Stockholm School of Economics
Master Thesis in Business & Management
Spring 2019

Will robots take our jobs?

A qualitative study about technology acceptance of artificial intelligence among radiologists

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Abstract

Information technologies coming from non-healthcare sectors have proven to be difficult to translate, implement and adopt in the healthcare sector. One important factor that influence the adoption process is the attitude towards the technology, what is called the *acceptance* of technology. In healthcare, the field of radiology will most likely be transformed by artificial intelligence (AI), due to the fact that diagnostic imaging is one of the most apparent applications for AI. Therefore, it is interesting to understand acceptance of AI in radiology. Even though there are a lot of articles discussing the potential of AI, there seems to be a lack of papers covering the acceptance of AI in radiology. With this in mind, the purpose of this study is to understand what factors affect the acceptance of AI among radiologists. For this purpose, 18 semi-structured interviews with physicians (radiologists and neurologists) and decision makers within radiology were conducted. An inductive thematic analysis of the empirical data was performed and then assessed for its fit to the Technology Acceptance Model 2. The authors find a relatively good fit to the existing framework. Furthermore, the study indicates how concerns of *job relevance* and *output quality*, as well as a new determinant called "*uncertainty*", has a major impact on the radiologists' acceptance of AI. Specifically, the study's empirically found antecedents; control and applicability, are experienced as important. In addition, the findings support that *subjective norm* and *image* may affect acceptance of AI to a greater extent than they have affected acceptance of previous technologies.

Keywords: artificial intelligence, technology acceptance, radiology, TAM, qualitative method
Supervisor: Anna Essén

Acknowledgements

We would like to thank our supervisor Anna Essén for all support throughout the process as well as all the great insights she has given us. Furthermore, a huge thank you to all physicians, decision makers and software suppliers that have participated and in other ways have made this study possible. Without your great and interesting insights, this thesis would not have been possible to write.

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Glossary and Abbreviations

AI: Artificial Intelligence.

Application: Healthcare information technology related systems and software.

CAD: Computer Aided Diagnostics. Systems that assist medical professionals in diagnostics.

(Referring) Clinician: A non-radiologist physician that serves as a client to the radiologist.

Decision maker: In this thesis, an individual with experience from radiology, who now holds a managerial position.

False positive/negative: An outcome that either supports (positive) or rejects (negative) the hypothesis falsely.

Neural networks: Artificial networks inspired by the complex processes of the human brain.

Physician: Medical doctor, in this thesis specifically meaning radiologists and neurologists.

Radiology: The medical specialty dealing with image diagnostics and medical imaging.

TAM: Technology Acceptance Model.

Voxel: A regular grid in a three-dimensional space used in image diagnostics.

1. Introduction

1.1 Background

The healthcare sector has become one of the most data-driven industries out there, influenced by applications such as image capturing and electronic health records (Sensmeier, 2017). Healthcare is different from other industries due to its close link to life and death (Mukherjee, 2017). The unique characteristics is related to its complicated system of multiple stakeholders (Sun & Medaglia, 2019), who all have their point of view. The current debate surrounding healthcare systems shows concerns about spiralling costs and inefficient care, due to increased number of patients (Lluch, 2011; Ingebrigtsen et al., 2014). Much of the critique directed towards care providers is rooted in mistakes by individuals (Lawler, Hedge & Pavlovic-Veselinovic, 2011). In research about paper-based systems for documentation and prescription, several studies observe one or more errors in up to 60% of medical records (Lawler et al., 2011). However, it is not only in documentation that errors occur. Scholars further found that one out of ten diagnoses in the United States in the year of 2000 were incorrect (Sensmeier, 2017).

1.1.1 Adoption of new technology in healthcare

The monetary and humanitarian costs for mistreatments and medical errors due to individual mistakes have been a main driver for increasing the use of technology within healthcare (Lawler et al., 2011). The concept of health information technologies (HIT) has been widened during the last years, as technology in the field has evolved, however, Lawler et al. (2011) have tried to define it by including, but not limit it to, technology such as clinical decision support systems, electronic health record and bar-code medication systems. Information technologies coming from non-healthcare sectors have proven to be difficult to translate and implement in the healthcare sector (Lluch, 2011; Rippen et al., 2013). It has been clear that it is far more than just technology characteristics that are important for success (Rippen et al, 2013). Scholars further highlight human as well as organizational issues, which limits the adoption of new technology (Lawler et al., 2011). Nevertheless, when adoption is achieved, reviews suggest that it comes with good outcomes, such as efficiency and effectiveness of care (Beeuwkes Buntin, Burke, Hoaglin & Blumenthal, 2011).

1.1.2 Definition of adoption

Adoption is a tricky concept that has been debated in literature (Tornatzky, 1983). When Renaud and Biljon (2008) discuss technology adoption, they describe adoption as a complex process that involves different steps, including becoming aware of the technology, embracing it, as well as using it in its full potential. Tornatzky (1983) proposes that the concept of adoption could be used "*to distinguish where the process changes from a primarily symbolic activity ("deciding") to a behavioural ("implementing") one*" (Tornatzky, 1983, p. 25). However, the wide variety of study settings and outcome measurement has made the true drivers behind adoption of new technology difficult to capture (Holden & Karsh, 2010).

