and at same time be easily accessible for doctors when needed and not accessible for those not authorized. To succeed proper regulation and new polices are required where these aspects are considered. (Rabbani et al, 2018)

In this topic some currently identified challenges and obstacles regarding ethical and legal aspects when considering implementing AI technologies into such organization as healthcare was introduced. The next section will introduce some economical and organizational aspects an organization like healthcare could experience as challenging when considering implementing such technology.

### 2.3.3 Economical and organizational aspects

Bughin et al (2017, p:34) suggests that the very first step towards successful adoption of AI technology and which adds value to the organization is to establish a solid AI business case and connect it to the organization´s strategy. For instance, Raghupathi & Raghupathi (2014) are saying that there are a lot of opportunities hidden in the healthcare data. By increasing association and understanding patterns and trends from this data by utilizing right sufficient technologies we have the possibility to make improvements on the patientcare, reduce costs and save lives. This requires people from the organization to look and to examine the proposed AI solution at its capabilities in the exact context about where and how the new solution is supposed to add value to the services that the organization is providing. This includes honesty and realizing its limitations, having knowledge about how AI works and also identifying and comparing how it differs from other formal technologies is very important and should be considered in the very first step. (Bughin et al, 2017)

The data an organization possesses and have access to are considered as very valuable and recognized as increasingly valuable assets for an organization. Knowledge about how and where the data is maintained it, is also considered as very important for organizations. This is due to that data is seen as the heart of an AI engine and is not possible to start without its heart. This mindset is of high importance for leaders, regarding their organizations possible future success. (Bughin et al, 2017 p:35) Healthcare providers processes regarding the collection and maintenance of the data are still considered as insufficient and are challenges needed to be solved when aiming for successful adoption of AI-related technologies. (Krishna, V. 2017)

As mentioned the data is considered as very valuable for organizations, as well is the quality of the data. The quality of such data becomes of high importance when we are discussing how AI tools are supposed to support data from EHR. This is an important step in the process of adapting AI into the workflows, because AI algorithms will react based on the quality of the data. (Derrington, 2017). Another challenge within this same topic about EHR are the challenges regarding current systems operating at hospitals. One example is the hundreds of different EHR systems, each with different data architectures. It is very difficult for providers to keep a single, comprehensive health record for a patient. The complexity of EHRs are considered to be the reason for integrations of many different EHRs within one hospital, meaning that getting a full patient medical history data is still a big challenge for any ML technology. (Krishna, V. 2017)

The potentials for well managed data can give the new insights in science, new sources of economic value and hold such as governments accountable (Kao et al 2014 p :114). Costs due to implementing AI into organizations are considered as high and in many cases even decisive for the decision of implementing these new technologies into a practice. Especially mid-size providers struggle with these costs and are waiting for implementing AI until it is more proven. It is also not only due to implementation costs but also maintenance and the required staffing, training and workflow changes due to full performance of the new technology in an organization which also can be considered as big investments. Some robotics for instance might need some instruments and accessories, which often are produced and replaced on per-procedure basis. As earlier mentioned the complexity of EHR, will also affect the financial part, since in many cases requirements on updates or changes when new technology is applied in to healthcare organizations are often required. (Krishna, 2017)

While planning implementing AI technology into an organization it is also very crucial in early phase to consider how the integration of this technology will support the organization to capture the expected benefits for the organization. In many cases this will require redesigning some AI insight processes into the workflow. In some workflows, this might mean involving automation or getting the right personnel who has the knowledge of the right data insight and has the capability of utilizing this. Either way what an organization decides to integrate, the human-machine interface will become a key factor in the workflow processes. (Bughin et al. 2017, p:36) Regarding cost of implementation, another interesting finding according to Krishna (2017), is that recent studies show that robotic surgery can cost up to 10 more than traditional surgeries, without evidence if the robotics had better patient outcomes than the traditional surgeries. There have though been incidents where the robotic surgery has led to some medical errors followed by legal costs for the healthcare provider. Another considered economic aspect when considering implementing ML for instance into radiology workflows, is that the ML algorithm is in need for large amounts of well-labelled images in order to train the models. To curate these models are seen as a highly time consuming and an expensive work. (Kohli et al, 2017)

According to Makridakis (2017) since AI and robotics shows great potentials in achieving or at least come close to human intelligence and can therefore be considered as a threat for jobs performed by humans during the coming 20 years. But Panch et al (2018) are claiming that fear of removing workforce in a sector like healthcare, due to implementation of AI are overstated. Hainc et al (2017) believes that AI within for instance radiology will more possibly lead to an augmentation, rather than replacement. According to Liew (2018) it is likely by applying AI into radiology and possibly making tasks of diagnosis more accurate and efficient, that it might have impact on reducing manpower. Liew (2018) implicates that this is due to less time being spent on tasks for a radiologist. If such scenario would appear in the future, it would be convenient to minimize these risks by starting to create new jobs with roles in healthcare for such employees that might be in the risk zone for such scenario. For an organization where AI is being utilized, it is important to invest in employees who has the potential to fill the gap between analytics and technical parts. Such employees should be able to form a unit with supporting machines and algorithms, this means coordinating them and to able to examine machines and software critically. Further, while investing in people who understands the technical part, it is also very important to develop an organization where also non-technical employees are supported and trained regarding interfacing with machines. (Wisskirhen et al. 2017.p:21)

Regarding the responsibilities of implementing new technologies and considering the economic aspects of it is according to Liew (2018) the CIOs or chief of data, line managers and department managers are such people that should be in charge of such implementation within a hospital. The duties of a CIOs also include to ensure that the system that is going to be implemented is able to integrate with the current IT systems and infrastructure, including buying the system and updates. When it comes to train the employees, for instance if a system is being implemented in radiology, it is considerable that the chief of radiology is the one ensuring the employees training of the system, including auditing before and after the implementation, ensuring patient safety. According to Bughin et al (2017.p:21) one of the biggest challenges when adopting AI technology into different sectors are about the ability to estimate how the new technology will potentially come to impact the sectors. Due to this, it is therefore challenging to evaluate and determine the great potential impact of AI for different sectors.

In this last section of the literature review regarding possible challenges that needs to be taken into consideration when an organization like healthcare are considering implementing AI or ML into its organization, which as presented above will come to have an impact on many aspects. The presented literature review will contribute as the framework for the questionnaire, which will be used as the data collection method for investigating if findings from the literature can be pursued as obstacles from a clinician´s point of view, who are the ones who could possibly in the future be working with such technology.

# 3 The Research

A scientific research is a way of solving problems seeking for clarifications of believes, rules, laws and principles of the research. A research is a creative process, which can be a theoretical, based on existing information or material, or the research can be empirical or observational. Empirical researches are based on theoretical methods, where the researcher is aiming to test if the hypothesis based on the applied theory can be realized in practical terms. Such hypothesis or research problem can be of different kind from solving a phenomenon, an effect, finding a solution or how something should be resolved, there are many different types of how an empirical research could be like. Within empirical research approaches the research can be separated into two main methodologies, quantitative or qualitative, which are also possible to combine in a research. This research is an empirical research, with a quantitative method as the chosen methodology. The distribution of these two types of scientific research can be visualized in the figure below. (Heikkilä, 2014, p:12-13)

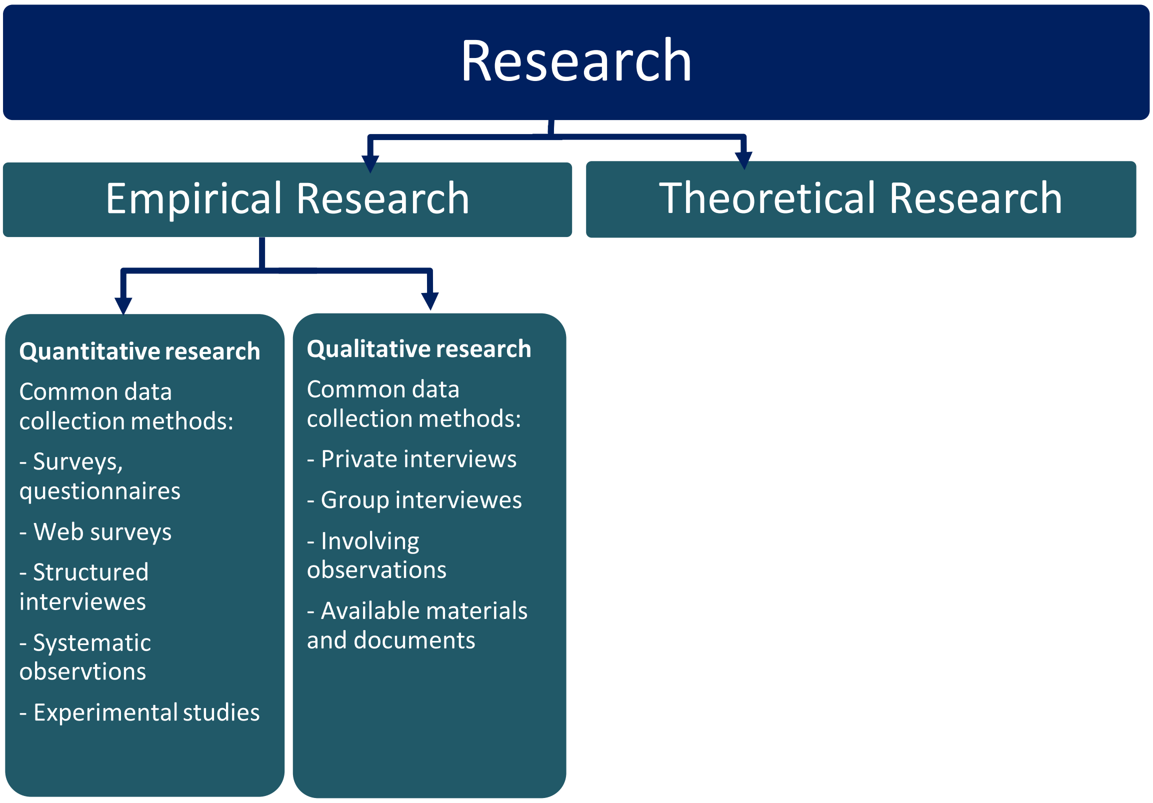


*Figure 4 - Scientific research methods*

The qualitative approach is often used in such research where the aim is to find purpose in people´s actions and what reasons are given for these actions (Gran, 2012, p:121) Generally, the main purpose in qualitative research is to help understanding the research subject, its acting and reasons for decisions (Heikkilä, 2014, p:15). Further as Gran (2012, p:121) says that qualitative approach helps finding functions and opinions in assignments, also finding purposes for concepts, sentences and voice actions. For instance, what is the purpose of using a screwdriver? In such sentence the purpose is asking for the meaning for using a screwdriver, purpose can also be used to find out if an action was considered successful or not. (Gran, 2012, p:121-122)

Qualitative research can also be called statistical research, since when utilizing this approach aims to measure results from questions by quantities and percentages. (Heikkilä, 2014, p:15). Quantitative method is about deciding the scope for specific qualitative features in the desired study unit, which requires such features that are possible to measure. Quantitative methods often consist of scope, quantities and strengths of things, processes and actions.

Qualitative method on the other hand focuses on what purpose actions are given due to how these actions are expressed. Quantitative studies should use concepts and hypotheses as starting point and then trying to find correlations between measurable features in the desired unit of study. (Gran, 2012.p:122-123) Below is a visualized table of the most significant differences between a quantitative and a qualitative method when conducting a research, table 1 is from Heikkilä (2014, p:15)

*Table 1 - Quantitative and qualitative*

| Quantitative | Qualitative |
|---|---|
| • Answers the questions: What?, Where?, How much?, How often? | • Answers the questions: Why?, How?, What kind of? |
| • Numerically large, representative sample | • Narrow, discretionary sample |
| • Describing a phenomenon based on numerical information | • Understanding a phenomenon, based on "soft" information |

This introduction to chapter 4 the "Research" introduced to what is considered as a scientific research and about the two main approaches to choose between when conducting a research, namely quantitative and qualitative methodologies, which are possible to combine in research. The chosen methodology for this thesis is empirical research, utilizing the quantitative approach. This was chosen due to achieve the objectives of this study, to test if the barriers found in literature can be pursued as obstacle among oncologists, pathologists and radiologists operating at hospitals. Therefor the following chapter will consist of an introduction about quantitative methodology.

## 3.1 Quantitative research

The quantitative research approach describes and analyses a phenomena or an effect by using measurement methods which are collecting numeric research data (Vilkka, 2007, p:14; Aira & Seppä, 2010, p:806). Quantitative research are studies about relations between measurable quantities of different kind and phenomena or features of different kinds. Qualitative research are studies about the meaning people ascribe themselves, their actions, others in a specific given setting. (Gran, 2012. p:122)

When utilizing a questionnaire as a data collection, the questions are often designed as structured questions. A Quantitative research is based on measuring and the result of such measurements are numeric values which contains observational studies that will be analysed with statistical methods and additionally being verbally explained. (Vilkka 2007, p:14) Survey as a research method are often used for data collection when conducting a quantitative research. In survey studies the common way of collecting data is made by using questionnaires or structured interviews. The questionnaires can be sent to respondents by letters or by e-mails. It is essential that each question is asked the same way for each respondent and that it is the same questionnaire each respondent is supposed to answer. In quantitative research it is also possible to use different kinds of registers as methods for collecting data. (Hirsijärvi et al 2006, p:125,128; Aira & Seppä, 2010, p:805-807) The questions used in a quantitative research are often not designed with open questions, with this type of method they are more constructive because of the need to make some classifications based on the answerers (Aira & Seppä, 2010, p:806). When conducting a quantitative research, it is essential to conduct a survey that is aimed for many people to answer. This kind of method is determinate to have access to a lot of data which requires amounts of answerers. When analysing the data, the research problem or question is going to be evaluated based on the collected data, the reliability and the validity for the study are depending on the amount collected data from the survey. (Heikkilä 2014, p:13)

It is possible to combine both qualitative and quantitative approaches in a research, in such research they are often applied in a sequential order. This can for instance in practice mean that observational data or semi structured interviews, which are considered to belong to the qualitative method is used for the purpose of exploring the hypothesis. After such, based on the findings conduct a larger epidemiological study, which would be a quantitative approach. Another example is for instance situations where the aim is to get better understanding of the findings from quantitative study, then a qualitative approach is added after analysing the findings from the quantitative phase. (Malterud, 2001, p:487)

Good quantitative research practices are achieved by implementing such good principles from the beginning. This includes developing a survey which is conducted by honesty, without favour and guaranteeing no harm to the respondents. Further, validity is a systematic method for measuring the absence of systematic errors, which should be done in an early phase in order to minimize the risk of resolving wrong things according to the research problems. Validity is hard to review in later phases in the research phase. The desired research problem or question should measure the thing that it is supposed to measure and nothing else, setting goals and measuring the validity will guide the researcher on the right path, such as ensuring data collection from right topics and establishing a survey within the right context for the targeted respondents. (Heikkilä, T. 2014 p:27) Reliability means accuracy of the results, meaning that the research results should not be random. A reliable research is required to be repeatable with similar results. Scientific results should not be generalized outside the qualification area of the scope. The researcher should be during the whole process critical and precise including in data analysis process after data collecting from a survey. This can be done when utilizing data analysing methods that the researcher understands. (Heikkilä, T. 2014 p:27)

## 3.2 Research process

To do a research is about studying a phenomenon and its relations, this applies to all research regardless topic. Research should not contain advertising for things, values, believes or to make a political stand beyond the values that should direct the scope of the desired topic for the research. A research is aiming to understand how things and actions are pursued in the world. (Gran, 2012, p:169)

To make a research often includes these 8 following steps:

1. Choosing a topic
2. Conduct a research problem and an eventual hypothesis.
3. Category selection for specification of the selected study object.
4. Choose the methodology and sources for data collection.
5. Data collection.
6. Analyzing data and see if the patterns in the data answerers the research question
7. Consider/evaluate the survey, strong and weak sides.
8. Conclusion

These 8 steps are presented by Gran (2012, p:171) who is also highlighting that these steps are optional, the researcher decides how to build up his or hers` research. This research utilizes a similar approach as Grans´, from Heikkilä (2014, p:23). The structure and the process are quite similar, the steps of this quantitative research process is visualized below in this chapter and was also introduced in the introduction chapter of this thesis.