1.1.3 The relationship between adoption and acceptance

One important factor that influence the adoption process is the attitude towards the technology, what is called the *acceptance* of technology (Renaud & Biljon, 2008). How to define acceptance is difficult, however, Davis (1986) developed his Technology Acceptance Model with the purpose to describe "*the motivational processes that mediate between system characteristics and user behavior*" (Davis, 1986, p. 10). Furthermore, acceptance is an area that has been widely studied for decades, still without a unified view of it (Venkatesh, Morris, Davis & Davis, 2003). As we will discuss below, the issue of acceptance is critical for new technologies, such as artificial intelligence (AI) in particular, but first we will introduce the topic of AI in radiology.

1.1.4 Artificial intelligence and radiology

Healthcare is generating a lot of data, which has increased extensively in volume during previous years (Krumholz, 2014). This great volume of data, often called Big Data, could be used for input in software which is able to process the data and recognize patterns. One application for this kind of software is to perceive medical images and interpret them (Marbury, 2018). This example falls under the definition of AI, which is an umbrella term for several different technologies. AI can generally be defined as "*a system's ability to interpret external data correctly, to learn from such data, and to use those learnings to achieve specific goals and tasks through flexible adaptation*" (Kaplan & Haenlein, 2018, p. 17). As an example, the technology could be used to build and train models that predict risk patients (Pan et al., 2017) or that can perform clinical diagnosis of cancer

(Jiang et al., 2017). Furthermore, it could be used to recognize and interpret questions - as well as answers - from patients, in order to give them proper feedback, or a diagnosis (Diprose & Buist, 2016).

In healthcare, the field of radiology is one of the most likely to be transformed by AI, due to the fact that diagnostic imaging is one of the most apparent applications for AI (Jiang et al., 2017). Following the trend in healthcare, the amount of data in radiology has increased substantially, leading to a rapid technological development of medical imaging, thus creating better images and a lot more of them. Today, a radiologist typically views 4000 images in a CT scan for patients with multiple trauma (Jha & Topol, 2016). Consequently, this puts more pressure on the radiologists who need to interpret many thousands of images to keep up with the pace.

The complexity of the material and the need to find very small differences in a large set of images makes the field of radiology and medical imaging a suitable area for machine learning algorithms, which potentially could outperform humans, since humans have cognitive limitations that computers do not (Chockley & Emanuel, 2016). The computer does not need to eat or rest in order to function, and together with its processing capabilities it is therefore superior in handling a lot of data and finding patterns quickly. In 2011, the accuracy of image predictions in international machine learning competitions was approximately 76 %. Five years later, in 2016, it was up to 97 % (Lakhani et al., 2018). This might explain, to some degree, why, in the diagnosis stage, the greatest proportion of PubMed articles covering AI (in 2013-2016) focus on data from diagnostic imaging (Jiang et al., 2017).

The current interest in this subject from scholars can be shown in the increased number of scientific articles that discuss AI in radiology. For example, when searching for the keywords “artificial intelligence” and “radiology” in Scopus (2018), one can see that during the period of 2005 to 2017 the number of articles went from 16 to 38. However, in 2018 the number of articles more than doubled (102 articles).

Even though this might give the impression that the idea of using AI is something new to radiologists, this is not necessarily true. Computer-aided diagnostics and imaging have been used by radiologists for up to 20 years in several areas of radiology, however, the techniques have been refined over the years (Jalal, Nicolaou & Parker, 2019). Nevertheless, when talking about AI today, most people think of the latest developments in machine learning and neural networks. These methods allow computers to identify complex patterns and develop its capabilities automatically (Jalal et al., 2019; Wang & Summers, 2012) making AI different from previous technologies.

1.2 Research gap

Even though there are a lot of articles discussing the potential of AI (e.g. Jha & Topol, 2016; Lakhani et al., 2018), there seems to be a lack of papers covering the acceptance of AI in radiology. Scholars have suggested that acceptance of new technology is an important factor to adopt technology (Renaud & Biljon, 2008). However, the existing literature covering acceptance of technology in radiology during the 21st century has mostly focused on Picture Archiving and Communication Systems (PACS) (Duyck et al, 2008 & 2010; Aldosari, 2012). As radiology is a technology-driven specialty, it is of high interest for researchers and decision makers in this field to understand the factors that influence acceptance of AI.

1.3 Research purpose and question

This study aims to examine how attitudes among physicians and decision makers in Swedish hospitals, can affect the acceptance of artificial intelligence among radiologists. However, it comes with a dual purpose. To begin with, we are interested in understanding how different factors are influencing technology acceptance. Furthermore, by applying the factors outlined in the Technology Acceptance Model 2 (TAM2), the authors' purpose is also to explore the fit of the framework to the acceptance of artificial intelligence. Based on this purpose, this study will focus on the following research question:

What factors affect the acceptance of artificial intelligence among radiologists?

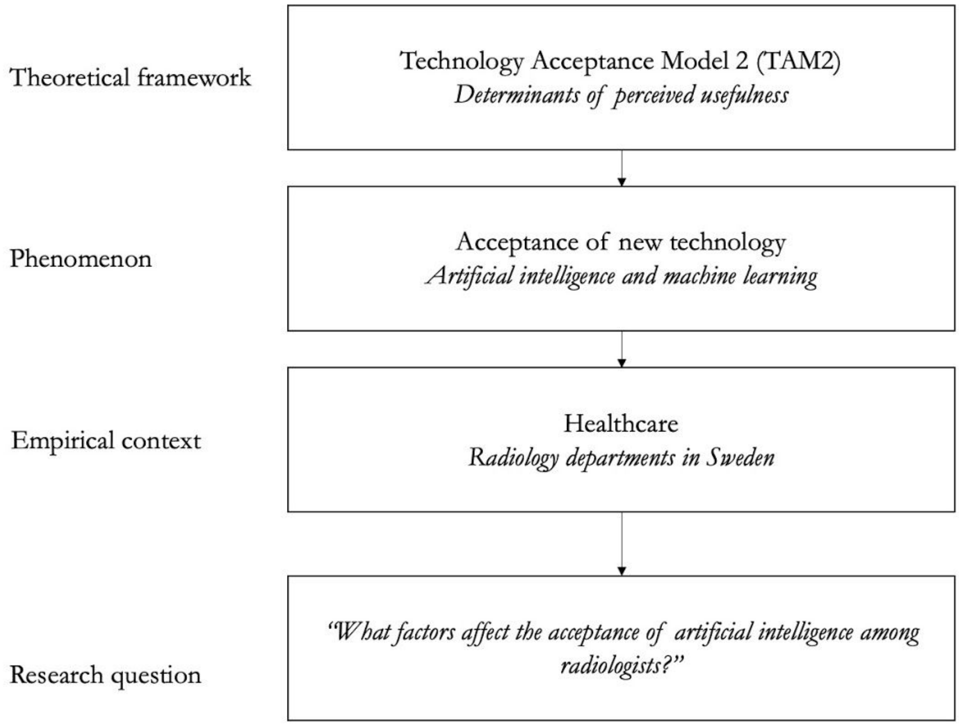


Figure 1.1. Overview of the focus of this study.

1.4 Delimitations

This study will mainly focus on the acceptance of AI among radiologists within Swedish hospitals. In order to fully understand why or why not individuals accept AI, and what shapes the broader adoption process, implementation and outcomes of AI in healthcare, other factors, such as political decisions and organizational work processes, could be of importance as well. However, these factors will not be covered in this study.

2. Literature Review

In order to understand what factors affect acceptance of AI among radiologists, this section will begin with a review of the literature on AI in radiology. This is to get a broad sense of the current state of the field. Second, we will move on to explore research about acceptance of AI in radiology. It will provide the reader with an idea about the field, and lay the foundation for this thesis. Third, we will take a step back and look at a more macro-perspective of the literature surrounding acceptance of AI in general. We believe that this action will enrich the study and add more knowledge about the study of acceptance and the use of different research methods. Also, this might add an understanding of how AI is different from other technologies. Lastly, a synthesis of the literature will be presented along with the research gap which this study aims to address.

2.1 Artificial Intelligence in radiology

The current research of AI in radiology could be placed in three apparent categories; (1) *articles of a technical nature*, (2) *exploratory, future-focused and visionary articles*, and (3) *comparative studies between man and machine*. A further exploration of these categories will be provided later in this review. However, it is necessary to comment on these findings before, in a broader sense. To begin with, AI is discussed in terms of opportunity and/or threat in different radiology settings (Chockley & Emanuel, 2016). Also, researchers argue about how it may come to impact people and what we can do about the challenges that arise from this impact (Choy et al., 2018). Should it be a discussion about "if" or "when" AI comes into play for the radiologist (Lakhani et al., 2018; Jha & Topol, 2016)? When conducting this review, we argued that it was easy to see that AI was a "hot topic" of interest to many, in a nascent stage of development, as most of the literature produced in our area of interest was written in 2010 or later.

2.1.1 Articles of a technical nature

Since AI is a highly technical subject and contains many different subcategories, it is no surprise that a large part of the literature covering AI in radiology discusses how it works and how it should be applied (Wang & Summers, 2012; Lee et al., 2017; Kohli, Prevedello, Filice & Geis, 2017; Lakhani & Sundaram 2017). An application of the technology that is frequently discussed as particularly useful is image recognition tasks, mostly using deep-learning methods such as convolutional neural networks and variational autoencoders (Hosny et al., 2018). Other applications for deep learning can be seen in classification of pulmonary tuberculosis (Lakhani & Sundaram, 2017), segmentation of tumors and other structures in the brain (Lee et al., 2017), and early detection of breast cancer (Kohli et al., 2017).