The research process will be presented in more detail in the following figure 5, “The Research Process” at the next side, but first there will be an introduction about the road for the first phase, “Defining a research problem” for this work, which the figure below will start from.

The focus for this thesis was conducted in several phases together with the supervisor. In the first phase a lot of time went spending on what has been done in the field of AI and healthcare, after realizing the wideness of this area of interest a decision about what type of AI technology needed to be decided and the decision for ML technology was conducted. After deciding this, the next step was to identify what kind of areas in healthcare are currently using this kind of technology and here some main areas were identified through literature review, which therefore came to be the target groups for this thesis, namely oncology, pathology and radiology. While conducting the literature review for investigating the topic the discovering regarding that this type of technology is not yet much utilized, but these professions seems to be some steps ahead some other professions within medicine. This led to the decision for the last scope for this thesis, which is to map or to find out the possible challenges or barriers when considering applying ML as a tool into clinical practice for the targeted professions. The researcher has a background in the field of healthcare, but not in the specific fields of healthcare that are utilized in this work. Some familiarity to the type of work these professions are performing the researcher do have knowledge about, which also led to the interest for choosing this scope.

Phase 1

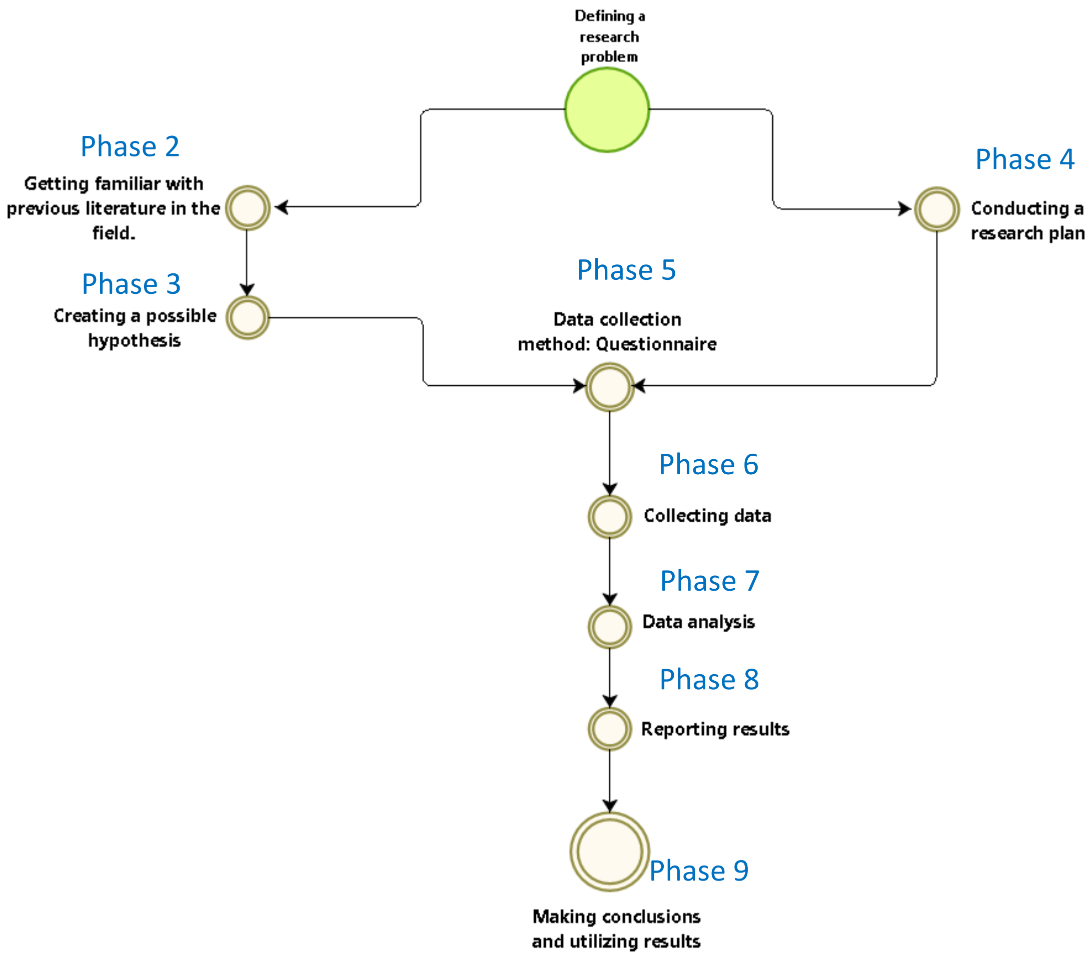


*Figure 5 - The research process and phases*

After the first phase was conducted, it is time for the second phase consisting of a comprehensive literature review of journals and articles containing "" ML" and "AI"-related topics in the healthcare sector including diagnostics was conducted, in order to get an understanding of what kind of solutions with this type of technology in this sector is currently available and what are considered being developed and these findings are presented in chapter 2, in "The literature review". In the third phase, "Creating a possible hypothesis" took place whereas identifying topics related to barriers for implementing such technologies into the healthcare sector and more specific, to the field of diagnostics within oncology, pathology and radiology took place. The objectives for this thesis was also developed in this phase, which also were presented in the introduction chapter and below:

1. How is AI and Machine Learning being applied into clinical settings today
2. What could be the potential barriers when implementing AI into clinical workflows.

3. Are the identified barriers from literature review possibly the same considered by clinicians within oncology, pathology and radiology when considering implementing machine learning into their clinical workflow.

The third phase was followed with the fourth phase “Conducting the research plan”, whereas the research plan was developed. The Central Hospitals in Finland was also contacted during this phase regarding applying for conducting a survey within their organization. Each hospital had their own procedures for how such application process which will be introduced in more detail in the next section “Target group”.

The fifth phase the “Data collection method” is conducted through a web-based questionnaire. In this phase the questionnaire was developed based on the findings from the literature review about identified challenges and barriers when considering implementing AI an ML into organizations like healthcare, which were presented in the last section of chapter 3. The questionnaire consists of statements, which are aiming to seek if the potential barriers when considering implementing ML into clinical workflow according to available literature can be considered as barriers according to clinicians within oncology, pathology and radiology at five Finnish Central hospitals. A more detailed description of the questionnaire will be introduced in this chapter in section 3.4 the “Questionnaire”. The sixth phase will consist of “Collecting the data”, which as mentioned will be utilized using a web- based survey tool, a tool called “Survey Monkey”. This will also be presented in this chapter in section 3.4.

The seventh phase will consist of “Data analysis” and will also be as the phase before, presented in this chapter, but in section 4.5. The data analysis consisting information about how the data captured from the questionnaire will be analysed. Finally the results from the survey will be presented in the eight phase “Reporting results” will consist of presenting the results gained from the data collection part, the web-based questionnaire. This will be presented in chapter 5 “Results”, which will be a chapter that is divided into two main sections. The first will consist of a total result review and the second will consist of analysing the findings correlated to the findings from the literature review going through each question one by one from the questionnaire.

For this research process to come to an end will take place in the ninth phase, which will consist of conclusion making for the research and will be presented in the 5$^{th}$ chapter “Conclusion” consisting evaluation of the research and suggestions for further research.

## 3.3 Target group

The target groups for collecting data in this research are oncologists, pathologists and radiologists operating at Central Hospitals in Finland. The participation for this research is completely anonymous, therefor the information about which hospitals has been participating will not be introduced in this work. The total amount of hospitals accepted to be a part of the study was 5 Central Hospitals. The conducted questionnaire for this research did not take stands at which hospital each respondent are operating at, this decision was made due to staying as anonymous as possible and the aim for this research is not to make any conclusion regarding where the respondents are operating.

A separate application for each hospital was made to each hospitals research unit applying to conduct a research at these selected hospitals, process and contact information was accessible at each hospital webpage. The application was sent in 5 different formats, but in general the hospitals expected a research plan and wanted a detailed description of how the data is being collected and presented and how their hospital will be affected from this research. This described application process took about 2-3 weeks per hospital. The researcher explained in the application about the web-based questionnaire which will be distributed to the desired target groups and guaranteeing the anonymity of both respondents and the hospitals, which will not be revealed. The researcher did not get any information about the respondent due to that the link to the web-based questionnaire was distributed to one selected person within the hospital organization who distributed forward the link by e-mail to the desired target group, namely oncologists, pathologists and radiologists working at the hospitals. The selected contact person from each hospital provided the researcher the information about the total amount of how many they had forwarded the link to. In order for the researcher to know the total response rate. A reminder about the survey was sent to the respondents after one week and the total response time came to be 2 weeks for each hospital. Meaning the respondents had 2 weeks access to respond to the questionnaire.

## 3.4 The Questionnaire

It is essential when developing a questionnaire that it is based on literature theory. It is nearly impossible to conduct a questionnaire without this basis. The study design and the concept are also precisely needed to be specified. (Heikkilä 2001, p:47-50) This basis is also conducted in this research process, the first step was to identify the topics through a literature review what could possibly be considered as challenges or barriers when considering implementing AI technology into organizations like healthcare. After this, conducting questions that could be relevant from the literature review within each topic and very important that questions in the survey should from the begging to the end reflect the overall research question. The language chosen for the questionnaire was Finnish, due to the target group working at Finnish central hospitals.

The statements in the questionnaire was carefully chosen and written in such format that the respondents would have a possibility to understand the questions, since it is not guaranteed that the clinicians are familiar with ML methods applied in clinical workflows. During the literature review and by continuously reflecting towards the scope of this thesis, the decision of topics in the questionnaire was conducted. These are the same topics introduced in the last chapter in the literature review, 3 topics; Professional aspects, Ethical and legal aspects and Economical and organizational aspects, consisting of 5 statement at each topic, a total of 15 statement was presented in the questionnaire.

The web-based tool used for collecting the data is a tool named "Survey Monkey". The design of the questionnaire was developed consisting of 4 pages, the first page contained a brief introduction to the topic of the research, about the researcher, practicalities, guaranteeing the anonymity and information about completely voluntary to participate. The questionnaire started with a brief introduction about the topic Machine Learning in clinical setting in order for the respondents to get an introduction about the topic for the questionnaire. In this introduction section, a brief introduction about the researcher and how the results are going to be presented was also introduced.

After this introduction section, the first question to the respondent was a question whether the respondent is operating as an oncologist, pathologist or as an radiologist, a question with these three options was given with only 1 possible option to choose.

After this introduction page and this one question, the questionnaire continues with 1 side per topic, consisting of 5 statements.  The 3 topics identified from the literature review are:

1. Professional aspects
2. Ethical and legal aspects
3. Economical and organizational aspects

The table 2 below will show the 15 statements asked in the questionnaire. Which are developed by the researcher based on the findings from the literature review and then designing the statements to such considered format that could be interpreted for clinicians reflecting their environment.

*Table 2 - Table of statements from the questionnaire*

| **Statement** |
|---|
| 1.1 There is enough scientific research to show that machine learning can support high quality diagnostics |
| 1.2 Machine learning technology can make diagnostics more efficient |
| 1.3 Machine learning technology can provide more accurate diagnostics. |
| 1.4 It is not a hindrance to the use of machine learning in diagnostics, due to the required new technical expertise |
| 1.5 Patients are positive about machine learning technology being utilized in their diagnostics |
| 2.1 It is ethically correct to let the machine learning do parts of diagnostics |
| 2.2 It is ethically right to use machine learning technology to assist doctors in decision-making in diagnostics |
| 2.3 It is ethically correct to allow machine learning technology to make decisions for a doctor in diagnostics |
| 2.4 According to patient safety legislation it is accepted to use machine learning in diagnostics |
| 2.5 Machine learning can make more effective decision-making on the basis of clinical data produced by clinical work within the current legislation. |
| 3.1 There is sufficient evidence of the cost benefits of utilizing machine learning in diagnostics |
| 3.2 The use of machine learning technology can reduce the number of administrative personnel needed |
| 3.3 The cost of implementing machine learning is not considered as a barrier for our unit |
| 3.4 The use of machine learning technology can reduce the number of doctors required |
| 3.5 Utilizing machine learning in diagnostics is changing our way of working, which is not seen as an obstacle |

Each statement is answered by choosing the most suitable option according to the respondent, utilizing the 5-likert scale from 1= “Strongly disagree”, 2= ”Disagree”, 3= “Cannot say”, 4= “Agree” and last number 5= “Strongly agree”. It is possible to only choose one option per statement. The questionnaire utilizes this method through the whole questionnaire, meaning no other answering possibilities. It is not possible to leave an empty answer, meaning the respondent must choose an option for completing the questionnaire.

The Likert-scale, from 1932 was developed as a method for measuring attitudes about specific groups, concepts or institutions. It is also common that researchers tend to develop their own scales for measuring values or attitudes, but there are a number of existing standardized scales for different measurement for several kinds of attitudes, such as social responsibilities which Likert scale can be utilized within. The term Likert scale can be used in two ways:

1) The summated scale way is to be constructed by developing a number of statements about a certain topic and are intended to provide statements to be consider as representative samples of all possible attitudes and options about the given topic. These statements are supposed to be clearly favourable and some clearly unfavourable. These statements are answered by rating each statement from strongly disagree to completely agree by a group of people.

2) To compute the summated scale, the chosen scale for this questionnaire, is for the individual items or rating scales, whereas the summated scale is computed. Such Likert items are also presented statements regarding a specific topic but the participants are given the options for answering as: strongly agree, agree, can´t decide, agree or strongly agree. In order compute these summated scale score, a numerical value is given to each answer, often 1 for strongly disagree heading up to 5 for strongly agree. If some statements are considered to be presented as negatively or written with unfavourable tone, the items should have reversed weighting, meaning 1 for strongly disagree and 5 for strongly agree. (Gliner et al 2017, p: 224)

The aim of this study is based on a quantitative methodology identify if the presented statements in the questionnaire could be possible challenges or barriers when considering implementing ML as a tool for clinicians in the field of oncology, pathology and radiology and if there are any identifiable differences between these three professions.