2.1.2 Exploratory, future-focused and visionary articles

Several studies have been conducted on AI's overall impact on the radiologist profession (Chockley & Emanuel, 2016; Lakhani et al., 2018; Jha & Topol, 2016; Choy et al., 2018). They present a good overview and description of future possibilities, and how AI could come to impact different areas of radiology. However, they do not go into any depth or explanation into the process of actually accepting AI. They focus more on the upcoming threat of AI towards radiologists (Chockley & Emanuel, 2016), preparing for an unavoidable future of machine learning (Lakhani et al., 2018; Jha & Topol, 2016), and living in a reality already highly affected by it (Choy et al., 2018).

2.1.3 Comparative studies between man and machine

Naturally, there is a need to evaluate new technology before actually taking the step and implementing it into everyday practice. It is evident in the literature of AI and radiology, that this is happening right now (Prevedello et al., 2017; Winkel et al., 2018). Both as a means to show that AI is "good enough" to be used in clinical settings (at least to guide the radiologists in their workflow prioritization) and to highlight risks in using the technology, like false-positives and false-negatives (Boehm et al. 2008).

2.2 Acceptance of artificial intelligence in radiology

The scarce literature relating to acceptance of AI in radiology, presents widely divergent opinions among professionals (Wang, Kalra & Orton, 2017), indicating a need to further understand acceptance. Similarly, but for radiation medicine, Gillan et al. (2019) concludes that it is important to consider how professionals perceive AI, to be proactive in informing change. Taking into consideration the limited number of acceptance studies covering AI in radiology, there's a lot to explore in this area. Furthermore, it is important to consider that the current models and concepts within acceptance research may not be up to date for assessing the acceptance of AI (Buckley, Kaye & Pradhan, 2018). Due to its self-learning abilities, AI is different from other technologies within healthcare. Because research about acceptance of AI in radiology is scarce, we will, in the following section, discuss literature about AI and acceptance in general.

2.3 Acceptance of artificial intelligence in general

Trying to understand acceptance of AI, researchers have highlighted the importance of psychosocial factors compared to prior technological disruptions (Buckley et al., 2018). Besides the importance of perceived ease of use, the factor of trust has been highlighted (Tulio Ribeiro, Singh & Guestrin, 2016; Bohanec, Robnik-Šikonja & Kljajić Borštnar, 2017). The issue of high complexity and the feeling of a "black-box solution" raises thoughts about perceived trust in AI. As users have limited insight and understanding of the underlying models of the software, they are less likely to use the technology (Tulio Ribeiro et al., 2016). However, it is not yet fully understood what attitudes and factors among users affect the acceptance of AI.

2.4 Synthesis

Even though research evidently has suggested how to use AI in radiology, provided us with technical explanations of the technology, future visions for radiologist-AI relationships, and compared radiologists with machines, there is yet no consensus what factors affect the acceptance of AI among radiologists. Even outside this area, for acceptance of AI in general, researchers have not yet presented an understanding of these factors. Consequently, the literature in this field is ambiguous and insufficient at the moment. Therefore, there is a research gap that needs to be filled, and this study aims to reduce this gap. By understanding the acceptance of AI among radiologists, we hope to add a layer in understanding the complex task of integrating AI and healthcare. If this phenomenon is not studied, it could result in misinformed investment decisions and unrealistic expectations among different stakeholders.

3. Theory

The authors will, in this section of the study, provide a presentation of the most important concepts and theoretical models. As the idea of acceptance of AI among professionals is a complex phenomenon, a common ground regarding the concepts of AI, as well as what theoretical models are used, is necessary. To begin with, we will provide a basic introduction of AI and how it is defined in this study. The second part of this section will be dedicated to the theoretical concept of the Technology Acceptance Model (TAM). Lastly, the theoretical framework of this study will be provided.

3.1 Artificial Intelligence

In order to follow the reasoning of this study, there is a need to at least have a basic understanding of AI. This section will provide a definition of AI and explore areas like machine learning and image recognition. Last, it will provide the reader with a basic introduction to how AI can be used in radiology. Hopefully, this will give the reader a rudimentary understanding of the field and create awareness about the importance to study it further.

3.1.1 Definition of AI

In this study, we propose to use Kaplan & Haenlein's (2018, p. 17) definition of AI: "*a system's ability to interpret external data correctly, to learn from such data, and to use those learnings to achieve specific goals and tasks through flexible adaptation*", since we believe that this definition captures the essence of our view on AI. We also believe, from this definition, that AI is a broad term under which several different technologies, applications and algorithms can fit. In the next section, we are going to talk about the specific AI in focus of this study.

3.1.2 Image recognition and machine learning

There is a plethora of different types of AI, which can be categorized, for example, by application, purpose, or techniques used. However, this study will focus on image recognition (computer vision) and machine learning. For those that are interested in learning more about AI subcategories, see appendix A.

For the human eye, it is easy to recognize the difference between cats and dogs. Even small children are able to make the distinction after some experience. For computers, it is a whole different story when it comes to designing algorithms that can recognize a cat or a dog in a picture. It is much more difficult to think of how to tell a computer to process an image and come up with a correct answer to the question: "is it a dog or a cat?", in comparison to showing a child some pictures and telling it the correct answers (Bradley, 2018). One way to simulate this for computers, is to let them learn from a large set of pictures in a way that resembles the process of a human brain, called *deep learning*. It is called deep learning because the learning happens in multiple layers, where each layer represents the data in some way (Bradley, 2018). To the computer, the picture is a large set of pixels, so it might have one layer which process the darkness of the pixels, another layer that looks at the edges of them and a third layer that combines the other ones (Bradley, 2018). Deep learning is a subset of machine learning, which is defined as the machine "[...] *improves its performance on future tasks after making observations about the world*" (Russell & Norvig, 2016, p. 693). The distinction between traditional machine learning and deep learning includes a greater number of learned concepts and/or functions in deep learning (Bringsjord & Govindarajulu, 2018). There are three main types of machine learning: *supervised, unsupervised* and *reinforcement learning* (see figure 3.1 below).

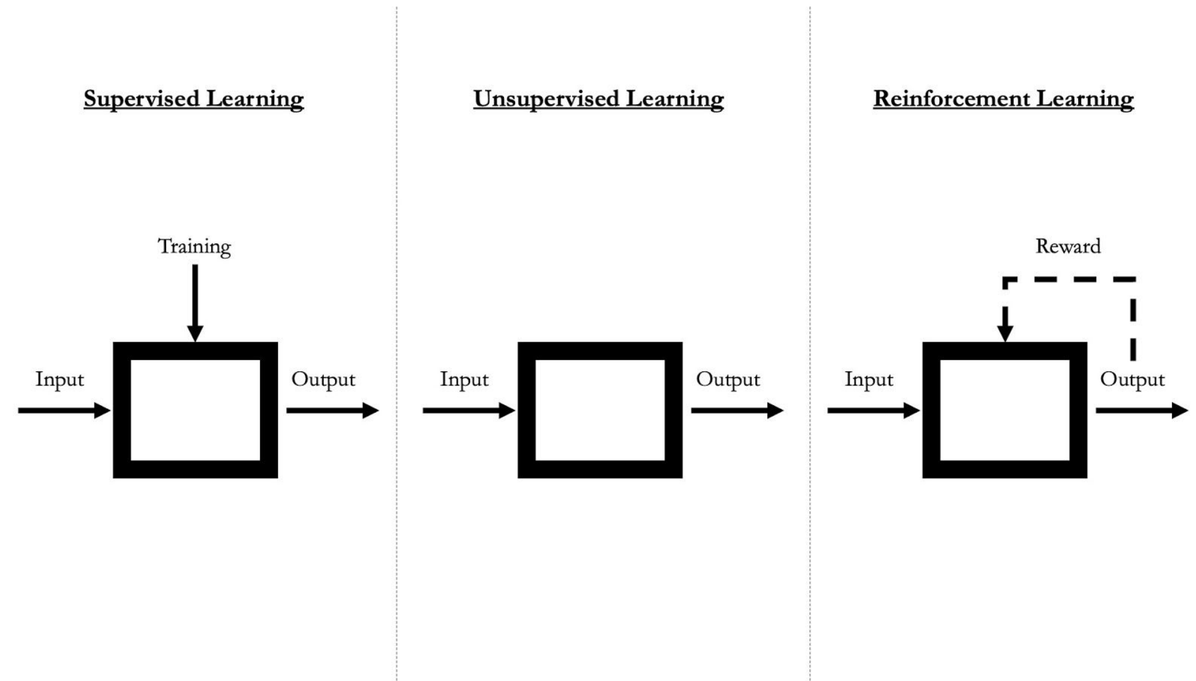


Figure 3.1. The three main types of machine learning.

For *supervised learning*, the algorithm is provided with data labels by human experts in the training phase. These labels act as the correct answers (known in machine learning as *ground truth*) to what output the algorithm should produce. The purpose of the training phase is that the algorithm should learn general rules that guide them from input to correct output (Choy et al., 2018). In contrast, *unsupervised learning* is done without providing the algorithm with these data labels, with the intention that the algorithm should find hidden structures in the data by itself (Choy et al., 2018). In *reinforcement learning*, the agent learns from punishments and/or rewards. Depending on the outcome that the agent determines as successful, it will try to figure out what action led to success or failure (Russell & Norvig, 2016). With the three types of machine learning in mind, the following section will present a brief overview of machine learning in radiology.

3.1.3 Machine learning in radiology

In radiology, machine learning can be used for example in: medical image segmentation, medical image registration, computer aided detection and diagnosis, brain function or activity analysis and neurological disease diagnosis, content-based image retrieval systems, and text analysis of radiology reports (Wang & Summers, 2012). Focusing on image recognition, the main use of machine learning in this area is medical image segmentation and computer aided detection and diagnosis, with most of the literature discussing the latter (Choy et al., 2018).