## 3.5 Data analysis

While conducting a quantitative research, the aim is to test the differences mathematically on the hypothesis, often also combining statistical measurements. The proper against converter is defined based on the research question and the research material, which will provide the requirements for the converter for each research. (Arja & Seppä, 2010p:806)

The chapter 3 contained information about the research methodology, what approaches are utilized, a comprehensive presentation about the research process, the target group for this thesis was also introduced and at the end a section about the development of the questionnaire and how the data captured from the survey will be analysed was presented in this chapter. The following chapter will consist of analysing the results based on data collected from the survey. The data analysis from the questionnaire will be made by using Excel and Powerpoint for visualizing the results. In the following chapter, the section regarding "Results in total" will be presented with a figure about total respondents and tables visualizing how the answerers are distributed and how the three professions of respondents have chosen their answer. Each statement will be analysed each statement one by one within the topics in the following chapter.

# 4 Results

The aim for this thesis is to identify potential barriers when considering implementing ML as a tool for clinicians in the field of oncology, pathology and radiology. The considered barriers introduced in the survey are based on the theoretical framework, which was introduced both in the literature review chapter and in chapter 3. These barriers or challenges are according to available literature about when considering implementing AI and ML into organizations like healthcare. The aim of this thesis and the research question is to test if these barriers from the literature review could be considered as barriers according to clinicians within Oncology, Pathology and Radiology operating at Central Hospitals in Finland. The quantitative method, utilizing a web-based survey is the methodology used for testing if the potential barriers and challenges according to literature could be the barriers according to this target groups.

The results from this survey will be presented in this chapter first looking at the overall results and then each question one by one within the topic as presented. The 3 chosen topics will not serve as a group of questions, the reason for using topic was to structure the question and the questionnaire based on the findings from the literature review. Meaning no conclusion or analysis of topic as such will be made.

## 4.1 Results in total

The selected contact person from each hospital provided the researcher with the information about how many clinicians the link to the survey was sent to. The link to the web-based survey was sent to 81 clinicians from 5 Central hospitals in Finland. The total amount of respondents for this survey came to result in 32 clinicians, from whom 4 are pathologists, 13 oncologists and 15 radiologists. This means a total of 39,5% response rate. According to Punch (2003) when utilizing such data collecting method that is distributed through mail the response rates are often between 30-40% or sometimes even less. The question that arises regarding low response rate if the responses received are the representatives of the samples or could they somehow be biased. A visualized figure below of the total responses from the data collection:

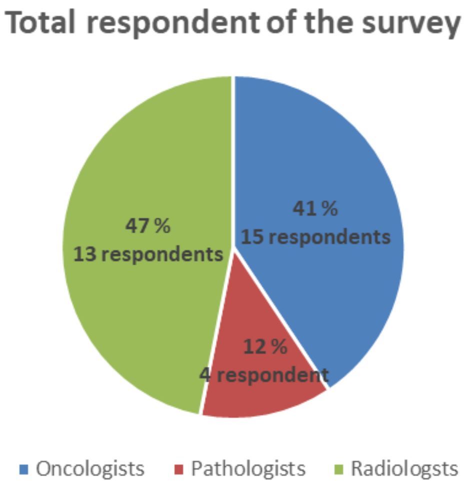


*Figure 6 - Total respondents of the survey*

As presented in the chapter above regarding these topics introduced in the questionnaire not being analyzed as a group consisting of these presented 5 statement per group. Therefor it is convenient to analyze them as one question each and not part of the presented topic. This means that the questions will be analyzed one by one and not making any conclusions about one topic as such. Thus, when analyzing each question, the questions will be presented according to the topic as in the questionnaire.

Since the low amount of responses for this study it is not possible to draw conclusions about the different fields and not possible for generalizing either. Though the respondents were due to answer within which field they operate in oncology, pathology or radiology the results analysis will look at them as a group and bring out differences between the fields when such appears.

As earlier mentioned in chapter 3 in the section about the questionnaire, the questionnaire starts with a brief introduction to the topic of the thesis and about the researcher. After this introduction, the respondents are asked to answer whether he or she operates as a pathologist, oncologist or a radiologist. After this, the questionnaire follows with a total of 15 statements, 5 statements per side, which are answered by using the 5-likert scale method. The scale is the same at each statement and looks like this:

1. *Strongly disagree*
2. *Disagree*
3. *Cannot say*
4. *Agree*
5. *Strongly agree*

First introduced will be the topic about concerning Professional aspects, containing the five statements related to this topic. The second topic Ethical and legal aspects and the third topic is Economical and organizational aspects, each topic including 5 statements.

The table 3 below will show the overall answers in percentage by chosen option of answerers by the respondents. The statement is in the column to the left, after this are the columns of answering options according to the scale 1 to 5, after this a column of total respondents for the statement and the column at most at right represent the median. The median is a value representing the middle of a set of variables, meaning it is the value that separates the lower half and the higher half of a data sample (Heikkilä 2014, p:278).

*Table 3 - Total review of answers*

| **Statement** | **1 Strongly disagree** | **2 Disagree** | **3 Cannot say** | **4 Agree** | **5 Strongly agree** | **In total** | **Medi-an** |
|---|---|---|---|---|---|---|---|
| 1.1 There is enough scientific research to show that machine learning can support high quality diagnostics | 2 | 7 | 9 | 13 | 1 | 32 | 3 |
| | 6,3 % | 21,9 % | 28,1 % | 40,6 % | 3,1 % | | |
| 1.2 Machine learning technology can make diagnostics more efficient | 1 | 0 | 2 | 21 | 8 | 32 | 4 |
| | 3,1 % | 0,0 % | 6,3 % | 65,6 % | 25,0 % | | |
| 1.3 Machine learning technology can provide more accurate diagnostics. | 0 | 4 | 2 | 23 | 3 | 32 | 4 |
| | 0,0 % | 12,5 % | 6,3 % | 71,9 % | 9,4 % | | |
| 1.4 It is not a hindrance to the use of machine learning in diagnostics, due to the required new technical expertise | 0 | 7 | 6 | 16 | 3 | 32 | 4 |
| | 0,0 % | 21,9 % | 18,8 % | 50,0 % | 9,4 % | | |
| 1.5 Patients are positive about machine learning technology being utilized in their diagnostics | 0 | 1 | 26 | 5 | 0 | 32 | 3 |
| | 0,0 % | 3,1 % | 81,3 % | 15,6 % | 0,0 % | | |
| 2.1 It is ethically correct to let the machine learning do parts of diagnostics | 0 | 3 | 1 | 26 | 2 | 32 | 4 |
| | 0,0 % | 9,4 % | 3,1 % | 81,3 % | 6,3 % | | |
| 2.2 It is ethically right to use machine learning technology to assist doctors in decision-making in diagnostics | 1 | 1 | 0 | 15 | 15 | 32 | 4 |
| | 3,1 % | 3,1 % | 0,0 % | 46,9 % | 46,9 % | | |
| 2.3 It is ethically correct to allow machine learning technology to make decisions for a doctor in diagnostics | 22 | 6 | 3 | 1 | 0 | 32 | 1 |
| | 68,8 % | 18,8 % | 9,4 % | 3,1 % | 0,0 % | | |
| 2.4 According to patient safety legislation it is accepted to use machine learning in diagnostics | 2 | 1 | 25 | 3 | 1 | 32 | 3 |
| | 6,3 % | 3,1 % | 78,1 % | 9,4 % | 3,1 % | | |
| 2.5 Accoridng to current legislation it is right to utilize machine learning for decision making baded on clinical data produced in clinical work | 1 | 0 | 13 | 17 | 1 | 32 | 4 |
| | 3,1 % | 0,0 % | 40,6 % | 53,1 % | 3,1 % | | |
| 3.1 There is sufficient evidence of the cost benefits of utilizing machine learning in diagnostics | 1 | 16 | 11 | 4 | 0 | 32 | 2 |
| | 3,1 % | 50,0 % | 34,4 % | 12,5 % | 0,0 % | | |
| 3.2 The use of machine learning technology can reduce the number of administrative personnel needed | 3 | 11 | 13 | 4 | 1 | 32 | 3 |
| | 9,4 % | 34,4 % | 40,6 % | 12,5 % | 3,1 % | | |
| 3.3 The cost of implementing machine learning is not considered as a barrier for our unit | 2 | 1 | 11 | 18 | 0 | 32 | 4 |
| | 6,3 % | 3,1 % | 34,4 % | 56,3 % | 0,0 % | | |
| 3.4 The use of machine learning technology can reduce the number of doctors required | 7 | 17 | 6 | 2 | 0 | 32 | 2 |
| | 21,9 % | 53,1 % | 18,8 % | 6,3 % | 0,0 % | | |
| 3.5 Utilizing machine learning in diagnostics is changing our way of working, which is not seen as an obstacle | 0 | 4 | 3 | 21 | 4 | 32 | 4 |
| | 0,0 % | 12,5 % | 9,4 % | 65,6 % | 12,5 % | | |

The following 3 figures will show a distribution among the professions at each statement within each topic. Meaning the first figure will consist of 5 statements within the "Professional aspects topic" and the figure after that consisting of 5 statements within the topic "Ethical and legal aspects" and the last figure will consist of the 5 last statements within the topic "Economical and organizational aspects". First introduced is figure 7, then figure 8 and at last figure 9;