3.2 Technology Acceptance Model

The Technology Acceptance Model (TAM) was widely introduced by Davis, Bagozzi & Warshaw (1989). It has become one of the most used and tested models for assessing computer usage, following the implementation of a new technology (Pai & Huang, 2011). TAM basically describes two important factors that affects the user's decision about when and how to use a new technology. The first one, *perceived usefulness*, is defined as "*the prospective user's subjective probability that using a specific application system will increase his or her job performance within an organizational context*" (Davis et al., 1989, p. 985). The second, *perceived ease of use*, is defined as "*the degree to which the prospective user expects the target system to be free of effort*" (Davis et al., 1989, p. 985). Furthermore, Davis et al. (1989) conclude that perceived usefulness strongly influences people's intentions to use a system while perceived ease of use has a minor, yet significant, effect on intentions as well. However, the effect of the latter seems to subside over time. In figure 3.2, the components of TAM are shown together with the relations among them.

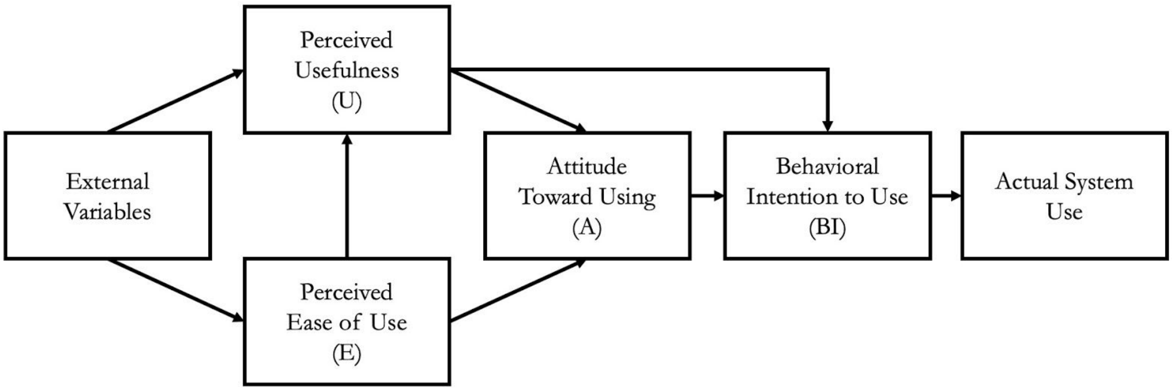


Figure 3.2. Overview of the components of the Technology Acceptance Model (TAM). Figure based on the work of Davis et al. (1989).

A user's behavioral intention to use (BI) a system is affected by the attitude toward using (A) it and the perceived usefulness (U).

$BI = U + A$

The perceived usefulness also has an additional effect on the attitude towards using the system, which might explain the significant impact that perceived usefulness seems to have on a user's intention to use a system (Davis et al., 1989). Additionally, perceived ease of use is affecting the attitude toward using a system at the same time as it has an effect on the perceived usefulness (Davis et al., 1989).

The goal of TAM is to provide a general and broad explanation towards user acceptance of a wide variety of information systems (Davis et al., 1989). It has been found in several studies to consistently explain about 40 % of the variance in actors' usage intentions and behavior (Venkatesh

& Davis, 2000). In order to keep it applicable to many settings, the model might look simplistic in its original form. Therefore, TAM has been extended and/or integrated with other theories by several authors to fit different purposes (Pai & Huang, 2011; Hsu & Lu, 2004; Chen, Gillenson & Sherrell, 2002; Melas, Zampetakis, Dimopoulou & Moustakis, 2011). As a matter of fact, TAM was initially itself an extension of Ajzen & Fishbein's (1980) theory of reasoned action (TRA), which emphasized the importance of behavioral intention (BI).

The original TAM model has been found favorable (Venkatesh & Davis, 2000), when compared to other models such as TRA (Ajzen & Fishbein, 1980) and the Theory of Planned Behavior (Ajzen, 1991), which is an extension of TRA. With that in mind, Venkatesh and Davis (2000) set out to extend TAM into TAM2. Later, TAM2 was integrated with Venkatesh's (2000) "model of the determinants of perceived ease of use". The new model was then (unsurprisingly) named TAM3 (Venkatesh & Bala, 2008).

3.2.1 The extension of TAM into TAM2

Venkatesh and Davis (2000) proposed to incorporate social influence processes (subjective norm, voluntariness, and image), cognitive instrumental processes (job relevance, output quality, result demonstrability, and perceived ease of use) and experience into TAM. They wanted to find the general determinants of perceived usefulness (see definitions in table 3.1) and perceived ease of use (Venkatesh & Bala, 2008).

Table 3.1. *TAM2 determinants of perceived usefulness and definitions (Venkatesh & Davis, 2000; Venkatesh & Bala, 2008).*

Determinants	Definition
Experience (EXP)	*The direct effect of subjective norm on intentions may subside over time with increased system experience.*
Subjective Norm (SN)	*The degree to which an individual perceives that most people who are important to him/her think he/she should or should not use the system.*
Voluntariness (VLN)	*The extent to which potential adopters perceive the adoption decision to be non-mandatory.*
Image (IMG)	*The degree to which an individual perceives that use of an innovation will enhance his or her status in his or her social system.*
Job Relevance (JR)	*The degree to which an individual believes that the target system is applicable to his or her job.*
Output Quality (OQ)	*The degree to which an individual believes that the system performs his or her job tasks well.*
Result Demonstrability (RD)	*The degree to which an individual believes that the results of using a system are tangible, observable, and communicable.*
Perceived Ease of Use (PEU)	*The degree to which a person believes that using an IT will be free of effort.*