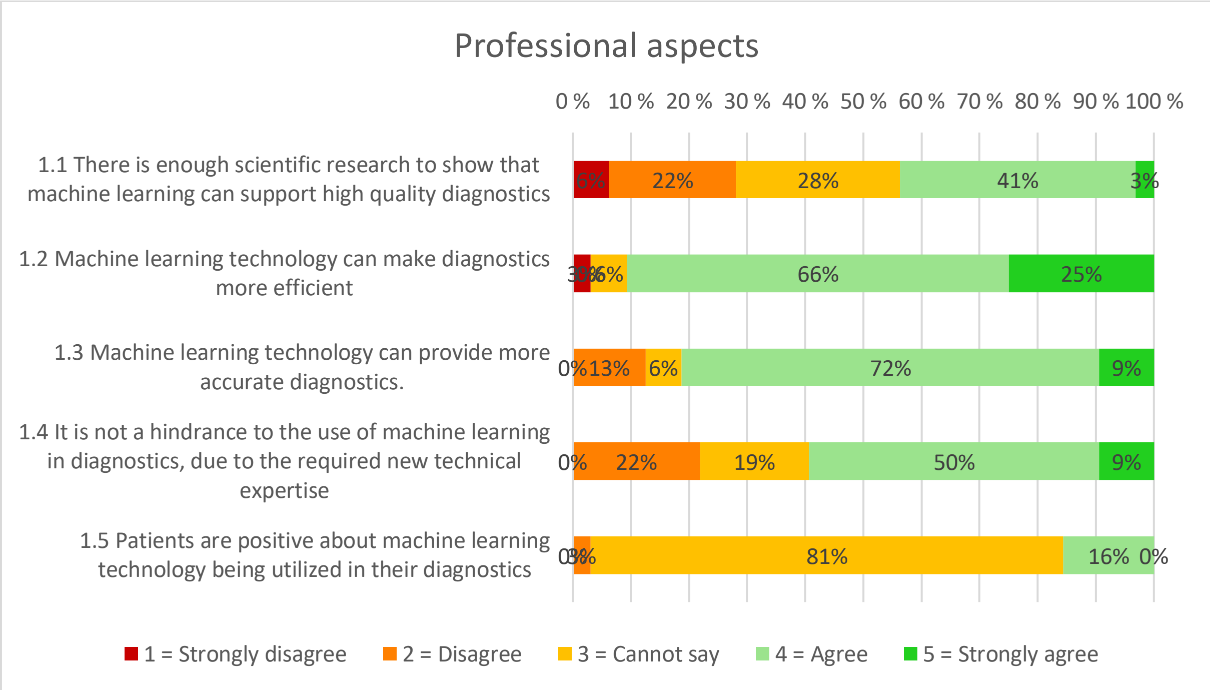


*Figure 7 - Results from topic "Professional aspects"*

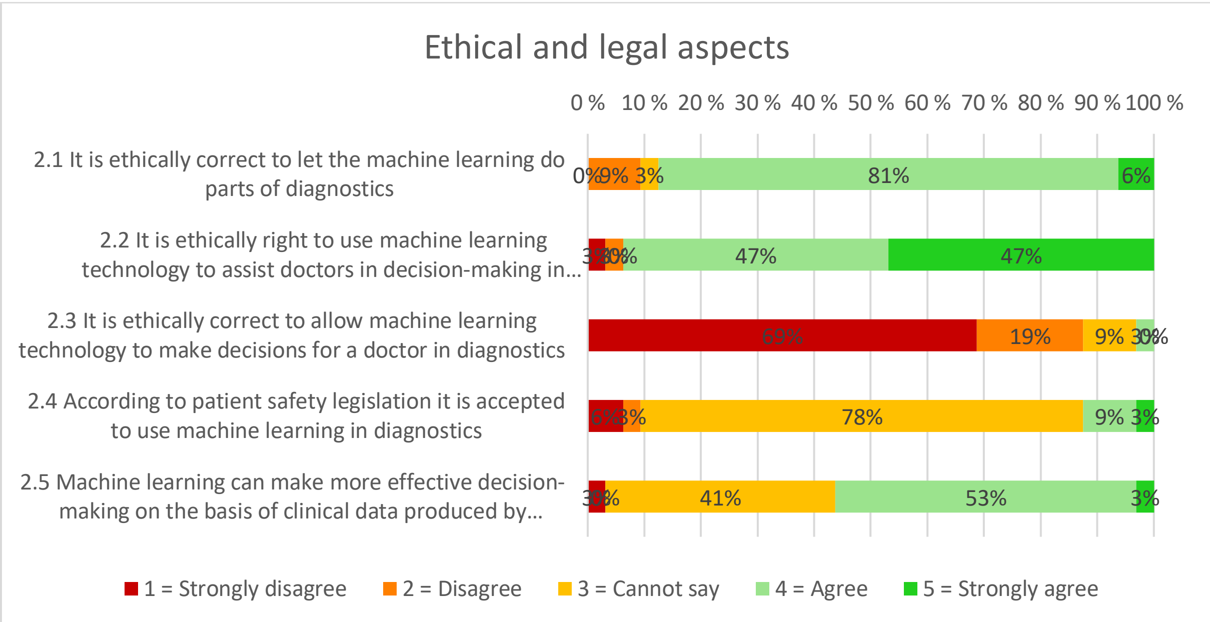


*Figure 8 - Results from topic "Ethical and legal aspects"*

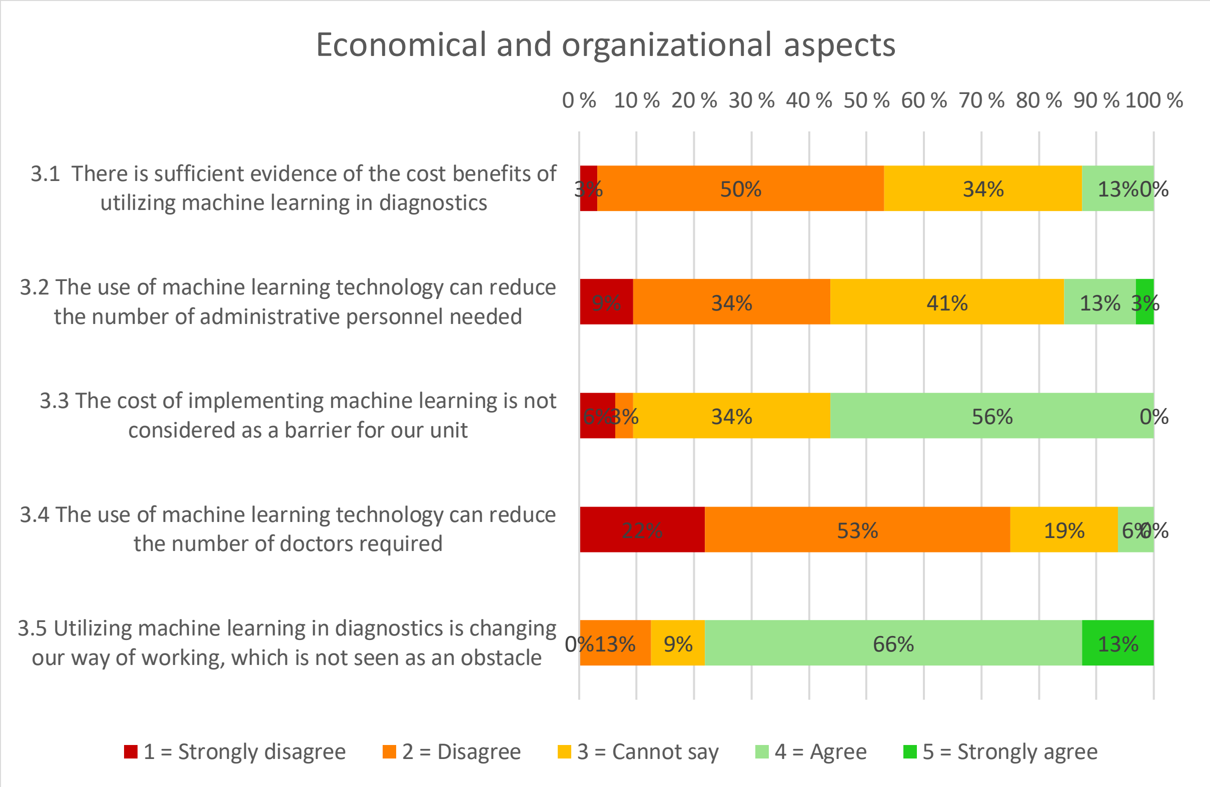


*Figure 9 - Results from topic "Economical and organizational aspects"*

After this introduction about the total answerers review from the survey conducted in this research, the following section within chapter 4 will come to consist of analyzing each statement one by one from the questionnaire. At each statement there will be presented a figure visualizing how the answerers were distributed by profession and by respondents in total and if differences among the profession are to be discovered will also be analyzed.

## 4.2 Professional aspects

In the professional aspect topic, the aim was to find out if these presented statements could be pursued as barriers when considering implementing machine learning in to clinical workflows by the respondents participating in this survey. Five statements were asked within this topic. Each statement will be presented and analyzed by an own figure where a total review of answerers is presented and a distribution of answerers according to profession; radiologists, oncologists and pathologist. Each statement is presented one by one. The first statement was asked as followed:

**"There is sufficient scientific research to show that machine learning can support high-quality diagnostics".** The results from this statement visualized in figure10 below.

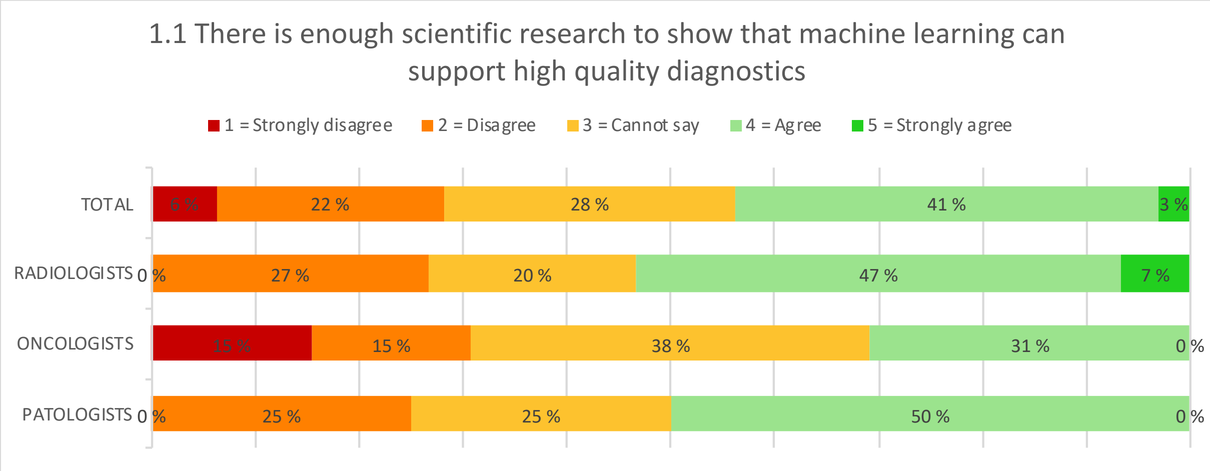


*Figure 10 - Results from statement 1.1*

The figure 10 “Results from statement 1.1” shows the results from the first statement. Only 6% answered “Strongly disagree”, 22% answered “Disagree”, 28% answered “Cannot say”, the statement “Agree” did receive 41% from all of the answers and the lowest at 3% for the answer “Strongly agree”. This figure shows that most of the answerers are between disagree, cannot say and agree but the most answers were given to the option “Agree” to this statement. As can be seen in the figure, the ones answering “Strongly disagree” were oncologists. Since the low amount of responses, no conclusion can be made, but the majority for oncologists within this statement lies on “Cannot say”. These answerers from this statement agrees well with findings from previous literature, for instance Derrington (2017, p:15) is saying that AI-based tools still lack comprehensive basis of experience and validation in medical practices. There are a lot of possibilities by adopting these tools but there are still actions needed in order to get acceptance into formal medical practice. Further according to De Bruijne (2016) ML techniques are increasingly appearing to take over successfully the fields of disease prognosis, image-based diagnosis and risk assessment, but there are still many practical and scientific challenges that needs to be treated in order to gain the full potential from this implementation of such technique. Liew (2018) is saying that relatively few departments in research and academic centers have so far being participated in both AI research and user acceptance testing.

Regarding the oncology aspect, Kournou et al (2015) are saying that though it is obvious that by utilizing ML method it is possible to improve the understanding about cancer progression, there is still a need for suitable level of validation before these methods can be integrated into clinical practice in everyday work. Rabbani et al (2018) is also highlighting that by integrating ML methods into clinical practices, both doctors and patients will in the future benefit from this, but these tools are determinate to be validated thorough future studies.

Further also Cabitza et al (2017) are saying that is very likely that healthcare sector will soon be transformed, due to ML techniques in valuable ways, but it might come with a cost of negative consequences which could be both reduced and managed with the help of further research of the effects of the consequences.  As earlier mentioned in the literature review within the section of AI in healthcare. Research within AI in medicine has truly expanded and has thereby come to prove the need for research patterns, as well as trends within the field of AI in medicine. (Tran et al, 2019)

It is possible to implicate that it is also according to literature no doubt about ML technologies might still be pursued as not enough scientific evidence to prove that such technology can support high quality. The need for validation is still needed. Though a 44% of answerers choose the option “agree” for this statement, which can have impact of the differences of knowledge within this field among the respondents.

The second statement within the first topic was presented as followed:

**“Machine learning technology can make diagnostics more efficient”,** answerers illustrated in the figure below.

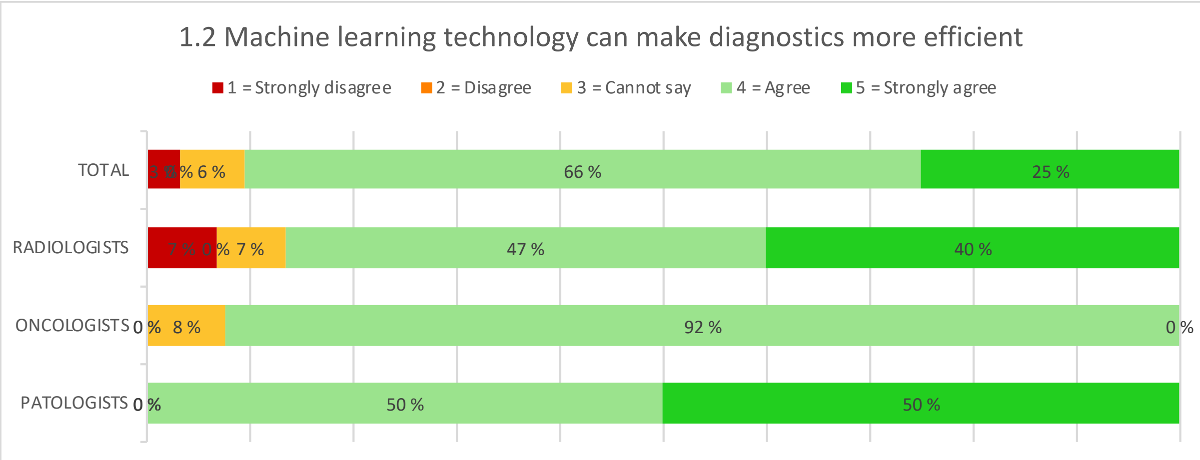


*Figure 11 - Results from statement 1.2*

Answerers to this statement as shown in figure 11 “Results from statement 1.1” above and as shown only 3% answered “Strongly disagree” and no responses for the option “Disagree” was given, therefor 0% for this answer and is not in the figure. 6% answered “Cannot say” and a total of 66% answered “Agree” and 25% “Strongly agree” to this statement.  The majority as shown lies more at the answers “Agree” and “Completely agree” for the statement “Machine learning technology can make diagnostics more efficient”. No significant differences between the professions are to be discovered, only that none pathologist answered “Cannot say”, their answerers are equal at “Agree” and “Strongly agree”. Another finding is that the only profession answering “Strongly disagree” to this statement were radiologists, though only 7%.

Diagnosis made by computer-assistant enables early-stage identifying of diseases and will have an impact on improving patient outcomes. These findings collaborate with findings from literature, such as AI methods enables more personalized treatments and suggest when right kind of diagnostical test is needed for a patient and contributing in minimizing side effects while increasing effects from a treatment. (Neill, 2013) Rabbani et al (2018) are saying that the main goal by utilizing ML into clinical practices is to provide at time, consistent and a personalized treatment plan regarding the patient treatment. Though, the decisions of adopting AI tools into healthcare should be demonstrated by important clinically improvements in patient outcomes. Meaning a predictive or a diagnostic AI tool should require value demonstration of effects of patient outcomes. (Cabitza et al, 2017)

The third statement within the first topic: **“More accurate diagnostics can be achieved with machine learning technology”**, answerers for this statement presented in the figure 12 below.

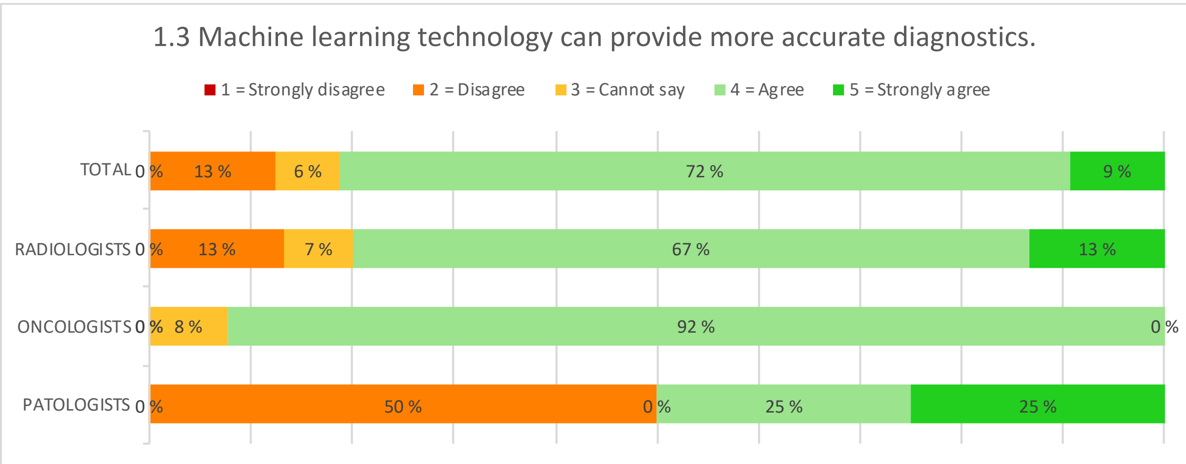


*Figure 12 - Results from statement 1.3*

As shown in figure 12 “Results from statement 1.3” none answerers were given to “Strongly disagree”, therefor not in the figure. 13% answered “Disagree”, only 6% answered “Cannot say”, but a total of 75% answered “Agree” followed by 9% answered “Strongly agree”. According to the results for this statement a clear majority is the option “Agree” among the respondents for this statement. No significant differences between the professions are to be made conclusions about, accept that no oncologist answered “Disagree”, their answerers are clearly at the “Agree” option. These results agree well with findings from literature, such as Rabbani et al (2018) are saying that by implementing ML methods into clinical practices, it is possible to implement research findings immediately which enables the clinicians to receive individual classifiers and predictive features for each patient, which are considered as great potentials also for approaching more personalized treatments for patients. Further Kournou et al (2015) are saying that probably the most challenging and most interesting task is the prediction of accurate disease outcomes. Due to this ML has become a convenient tool for research within medicine, since its ability to recognize patterns and relationships from such complex data and are therefore also an efficient tool for predicting future outcomes, example of such is what type of cancer a patient might have. However, the development of ML into clinical settings are still considered as being at a beginner. This is due to many possibilities of techniques and parameters to be utilized makes it difficult to estimate how accurate they will perform in clinical context, such as the possibility for biases. (Challen et al, 2019, p:236) Though ML are operating on big data and by increasing the sample size does not make a system protected from biases if there are lacking essential clinical measures of variables. For instance, if the model is estimated with data from electronical medical journals alone, the likelihood of being biased is quite high due to missing information about such as basic diseases. Meaning it is of high importance to consider these when considering the purpose of a ML system and what kind of accuracy is the desired outcome from such model. (Crown, 2015)

The fourth statement within the first topic, professional aspects were asked as followed: **"It is not a hindrance to the use of machine learning in diagnostics, due to the required new technical expertise"** and answerers for this statement is visualized in the figure 13 below.