One of the processes, subjective norm, was left out of the original model, but included in TAM2. Venkatesh and Davis (2000) argued that even though Davis et al. (1989) did not find any significant effect of this process, others had found the effect of subjective norm significant. Due to the mixed results, they wanted to investigate if subjective norm in fact should be a part of their model, TAM2 (see figure 3.3 below). The authors found that it had a significant influence on perceived usefulness via internalization and identification as well as a direct effect on intentions for mandatory settings, but not for voluntary ones (Venkatesh & Davis, 2000). While the effects of cognitive instrumental processes remained significant during the research period, the effects of social influence processes did not. Venkatesh and Davis (2000) recognized the need to further develop their model and one of the improvement areas concerned looking into how changing social environments would affect technology acceptance. Later, this conclusion has been supported by Legris, Ingham & Collerette (2003), who also saw the need for integrating TAM into a broader model that includes organizational and social factors.

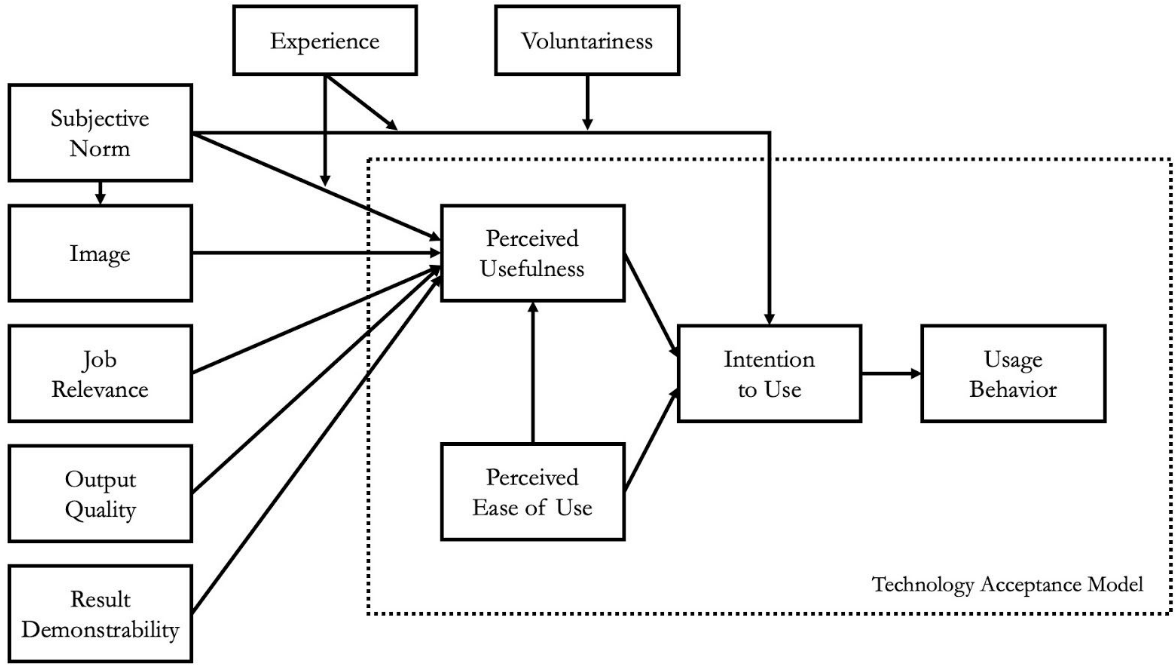


Figure 3.3. An overview of the extension of TAM into TAM2. Figure based on the work of Venkatesh & Davis (2000).

3.2.2 TAM in healthcare and its critique

The use of TAM in healthcare has provided researchers with mixed results regarding the validity of its determinants when the model is applied to physicians. Specifically, perceived ease of use has been debated to have less of an impact on professional workers' acceptance in comparison to "non-professionals" (Hu, Chau, Sheng & Tam 1999; Chismar & Wiley-Patton, 2003). This could be explained by physicians having an easier time to adapt to new situations and a higher general level of competence than that of workers and students who TAM has been used for in other studies (Hu et al., 1999). Furthermore, Holden & Karsh (2010) found mixed results regarding the effect of subjective norm on intention to use health IT. However, Yi, Jackson, Park & Probst (2006) found a significant relationship by addressing specific sources of social influence. Further, Yi et al. (2006) argue that the nature of medicine, with high degree of professionalism and specialization, provides an environment where physicians highly value the opinion of their peers. While there are mixed results regarding the validity of several determinants, there is a consensus in the literature that the relationship between perceived usefulness and intention to use (or actual use of) health IT is significant (Holden & Karsh, 2010).