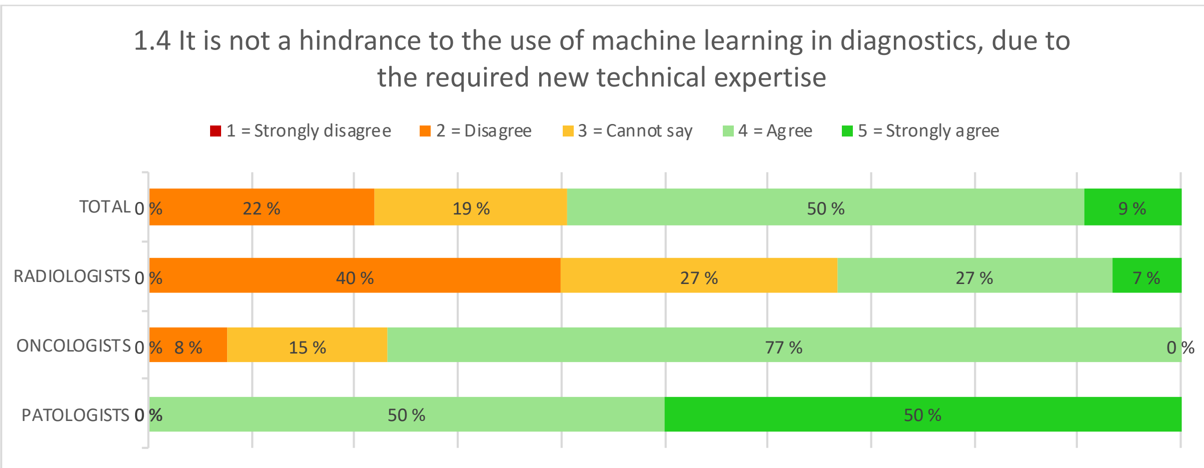


*Figure 13 - Results from statement 1.4*

Same as the statement before, none answerers for "Strongly disagree", therefore not visualized in figure 13. 22% answered "Disagree ", 19% answered "Cannot Say", 50% of all answerers were given to the option “Agree” and 9% for the answer “Strongly agree”. Same for this statement as the statement before, the majority of answerers is located on option “Agree” for this statement. Some differences among the professions are possible to identify, namely the majority of answerers by radiologists are given to the option “Disagree” while the majority for this answer lies on the option “Agree” and equal of 27% of answerers were given to option “Cannot say” and “Agree” for this statement. Which is an interesting finding since according to findings from literature there are suggestions about radiologists becoming the one´s between AI and clinicians. Further according to Erickson et al (2017) within Radiology ML is already being applied in practice and there the growth is expected to grow rapidly. Liew (2018) is saying that due to radiologists possesses capabilities to make clinical assessments based on data and are therefore potentially going to exceed diagnostic algorithms in this field, which will make radiologists suitable in a role between the AI technology and radiologists. Further, Jha & Topol (2016) considers the main purpose for both radiologists and pathologists to interpret and extract information from medical images are therefore considered as “information specialists”. Many of such tasks could be performed by an AI.

Krishna (2017) emphasizes the aspect of social resistance, which is said to be the biggest barrier in the scope of adopting AI into a healthcare organization. A high barrier to overcome is to ensure that the professionals, such as nurses and doctors are comfortable using the new technology. Wisskirhen et al (2017 p: 24) are also highlighting that employees should be involved already early in the development phase and in the change process, which will possibly contribute to employees and the organization to grow with the new technology themselves. Char et al (2018) are saying that clinicians who ML systems have the potential to become more educated about how it is developed and its construction including its data sets and about its limitations. By staying ignorant about ML system and its constructions could lead to outcomes that are considered as ethically problematic. Erickson et al (2017) emphasizes that is essential to understand the properties of ML tools because it will help ensuring it being applied in the most effective and safest manner.

In conclusion according to Celi et al (2017) it is important that both the domain of medicine and data science are starting to connect already at medical school level. Meaning also that clinicians should not experience their being replaceable by another domain with no return from. The connection of both domains are crucial, meaning that data scientist are not supposed to discover new knowledge and develop predictive algorithms in isolation from the domain of medicine, the goal should be to develop a place for both domains in order to discover and providing the necessary with the common goal of providing and improving excellent clinical systems that enables excellent care for the populations and individuals, at every step of the care.

The last statement within the first topic, goes as followed **“Patients are positive about machine learning technology being utilized in their diagnostics”** and the results are presented in the figure 14 below.

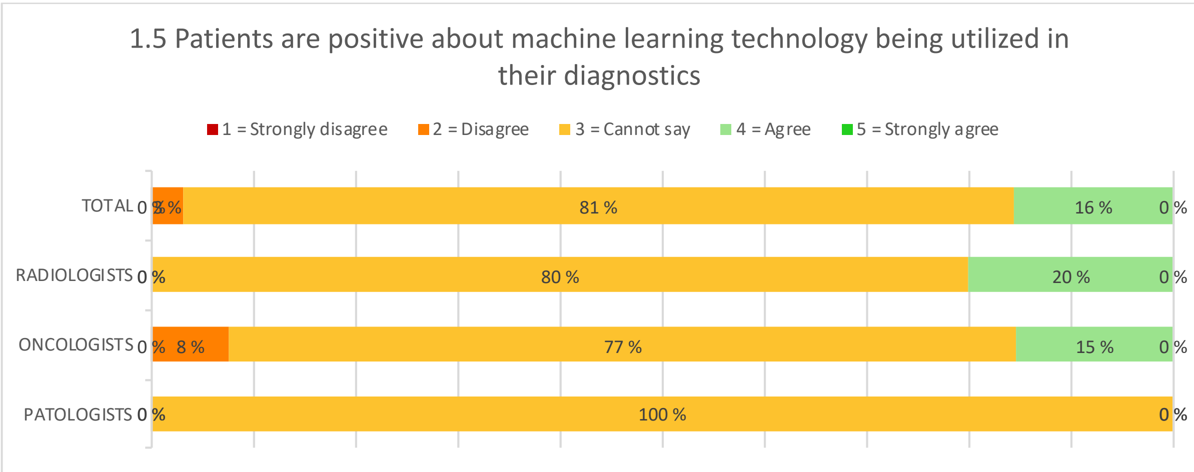


*Figure 14 - Results from statement 1.5*

As shown in figure 14 “Results from statement 1.5” as the two statements above, none answerers
were given the option “Strongly disagree”. Only 3% answered “Disagree” and a total 81% answered “Cannot say”, 16% answered “Agree” and 0 answerers were given to the option “Strongly agree”. As shown in the figure the majority for this statement is according to the results
“Cannot say”. No significant differences between the professions can be discovered, except pathologists only answered “Cannot say” for this statement.

The aim with this statement was to identify if there are potential barriers to be considered about the thoughts of patients´ regarding technology being applied into their clinical process. According to Richman (2018) the fundamental elements of regulations in healthcare might need to rethink these elements. For instance, a such aspect who will come to have the responsibility of monitoring the quality of care or decisions for a patient. In the traditional clinical practice, a doctor and a patient establish a relation when they meet face to face and by establishing this relationship, this doctor will have the responsibility of the care for this patient. In the digital world, who will carry this responsibility and will the patient accept to be treated by an algorithm or with a doctor he or she has never met. Chat et al (2018) believes that such challenges regarding questions about the trust relationship between patients and ML systems and the potentials for biases are aspects that needs to be targeted quickly. Further Park & Han (2018) are saying that adoption of AI tools into clinical practices will evolve many hierarchical steps but should in the end be based on the best interests of patients.

This chapter provided the results gathered from the questionnaire in a topic called "Professional aspects" and where analyzed by each question one by one and none conclusion about the topic as such can be made. The next section will introduce the results from the questionnaire consisting of also 5 statement, but regarding ethical and legal aspects within implementation of ML.

## 4.3 Ethical and legal aspects

Ethical and legal aspects is the second topic in the survey. This topic is aiming to identify if these presented statements could be pursued as barriers within the perspective of ethical and legal aspects when considering implementation of ML into clinical workflows, according to the respondents in this survey. Five statements were asked within this topic. Each statement will be presented and analyzed by an own figure where a total review of answerers is presented and a distribution of answerers according to profession; radiologists, oncologists and pathologist. Each statement is presented one by one, as the topic introduced before.

The first statement in this topic was presented for the respondents as followed:

**"It is ethically correct to let the machine learning do parts of diagnostics",** answerers illustrated in the figure below .

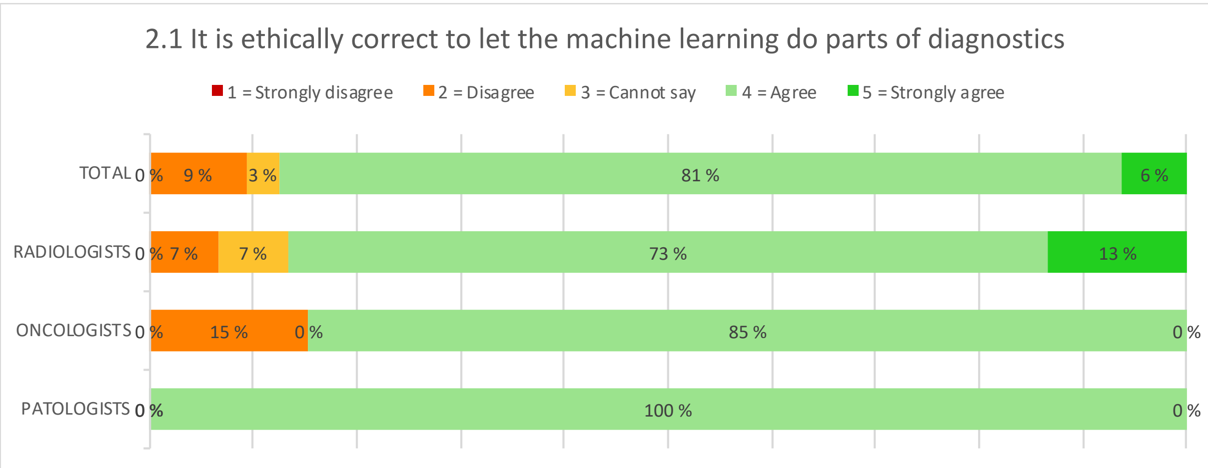


*Figure 15 - Results from statement 2.1*

As shown in figure 15, 0% of answerers were given to the statement "Strongly disagree", therefor not visualized in color in the figure. 9% answered "Disagree" and 3% answered

“Cannot say”. A total 81% of the answerers were given to the answer “Agree”, which is a clear majority for this statement and 6% answered “Strongly agree”.

Which is an interesting finding since this thesis aims to find if the presented statements can be possible barriers for implementing ML into diagnostics, it is possible to implicate that these respondents do not see it as an obstacle that a ML technology could possibly in the future be making parts of their diagnostic processes. Then again, according to Krishna (2017) due to the still uncertainty of AI technologies effectiveness and that some procedures could have been performed more successfully by a clinician. This makes the legal, regulatory and ethical risks the biggest concerns the healthcare sector phases when it comes to accepting and adopting AI solutions into its organization.
No significance differences between the professions are to be discovered, except Pathologist only answering “Agree” to this statement.

The second statement in the topic “Ethical and legal aspects” was presented as followed: **“It is ethically right to use machine learning technology to assist doctors in decision-making in diagnostics”** and illustrated figure of answerers below.

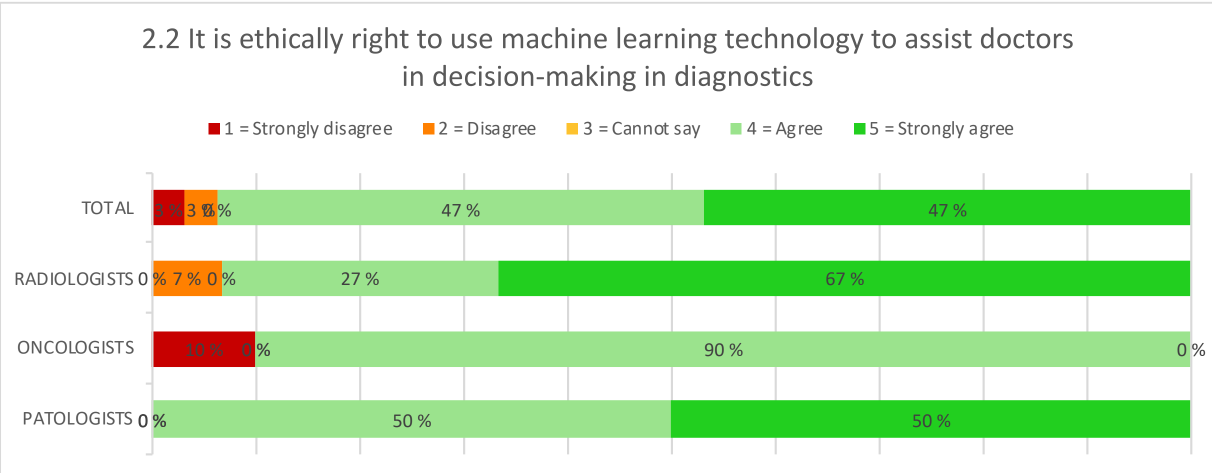


*Figure 16 - Results from statement 2.2*

As shown in the figure 16: “Results from statement 2.2” above, this statement resulted in 3% of answerers to the option “Strongly disagree” and the same 3% was also given to option “Disagree”. None answerers were given to “Cannot say” option for this statement. Both “Agree” and “Strongly agree” are answered by 47%.

According to the answerers, it is possible to implicate as the statement before that the respondents does not see this statement as an obstacle for implementing ML technology as an assistance for clinicians in decision making. Since the majority answered both 47% on “Agree” and “Completely agree”. To this statement 3% answered “Completely disagree” and “disagree”, due to the amount of responses for this survey 3% of an answerers is one respondents answer. Regarding this statement the one answer for “Strongly disagree” was given by an oncologist and the one answer for “Disagree” was given by a radiologist. The majority of answerers given to “Strongly agree” was given by radiologists, most of oncologist answered “Agree” to this statement. Pathologists were equal on answerers for both “Agree” and “Completely agree”.

The aim of this and the statement before was to identify if there could be differences from the ethical point of view between ML could do parts of diagnostics and if it is ethically to assist doctors in decision making. As results shown from both statements there are no significant differences between these two statements. Leug et al (2016, p:187) suggests that implementing ML into clinical setting should be considered as a tool that can shorten the time spend on analyzing and scoping the search field of hypotheses, which still in the end are required to be validated by a human. Findings from this and the statement before shows that these respondent in general “Agrees”, according to the majority, that ML could support doctors in decision making and it is ethically correct to let ML support within diagnostics. Jiang et al (2017) are saying that research still seeks for applications of guidelines and standards in order to develop safe usage of AI within healthcare. This does not explicitly mean that it is unethical, but refers to the safety aspect which is an essential aspect within the care of patients.

The third statement for this topic was stated as followed:
**“It is ethically correct to allow machine learning technology to make decisions for a doctor in diagnostics”,** answerers illustrated in the figure below.

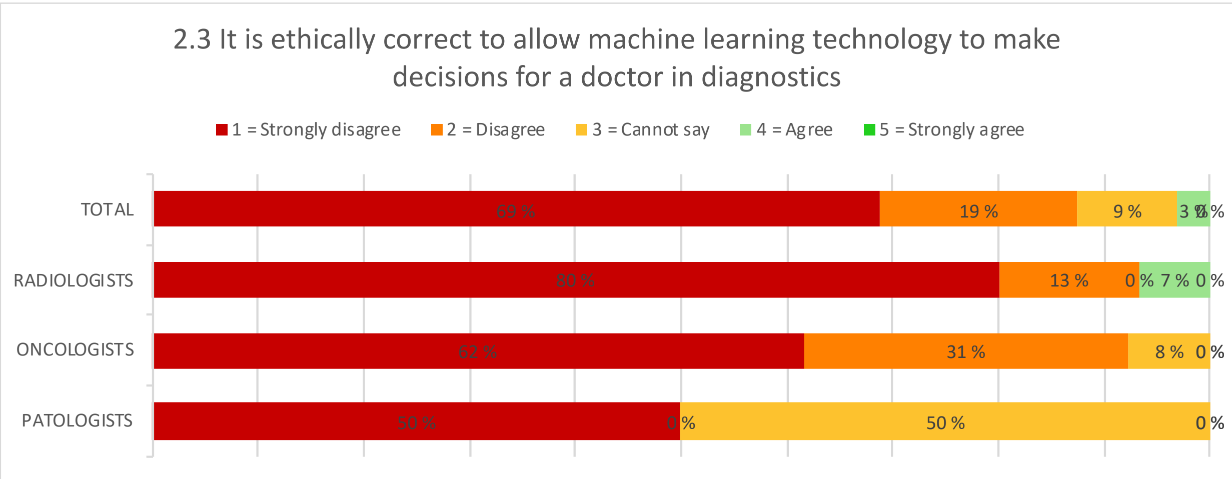


*Figure 17 - Results from statement 2.3*

As shown in figure 17 a total of 69% answerers were given to the option “Strongly disagree” followed by 19% answering “Disagree”. 9% answered “Cannot say”, 9% “Agree” and 3% answered “Agree” and none answerers were given to the option “Strongly agree”. This is the first statement so far in the complete questionnaire that resulted a majority answering “Strongly disagree” and “Disagree”.

This is the first statement so far in the complete survey that resulted in majority answering “Strongly disagree” and “Disagree”. It can be implicated that this might have correlations about the discussions about ethics and AI in various sectors. Which is also according to Krishna (2017) the biggest concerns the healthcare sector phases when it comes to adopting AI technologies into its organization are namely the regulatory and ethical issues. According to Richman (2018) there is a high need of new regulations regarding the responsibility of monitoring the patient care. Regarding such aspect who will come to have the responsibility of monitoring the quality of care or decisions for a patient. Within traditional clinical practice a doctor and a patient establish a relation when they meet, and thereby the responsibility of the care lies on that doctor in question. The question arises about who will come carry this responsibility when a patient is treated by an algorithm. Another interesting highlight regarding the need of redefined regulations by Richman (2018) is that the current regulations prohibits everyone else than a licenced medical doctor to practice medicine, which are currently being controlled by the medical board.
Summarizing findings within this statement and according to literature in the field, it is possibly to implicate that it would not be ethically correct to allow ML technology to make decisions for a doctor in diagnostics can be interpreted as a barrier for implementing ML into clinical workflows. This is based on currently no established regulation of such kind and according to the respondents participating in this survey whom strongly disagree to such decision making by a ML technology.

The fourth statement to this topic, “Ethical and legal aspects” was presented in the survey as followed:
**“According to patient safety legislation it is accepted to use machine learning in diagnostics”** and the answerers are illustrated in the figure below.

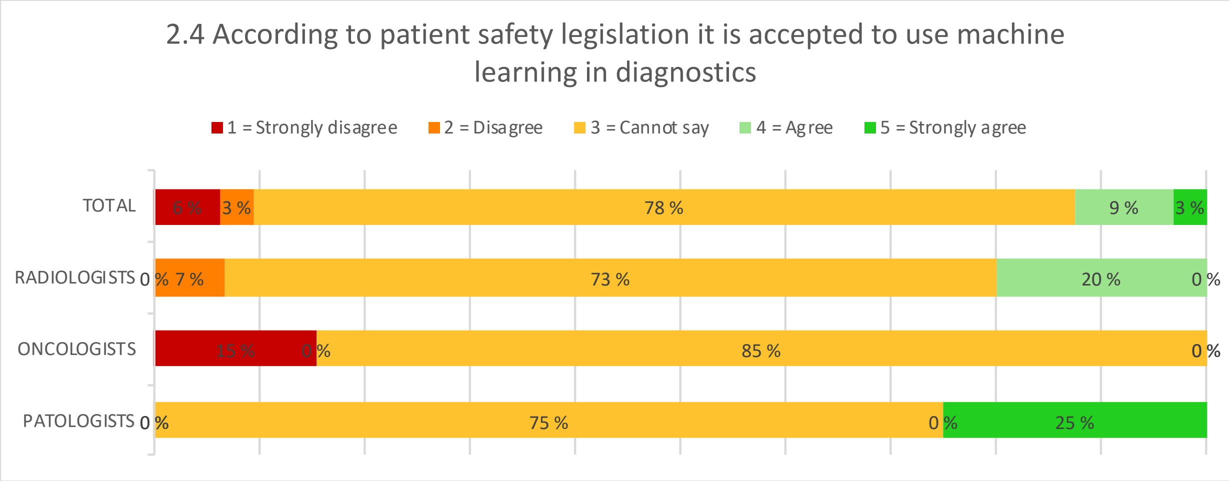


*Figure 18 - Results from statement 2.4*

As shown in figure 18, answerers for this statement contained of 6% answering “Strongly disagree” and 3% answering “Disagree”. Majority of answers for this statement lies on the option “Cannot say” with 78% of answerers. 9% answered “Agree” and only 3% answered “Strongly agree”. No significant differences in answerers within this statement is to be discovered, other than the only profession answering “Strongly disagree” were oncologists. The aim with this statement was to identify if these respondents have the knowledge regarding patient safety legislation and if it is according to patient legislative acceptable to use ML technologies in diagnostics.

The majority of answers for this statement lies on the option “Cannot say”. Which could be implicated that the respondents cannot say whether it is accepted according to patient safety legislation to use ML in diagnostics or not. Which agrees with findings from literature, as earlier mentioned by Jiang et al (2017), that research still seeks for applications of guidelines and standards in order to develop safe usage of AI within healthcare, such guidelines should for instance describe how AI is going to be regulated, what rules are to be applied within clinical tests and also justify the purpose of AI.

The fifth and the last statement in the topic of “economical and legal aspects” was presented as followed:

**“Machine learning can make more effective decision-making based on clinical data produced by clinical work within the framework of current legislation”** and the results are illustrated in the figure below.

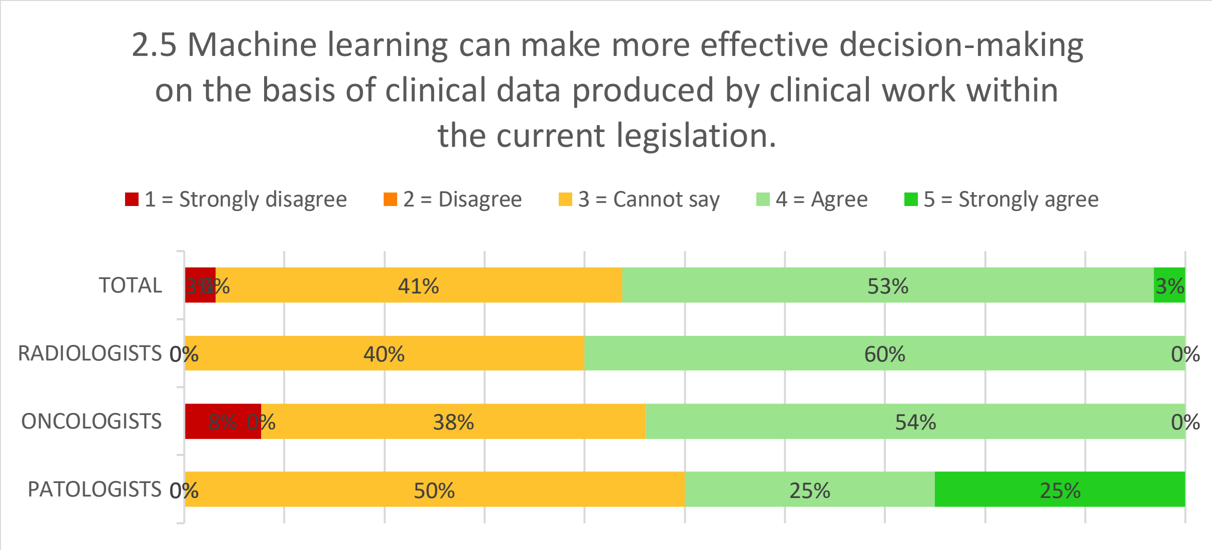


*Figure 19 - Results from statement 2.5*

The aim with this statement, was to investigate if there could be barriers to recognize, from a legislative perspective, when using ML technology in such clinical setting based on such data that is produced by the clinicians. As shown in figure 19 3% of answerers were given to option “Strongly disagree” and none answerers for “Disagree”. 41% answered “Cannot say” and 53% chose the option “Agree”. Only 3% were given to answer “Strongly agree”, which was given by an oncologist. As visualized this statement shows quite equal respondents for both “Cannot say” and “Agree”, 41% “Cannot say” and 53% “Agree”. ¨

It is implicated that a small amount makes this statement lie more to the “Agree” option. Which according to these respondents agrees that by utilizing ML technology into decision making, based on data produced by clinical work is legally right. Since there are not that much of a difference between “Agree” and “Cannot say”. Due to the low response rate, no conclusions or generalization is possible, but regarding this topic it is implicated that it could need some research around the earlier mentioned point about what kind of data is accepted to be used with ML technology. Which can also be reason for 41%answering “Cannot say” because the lack of knowledge if it is actually more effective combining such technology into decision making utilizing data from clinical settings. As Viceconti et al (2015) are saying regarding medical data and confidentiality, it is a tricky area. Since, in many development countries, the medical data is considered as very sensitive data which is legally owned by the patient. The providers within healthcare are obligated to taking the confidentiality into account in matters that regards the patient care. In other sectors than healthcare, it is usually right to collect and analyze the data at the same location. Because it is not considered as “sensitive data” when the data is being collected and analyzed at the same location, which is not the case regarding medical data in the healthcare sector.

In conclusion regarding ethical and legal aspects, Char et al (2018) highlights the importance of taking in account the ethical challenges that are associated with implementing ML into such sectors as healthcare if the benefits from it is going to be realized. Also, according to Krishna (2017) legal, regulatory and ethical risks the biggest concerns the healthcare sector phases when it comes to accepting and adopting AI solutions into its organization.

This chapter provided the results gathered from the questionnaire in a topic called "Ethical and legal aspects" and where analyzed by each question one by one and none conclusion about the topic as such can be made since the – showed that it is not possible to look at this questions or statements as a group. The next chapter will introduce the results from the questionnaire consisting of also 5 statemen regarding economical and organizational aspects within implementation of ML into clinical workflows.

## 4.4 Economical & Organizational aspects

Economical and organizational aspects is the third and the last topic in this survey. This topic is seeking for the possibility of the five presented statements could be considered as barriers when considering implementing ML into clinical workflows. Five statements were asked within this topic. Each statement will be presented and analyzed by an own figure where a total review of answerers is presented and a distribution of answerers according to profession; radiologists, oncologists and pathologist. Each statement is presented one by one, as previous topics.

As shown in figure below, the first statement within this topic is presented as followed:

**"There is sufficient evidence of the cost benefits of utilizing machine learning in diagnostics"** and an illustrated figure of answerers below.

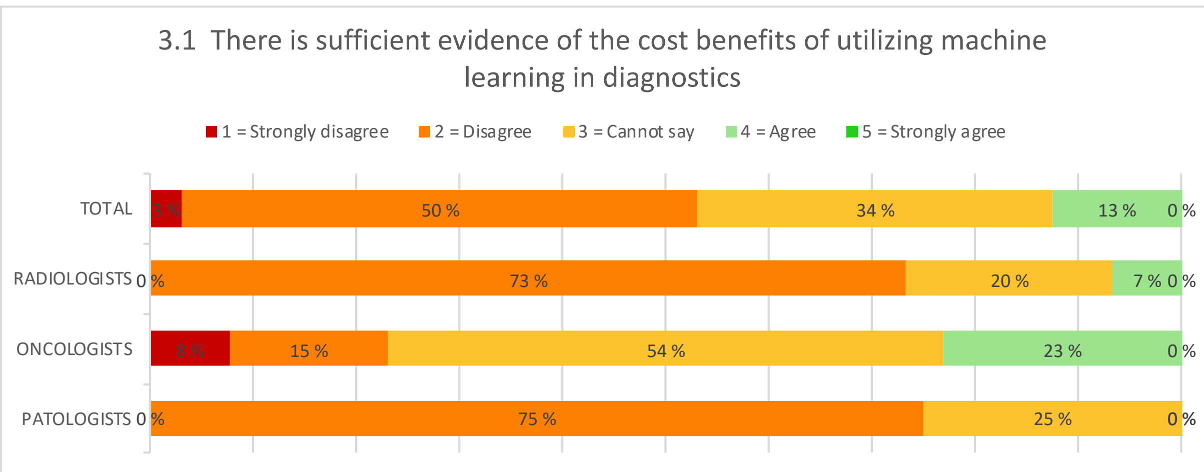


*Figure 20 - Results from statement 3.1*

Figure 19 shows that 3% answered “Strongly disagree” and 50% answered “Disagree” to this statement. 34% answered “Cannot say” and 13% answered “Agree”, no one answered “Strongly agree”. Majority for this statement is “Disagree” with 50% of answerers followed by 34% saying “Cannot say”. No significance differences between the respondents are to be discovered except that some oncologists chose option “Strongly disagree” and none pathologist answered “Agree”. to this statement, then again the majority of answerers for option “Agree” were chosen by oncologists. The aim of this statement was to seek if there could be barriers regarding lack of evidence of cost benefits within this implementation field, which could be a possible barrier for fields in diagnostics.

It is implicated that this could be a pursued obstacle when considering implementing ML into diagnostics if there are assumptions of not enough evidence of the cost benefits, since the answerers pointing at disagree, but also lack of knowledge due to 34% answering “Cannot say”. Most of the answerers for “Disagree” are from radiologists and pathologists.

The second statement to the same topic, was presented as followed:

**“The use of machine learning technology can reduce the number of administrative personnel needed”.** Which is aiming for possible pursued obstacles among the respondents when it comes to decreasing costs for administrative personnel, because ML technique could replace some of the manual work. The figure below visualizes the answerers for this statement.

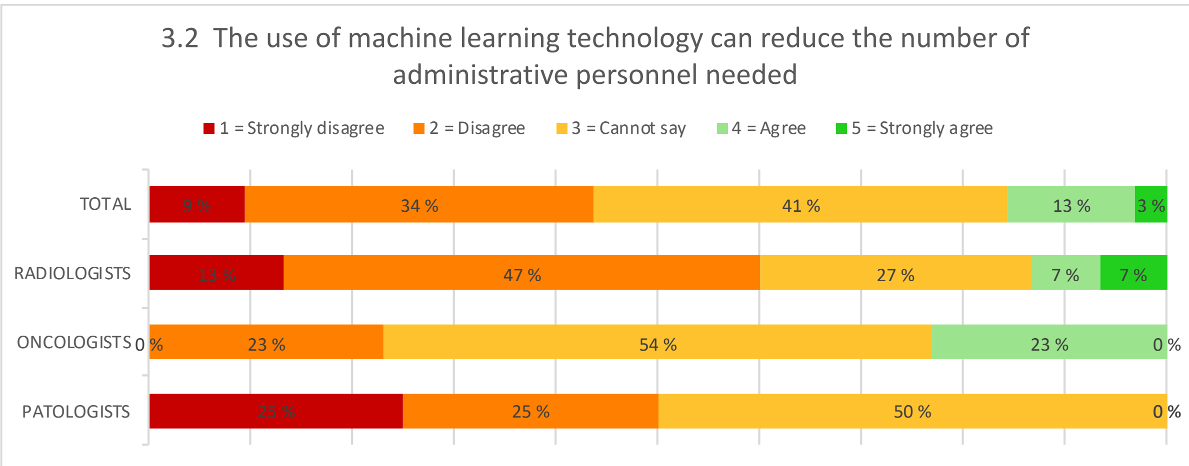


*Figure 21 - Results from statement 3.2*

As shown in figure 21, 9% answered “Strongly disagree” and 34% answered “Disagree”. 41% answered “Cannot say”, 13% answered “Agree” and 3% “Strongly agree”. Answerers for this statement are quite outspread but the majority lies on the option “Cannot say”. The majority lies on the answer “Cannot say”, followed by “Disagree” as the previous statement. Whether this is considered as a barrier is difficult to draw conclusions about, it would need some further investigation and clarification for instance about what tasks are going to be automated. Though, according to these respondents it is possible to implicate that they do not see the ML technology enabling reducing administrative personnel needed.

The third statement in this topic was presented as followed:
**“The cost of implementing machine learning is not considered as a barrier for our unit”.** Aiming to seek if there are considered obstacles due to implementation costs of ML technology into the respondents working units. Answerers for this statement as illustrated in the figure below.

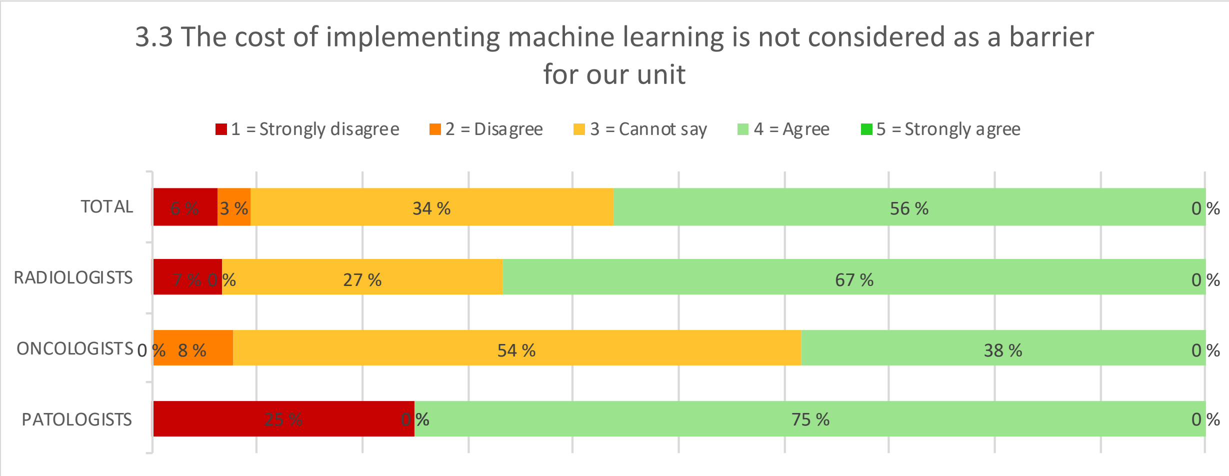


*Figure 22 - Results from statement 3.3*

As shown in figure 22 above, 6% answered “Strongly disagree” and 3% answered “Disagree”. 34% answered “Cannot say” and 56% “Agree”, none answers were given to the option “Strongly agree”. It is possible to implicate, according to the results that the costs of implementation can be considered as an obstacle and the knowledge about costs might be low since 34% answered “Cannot say”. Though, it is to be implicated that 56 % of the respondents agrees to that cost of implementation is not considered as a barrier at their units. No oncologist answered “Strongly disagree”, but oncologists were the only profession with the majority of answering “Cannot say”, though the majority of answerers were given to answer “Agree”.

According to Krishna (2017) costs due to implementation of AI technology into organizations are considered as high and crucial for some organizations and therefore deciding not to implement. Mid-size providers struggle with these costs and are waiting to implement until more proven AI technology. Notably is also that the cost is not only related to implementation cost. Maintenance, training, workflow changes and staffing are both time consuming and money consuming. Panch et al (2018) is highlighting another perspective, the fear of cost implementation should lie on the opportunity costs of not including AI, or only in small scales, the full potential of AI will not be realized in health systems. Another crucial issue to be addressed is according to Tran et al (2019) is that by applying AI into the field of medicine, AI models needs large amounts of clinical datasets, especially datasets with labels for training the AI models. Such will come to need endorsements from medical experts, which are considered as very time consuming and very expensive.

The fourth statement in this topic is presented as followed: **"The use of machine learning technology can reduce the number of doctors required"** and the answerers are visualized in the figure below.

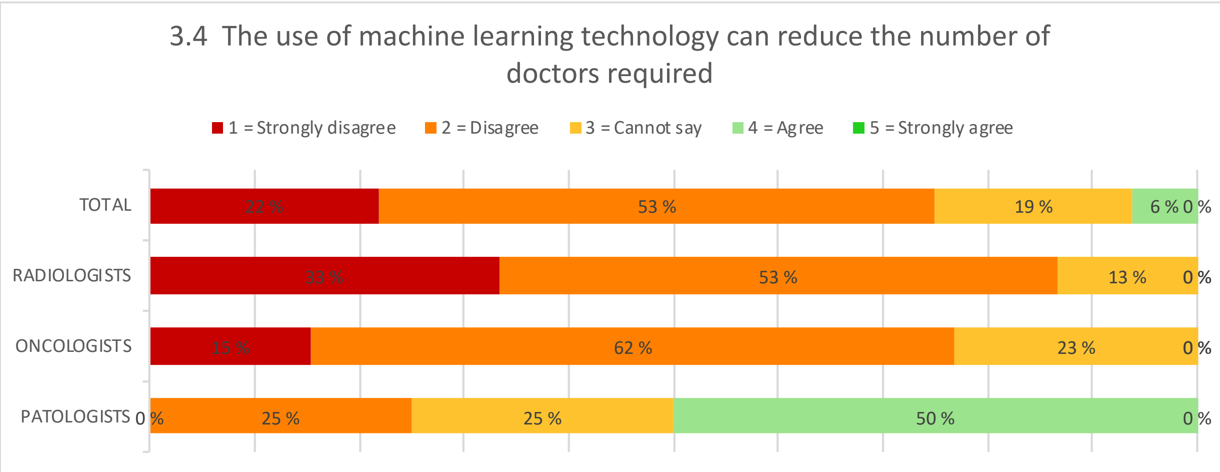


*Figure 23 - Results from statement 3.4*

The goal with this statement was to identify if the respondents consider implementing ML technology can lead to reducing the amount of needed doctors. To this statement, as shown in figure 23, 22% answered "Strongly disagree" and 53% answered "Disagree". 19% answered "Cannot say" and 6% answered "Agree", none answers were given the option "Strongly agree". The majority for this statement resulted in 53% "Disagree" followed by 22% "Strongly disagree". It is possible according to the answerers to implicate that these respondents do not think there will be any reduction in the amount of needed doctors due to ML technology. As can be seen in the figure, the only profession choosing "Agree" answer to this statement were pathologists and also the only ones where no answerers were given to answer "Strongly disagree".

This statement does not explicitly take stand to whether it can be considered as a barrier, but it is to be implicated that if the majority would have been reversed, meaning a majority of answerers “Agree” it could be possible to make conclusions that such might be an obstacle if people are afraid of losing jobs, instead further discussions about in what extend ML and AI technology should be replacing tasks performed by clinicians. Further, as Ho et al (2019) are saying that the “hype of AI” has brought up the assumptions about doctors, especially radiologists will be replaced with implementation of such technologies and in what extend in their daily clinical work. What is though expected, is that AI applications are going to be applied in daily workflows, such as within PACS (picture archiving and communication systems) in near future.

Panch et al (2018) again are saying that the fear of removing workforce in the healthcare sector, due to implementation of AI technologies, are overstated. According to Andrew H. Beck in Dolgin (2018) Machine learning will come to assist in specific tasks, but when it comes to the clinical work of synthesizing with careful judgement is required about such clinical information as genetic profiles, EHRs, cell stains and protein annotations. Based on careful synthesizing and putting together different information and thereby defining a diagnosis and creating a treatment plan for a patient is what human doctors, such as pathologists do their best. Leug et al (2016, p:187) are also highlighting that humans have great capabilities when it comes to human actions, such as grabbing things, responding by words and human perception, such as seeing images, hearing a speech. Therefor when it comes to implementing ML techniques into clinical settings, the aim should not be to replace human work. It is something that should be more considered as a tool that can shorten the time spend on analyzing and scoping the search field of hypotheses, which still in the end are required to be confirmed by a human.

Kohli et al (2017) is also implicating that if such scenario would occur, where the machines replaces radiologists, it will be in the far future, but in order to gain from a successful implementation of ML into the domain of radiology, it will come to require new knowledge regarding data science and statistics in order to interpret the results delivered by ML.

The last statement for the topic “Economical and organizational aspects” in the complete survey, goes as followed: **“Utilizing machine learning in diagnostics is changing our way of working, which is not seen as an obstacle**” and the results are visualized in the figure below.

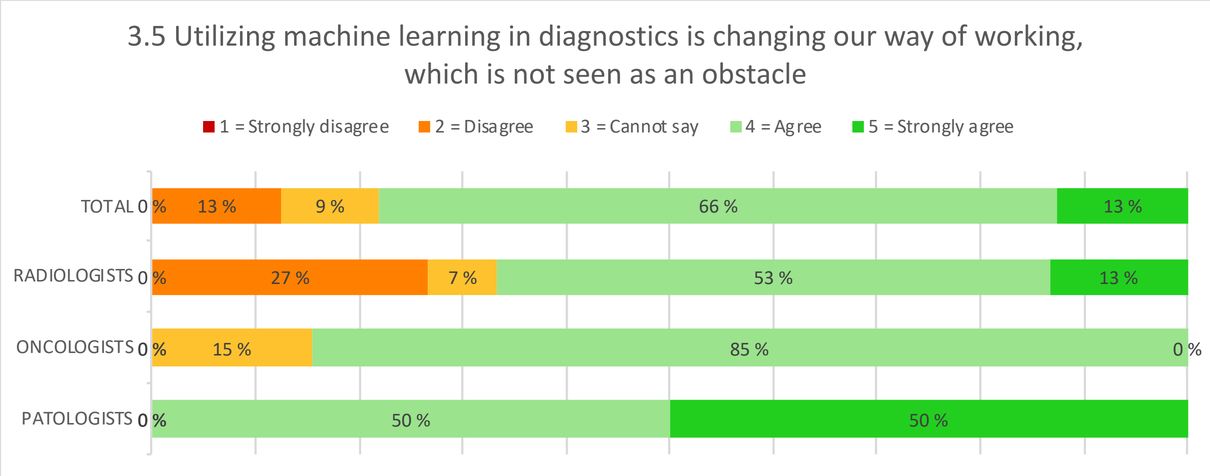


*Figure 24 - Results from statement 3.5*

As shown in figure 24, 0% answered “Strongly disagree” and 13% answered “Disagree”. 9% answered “Cannot say”. The majority lies on the answer “Agree” with 66% and 13% answered “Strongly agree”. The aim for this last statement was to seek if there could be any considered obstacles within the topic of changing the current way of working and seeking of attitudes regarding this. Which could be considered as a barrier, since according to Krishna (2017) there is a need for cultural shift among healthcare providers and patients for AI to become a part of the healthcare field. Organizations attitudes for AI should also be transformed to a direction where they see AI technology as a supplement and for a better care for patients. As can be discovered from the figure, the only profession choosing “Disagree” for this statement were Radiologists.

Which according to the results can be implicated as not considered as an obstacle.
According to the results from this statement, it is possible to implicate that the majority of respondents could be positive for a change in their current way of working. Bughin et al (2017, p:36) are saying that in many cases, when implementing an AI technology to an organization, the greatest challenges does not concern the technical part. It is the change-management challenges, by this meaning the transformation from what people do to what or how they will be doing their work within an organization.

This chapter 4 consisted of analyzing the results from the conducted survey, the selected data collection method from the desired target groups for this work. The survey consisted of 15 statements, within 3 topics. They were analyzed each one by one together with findings from the literature. The next chapter will be the Discussion chapter, consisting of summarizing the findings in answering the three research questions for this thesis.

# 5 Discussion

This thesis aims to identify potential barriers when considering implementing ML as a tool into the diagnostic work of oncologists, pathologists and radiologists, which has been made through three main research questions. These presented questions were introduced in the beginning of this thesis in the introduction chapter and in the research chapter. The summary of findings concerning each research question will be introduced in this chapter. The summary of findings from the first question will begin below.

### How is AI and Machine Learning being applied in clinical settings today?

To answer this research question, a literature review was conducted. Based on the findings from the literature review AI techniques in the field of healthcare and medicine is being used to support diagnosis and to avoid false diagnosis. Due to the rapid progress of technology it is possible to improve treatments, making the right therapeutic decisions and being able to predict the outcomes for clinical scenarios. (Siuly et al, 2018) AI can also be used for improving the operational and predictive cost managements (13D Research, 2017).

AI tools can support doctors in diagnostical decisions (Weber, 2015), such as pattern recognitions within radiology and pathology and in developing predictive models such as within oncology (Cabitza et al, 2017). For example, pattern recognition such as recognizing capillary patterns for a pathologist are being utilized with ML (Dolgin, 2018). Alzheimer disease detection is a neurodegenerative disease whereas ML is being applied, also other types of dementia based on MRIs are being detected by using ML technology (De Bruijne, 2016). AI can also assist doctors in identifying a specific tumor from medical images (Kohli et al, 2017) and in interpreting mammography images (Ihme, 2018). AI show great potentials in supporting doctors with updates about studies within their operating field (Ahlén & Bravo, 2017).

AI tools have also shown potentials within assisting in developing new and more accurate drug combinations, such as within oncology. AI have also contributed in discovering combinations treatments consisting of drugs and other alternative treatments, such as patients suffering from insomnia. (Neittaanmäki & Lehto, 2017) AI is currently being used as a risk detection tool, whereas the tool is calculating the possibility for a patient to fall ill in an artery disease (Ruokoniemi & Rannanheimo, 2018), another AI tool is used for the prediction of chronic diseases among patients, detection if they are misdiagnosed or undiagnosed (Wang et al, 2015). Predicting disease outcomes (Jiang et al, 2017) such as identifying peripheral artery disease (PAD) also its prognosis and mortality risk (Ross et al, 2016) as well in predicting asthma outcomes and the risk of falling ill in diabetes type 2. (Luo, 2016) AI can also be assisting monitoring, predicting and diagnosing patients with heart failure. (Ruokoniemi & Rannanheimo, 2018)

AI enables more personalized treatments and suggests when the right kind of diagnostical test is needed for a patient and contributing in minimizing side effects while increasing effects from a treatment. (Neill, 2013) This was a short summary of the findings from the literature review answering the first research question for this thesis. The second question with findings will be summarized below.

**What could be the potential barriers when implementing AI and Machine learning into clinical workflows?**

This research question is aiming to find through the literature review what could be considered as barriers when considering implementing AI and ML into clinical workflows. Most of the findings from the literature review are referring to challenges or barriers from an organizational point of view, whereas social resistance is said to be the biggest barrier an organization like healthcare faces when it comes to adopting AI technology. (Krishna, 2017) This is also highlighted by Bughin et al (2017) that in many cases, when implementing AI technology into an organization the greatest challenge is not attached to the technical part, it is the change management that is considered to be one of the greatest challenges. Example of such is an organization's attitude towards AI, which should be transformed in a such direction where the new technology is considered as a supplement or a tool for providing a better care for patients (Krishna, 2017) instead of considering such technology as a threat, which some clinicians might fear due to believes that such technology could contribute to job losses (Makridakis, 2017). Another aspect regarding job losses due to more automated tasks, is the agreement of what tasks should be automated and which should be kept as human tasks, also addressing how such technology will change practices within diagnostics is crucial. (Liew, 2018) There are also considered challenges about realizing the benefits from using ML methods in clinical practices, due to the lack of such validation it could be considered as an barrier when considering the benefits from such implementation, for both patients and professionals (Rabbani et al, 2018).

Hospitals are considered to be the most complex entity within healthcare and are therefore required to answer to different policy reforms and technology innovations. In order to answer to these, they are faced with challenges regarding costs, quality and operational efficiency when providing medical and care services. (Bohmer, 2009) Further, economical, safety and educational issues regarding implementation of AI needs to be taken into account (Finnish Ministry of Finance, 2017). Due to no established regulations and standards are considered as an obstacle for algorithms being applied into clinical workflows (Rabbani et al, 2018).

Other possible barriers discovered from the literature review are concerns regarding principles of patient safety and data privacy, how will such concerns be guaranteed and maintained when implementing such technology (Liew, 2018). Such as anonymisation and protection of patient health data are considered as ethical obstacles, meaning guaranteeing access to authorized professionals and no access for those not being authorized (Rabbani et al, 2018). There are still considered to be lacking regulation about guaranteeing the safety and the impact of such system, which is clearly considered as an obstacle for implementation (Jiang et al, 2017). To conclude, the key elements holding back adoption of AI within healthcare organizations are legal, ethical and regulatory challenges (Yang & Chen, 2018). Which according to Richman (2018) is a big obstacle since current regulations were made for traditional healthcare delivery systems and are not suitable for new technologies.

The lack of people within the organization who have knowledge about how such system works, how it differs from other technologies, how such system should add value to an organization and knowledge about its limitations, are considered to be an obstacle for many organizations, therefore investing in such knowledge in the organization is considered as crucial. (Bughin et al, 2017)

Costs due to implementation can be a big reason for not implementing AI technology into an organization. Costs due to maintenance, training and changes within workflows are also considered as high investments (Krishna, 2017). Redesigning workflows is required in many cases when implementing AI in a such way that will support AI insights and ensuring the expected benefits (Bughin et al, 2017). Some are also fearing to become the removing workforce within healthcare when considering adopting AI tools (Panch et al, 2018).

This was a summary of the findings from the literature review answering the second research question. The third and the last research question for this thesis will be presented below.

**Are the identified barriers from the literature review possibly the same considered by clinicians within oncology, pathology and radiology when considering implementing machine learning into their clinical workflow?**

The third and the last thesis question was answered through a quantitative approach, whereas conducting a survey based on findings from the two previous research questions was made. The survey consisted of 15 statements where the aim was to seek if the findings from the literature review could possibly be the same considered by clinicians within oncology, pathology and radiology when considering implementing machine learning into their clinical workflow.

From the results of the survey could be seen that a majority of 80-90% of the respondents answered either agree or strongly agree to the statements regarding if ML can make diagnostics more efficient and accurate. However, to the statement whether there are clinical ready models and if there is enough scientific evidence about successful usage of ML tools, the answers where somewhat more scattered with 44% agreeing or strongly agreeing, 28% could not say and 28% disagreed or strongly disagreed. This implicates that clinicians see the potential in utilizing ML in diagnostics but there still needs to be done research on the topics before it can be implemented successfully. These findings agrees well with previous findings that are also highlighting that there are great potential in implementing ML into diagnostics to make it more efficient and accurate, but there are still many practical and scientific challenges that needs to be treated before these methods can be successfully integrated into clinical practice in everyday work. (Derrington, 2017; De Bruijne, 2016; Kournou et al, 2018; Rabbani et al, 2018; Cabitza et al, 2017 ; Tran et al, 2019)

Findings from the literature says that social resistance is said to be the biggest barrier an organization like healthcare faces when it comes to adopting AI technology. (Krishna, 2017) This is also highlighted by Bughin et al (2017) that in many cases, when implementing AI technology into an organization the greatest challenge is not attached to the technical part, it is the change management that is considered as the greatest challenge. The results from the survey is somewhat inconsistent with that presented earlier in the literature and the results implicates that a great majority of respondents does not see it as an obstacle that by utilizing ML in diagnostics would lead to changing their way of working. Another finding is that according to the respondents the majority, both answering agree and strongly agree, are saying it is not considered as a hindrance to the use of ML in diagnostics, due to the required new technical expertise. Both findings can be implicated as positive attitudes regarding such change required due to new technical expertise and changes with current way of working.

According to findings from the literature review there are currently no establish regulations, standards and ethical guidelines for the usage of AI in healthcare (Rabbani et al, 2018; Ho et al, 2019; Jiang et al, 2017). Findings from the survey shows that there is a clear majority of respondents who agrees or strongly agrees to the statements about if it is ethically right to use ML as a tool for clinicians within diagnostics and for such technology to assist doctors in decision making. This shows that the respondents do believe that the purpose with such usage with ML would be accepted. However, the results show that with the majority of respondents, with 88% disagreeing and strongly disagreeing to ML making decisions for clinicians. This result is comparable to findings from literature, for instance according to Richman (2018) the current regulations prohibit everyone else than a licenced medical doctor to practice medicine, which are currently being controlled by the medical board. Furthermore, according to Jiang et al (2017) there are obstacles with implementing such technologies due to no current regulation. Therefore, barriers could occur if there was to be suggested that ML would be making decision without the involvement of human doctors.

A considered barrier could be regarding if there is sufficient evidence of the cost benefits of utilizing ML in diagnostics. Over half of the respondents disagreed or strongly disagreed to this statement followed by one third answering “Cannot say” and only 10% agreeing. This could be considered as an obstacle when proposing a ML tool for a unit if the professionals does not agree that there is enough evidence of cost benefits from utilizing such technology, at least something that would need further validation.

Ho et al (2019) are saying that the “hype of AI” has brought up the assumptions about doctors being replaced by such implementation. The results from this survey shows that it is implicated that the respondents do not share such assumptions about ML or AI technology will be contributing to reducing the amount of human manpower needed. According to the results there is a clear majority on both answerers “Cannot say”, “Disagree” and “Strongly disagree” to the statement about the use of ML technology can reduce the number of administrative personnel needed. As literature has provided some insight that there are fears about job losses within the healthcare sector due to AI. According to these findings such conclusion is not possible to make whether these respondents fear of such, but it is to implicate that they do not believe that ML technology will reduce personnel needed for administrative work or doctors. Another finding from the survey within this topic is a clear majority answering “Disagree” and “Strongly disagree” to the statement about ML will reduce the amount of doctors needed. This is supported with findings from the literature review. Panch et al (2018) are saying that the fear of removing workforce in the healthcare sector, due to implementation of AI technologies, are overstated and Andrew H. Beck in Dolgin (2018) is saying that ML will come to assist doctors in specific tasks, but when it for instance comes to the clinical work of synthesizing clinical information with careful judgement, will still be required by human doctors.

This was a summary of the main findings while answering the three main research questions. The following chapter will be last chapter in this thesis consisting of conclusion, evaluation of the research and finally suggestions for further research based on this thesis.

# 6 Conclusion

This chapter will summarize the main conclusions based on the findings from the survey in correlation with findings from the literature review. The 15 statements presented in in the survey according to topics, are not considered to be analyzed as a group consisting of these

5 statements within each group. Instead they are to be analyzed each question one by one. If these are to be considered as barriers within oncology, pathology and radiology is hard to state a definite answer to. However, there are some areas that could be implicated as barriers or areas that could benefit from being enlightened based on the results from the conducted survey and the literature review made through this thesis.

According to answerers from the survey and the literature review there are some needed validation and more scientific proof about ML supporting high quality diagnostics. However, according to the respondents, agreeing with previous findings from literature, it is recognized that ML technology can support efficient and more accurate diagnostics. Another finding is that the majority of respondents from the survey answered “Cannot say” on the statement if patients are positive regarding ML technology being utilized in their diagnostics, which according to the literature review lacks research about.

According to findings from the survey, the respondents agrees to ML assisting clinicians and doing parts of diagnostics but does not agree to ML making decisions for clinicians. This result is consistent with those reported in previous findings. Possible conclusion to this is that it could be considered as a barrier if there were suggestions about ML technology making decisions for clinicians within diagnostics. Furthermore, according to patient safety legislation it is implicated that there could be some lack of knowledge about current regulations and ethical guidelines about whether it is accepted or not to utilize ML within diagnostics and to what extent. This could be implicated as a barrier when such implementation is considered and the results from the survey corresponds well with findings from the literature review.

The majority of answerers disagree to the statement regarding if there are sufficient evidence of cost benefits when utilizing ML in diagnostics, which can be implicated as a barrier if the evidence about such benefits are considered as not enough. This could become a barrier when considering implementing such technology and discussing the benefits and the supposed added values from an implementation like that. The results from the survey shows that majority of respondents does not believe that ML will reduce the needed amounts of doctors, which not explicitly mean that this could be a considered barrier, but according to previous findings there are some fear of losing jobs due to applying AI tools among clinicians and other professions within healthcare. Therefore, such fear could be implicated as a barrier. Another finding from the survey that differs from findings from the literature review is that most of the respondents does not see that implementing ML technology will reduce administrative personnel needed. According to the literature there are tasks within clinical workflows that could for instance be automated, such as some administrative tasks and would therefore change the current way of working by enabling time to other tasks.

This was a summary of the findings and conclusions from this research based on the results from the survey, answered by clinicians within oncology, pathology and radiology, in correlation to the conducted literature review. The next section within this chapter will provide an evaluation of this research followed by suggestions for further research within this topic.

## 6.1 Evaluation of research

This research started with a literature review within the field of AI and ML within diagnostics by oncologists, pathologists and radiologists, which are fields within diagnostics that are increasingly starting to apply these methods. Interesting though was the challenge of finding literature within the scope of “barriers” and “challenges” pursued by clinicians implementing such technology, which is something led to decision of conducting a research within this topic. When this decision was made, there were many directions to choose among it became time for narrowing down the aspects of barriers it was essential to keep in mind who are the target groups and what aspects can they answer when designing the research and the survey.

The survey conducted for this thesis were all structured interviews, consisting of 15 statement answered by options from “Strongly disagree” to “Strongly agree” with “Cannot say” option in the middle. Afterwards, looking back at the questionnaire and the statements, there could have been an open answer section for some of the statements being possible for the respondents to write additional information or own thoughts. The scope of this thesis was to test if the discovered barriers according to the literature could be the same barriers in the context of implementing ML into clinical workflow among the target groups operating at Central Hospitals in Finland. Due to this scope, no open answer section was added to the questionnaire. However, it would have been possible to collect some additional information or thoughts from the clinicians and maybe additional in-depth interviews for some answerers.

Open questions could also have been considered, enabling the respondents to answer freely about what they consider as barriers. The decision for choosing not having such questions as a possibility in the questionnaire was due to that ML in clinical workflows, at least in Finland is quite new and the possibility of misinterpreting the question, analysing and making conclusion based on the results could have been more demanding.

While conducting the literature review, it became obvious that there are a lot of barriers connected to the technical part in the scope of integrating ML solutions into existing health systems. However, this was left out of scope of the questionnaire since the aim of this thesis was to get an understanding about possible pursued barriers according to clinicians and not according to the people more connected to the technical part of the implementation.

## 6.2 Further research

Along the work of this thesis many considered topics for further research have arisen, both from the literature review and the survey. It is recommended to further research the differences in fields of medicine when considering implementation on ML technology into diagnostic processes and if there are fields that are more mature than other, where it would be more convenient to wait with implementing and eventually utilize later from other fields. A more ethical twist to this topic would also be to study who or what makes the decision about what clinical unit starts utilizing and which does not.

Regarding the topic of barriers from the economical and organizational aspect, based on both the literature review and the survey it is implicated that it would be beneficial with further research about evidence of the cost benefits of utilizing ML technology within diagnostics, such as looking into the existing evidence of this in the field. Within the same topic it is recommended to conduct further research on the costs and potential savings when an organization like healthcare implements ML or other AI solutions into their organization.

Another topic which was decided already in an early phase to be excluded from this research was the topic of technical aspects. These aspects were left out of scope because of the target group are clinicians and this thesis aims to identify potential barriers within their clinical workflow. However, it is recommended to further research the technical aspects of such implementation and is something that would need to be taken into serious consideration when considering such implementation. Another interesting angle to this topic would also be what would it require from the clinicians versus the software development field. Another considered angle connected to the technical aspects is the quality of data. Quality of data is considered of high importance when we are discussing how AI tools are supposed to support data from EHR, meaning how compatible are the current operating systems and what is the format of stored data, which is an important step in the process of adapting AI into the workflows. Other challenges within the sciences and practices that needs to be addressed are, for example improving the access to data, how to train strong models on little data, how manage to make best use of the structure of the images and specific properties of medical imaging data when designing the models (De Bruijne, 2016).

An interesting topic for further research within the scope of legal and ethical aspects, could be the angle of what kind of data regarding the patient is agreed or accepted for the usage or training of a ML model. This issue was also not found in literature about exactly what kind of patient data is ethical and legally legitimated to apply with ML or AI technology.

Another aspect is the patient aspect and if they are willing to let a ML technology be a part of their diagnostics and how big part would be acceptable versus non-acceptable. According to results from the questionnaire a total of 81% answered “Cannot say” regarding that patient are positive about utilizing ML to be a part of their diagnostics. No general conclusion is possible to draw based on this finding, but the answer tells that the majority of these respondents cannot say if the patients are positive about applying this technology into their diagnostic process, which is something that would need to be validated when considering implementing ML into clinical workflows where patient diagnostics are involved.

According to the results from the survey it is possible to implicate that the respondents participating in the survey does not see it as an obstacle to change their way of working by implementation of ML into their workflows. This is something that would need further research about how it will come to affect their workflows. This presented statement takes stand to workflow as such, and is not specified how it will affect their workflows.

In the scope of this thesis the target groups were chosen to be oncologists, pathologists and radiologists, which are professions where AI and ML tools are in some extend being applied within. AI within these areas and diagnostics are fields that are also increasing among research. It would be interesting to study the differences between clinicians who have implemented such tools and clinicians who have not, whereas barriers could be discovered and potentially gain insight to what needs validation before taking into practice.

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