Several researchers have tried to develop a model that is better than the original one at predicting healthcare professionals' acceptance of a new technology. For example, Gagnon, Orruño, Asua, Abdeljelil & Emparanza (2012) used an extended TAM and found that, in a healthcare setting, the most important factor was a perception of appropriate organizational infrastructure, training, and support. In addition, other researchers have expressed the need to develop the model by conducting more in-depth analyses of factors that are important to healthcare practitioners, such as belief elicitation studies, to identify the salient beliefs that clinicians have about using health IT (Holden & Karsh, 2010).

Given the research available in the field today, the determinants of TAM in healthcare need to be studied further since there are results indicating possible differences between healthcare and non-healthcare settings. Also, studying the professional identity of physicians, their characteristics, and social influence processes might lead to a greater understanding of how TAM should be applied in healthcare.

3.2.3 Qualitative use of TAM

Lin, Hu, Schroeder & Chen (2002) argue that TAM is seen as a dominant model in acceptance studies. In previous TAM studies, the main method of research has had quantitative focus, rather than qualitative (Vogelsang, Steinhueser & Hoppe, 2013). This is how the TAM model has been used widely in research and it has contributed with quantifiable evaluation of acceptance to the field of implementation science (Vogelsang et al., 2013). However, due to the focus on quantitative measures and surveys, it is difficult to explore the individual reasoning behind the answers, and how factors shape acceptance. With this in mind, Vogelsang et al. (2013), argue that the model could be developed further and researchers could gain a deeper understanding of the determinants of TAM by using qualitative methods such as semi-structured interviews.

One example of this is the work of Ouadahi (2008), where the author develops a model of receptivity to new informations systems. The study moves beyond "what" can predict acceptance and describes more "how" endorsement or rejection of a system is formed among the users. With a qualitative approach, Ouadahi (2008) contributes to the literature by building new theory based on the ideas of the Theory of Reasoned Action (Ajzen & Fishbein, 1980), the Theory of Planned

Behavior (Ajzen, 1991) and TAM. Considering the small sample size, however, the research paper mainly serves as a suggestion for further investigation and empirical testing of the proposed model.

3.3 The theoretical framework of this thesis

This thesis will base its theoretical framework on the ideas laid out by Venkatesh and Davis (2000) in their TAM2 model, which incorporates social influences and cognitive instrumental processes that shape the acceptance of technology, as described in section 3.2.1 and table 3.1. Additionally, TAM2 focuses on determinants related to perceived usefulness, which has shown to be significantly influential to technology acceptance (Venkatesh & Davis, 2000). Furthermore, the findings by scholars such as Buckley et al. (2018), suggest that psychosocial factors are of increasing importance when accepting AI. We want to increase our understanding of these psychosocial factors as well as of the factors that make up the TAM2 model. Our purpose is to understand "how" these factors influence acceptance and relates to one another, rather than only "what" factors determine acceptance. Therefore, this study will use a qualitative approach, following the ideas of Vogelsang et al. (2013) and Ouadahi (2008).

4. Methodology

The methodology section of this thesis aims to describe the research methods used during the study. First, we will describe the setup of, and findings from, an exploratory pre-study conducted by the authors in an initial phase. Second, there will be a thorough description of our chosen method and the structure of the main study. Finally, the authors will present a reflection regarding the quality of the study, trying to increase the transparency and explore the validity of the research process.

4.1 Pre-study

The intersection of healthcare and new technology was a specific area of interest to the authors, therefore, it became the foundation of this study. With our understanding of complex processes within today's hospitals as well as AI, we knew, in an early stage, that these phenomena could be interesting to explore further, both for ourselves as well as for academia. We started off trying to understand how structures change when new technology disrupts organizational processes. Then, after considering time limitations as well as what theory to apply, we decided to focus on digital transformation and implementation of AI. To start with, a pre-study was performed, containing a literature review and interviews with two suppliers of AI applications and a decision maker, with the aim of identifying where we could make an academic contribution as well as explore what sources to collect information from.

4.1.1 Literature review

In order to get a wider understanding of the research field, we made an initial search of previous studies of AI as well as technology acceptance. Searches were performed on the Scopus database as well as on Google Scholar using the terms: "artificial intelligence", "machine learning", "healthcare", "health care", "acceptance", "technology", "image diagnostics", "medical imaging", "physician" and "radiology" as well as "TAM" (several of the searches were made in various combinations).

From the articles we found in the initial phase, we were able to identify some studies related to our scope. We used these in order to explore adjacent studies, as well as to look at common themes among them. However, due to the fact that we found very few articles using the keyword combination “radiology”, “acceptance” and “artificial intelligence” or “machine learning”, we broadened our search and replaced “artificial intelligence” as well as ”machine learning” with “technology” and witnessed a substantial increase in the number of hits. As a result, we chose to review literature related to the acceptance of both AI as well as other technologies used within radiology. In addition, we searched for “acceptance” and “artificial intelligence” to explore the concept of acceptance in other settings than that of the radiology department. We reasoned that this would increase our understanding and that the knowledge would be transferable to our chosen field of study.

4.1.2 Pre-study interviews

In order to refine our plans regarding data collection and procedures, a total of three pre-study interviews were done (see table 4.1). Two of the interviewees were currently employed at different global suppliers of image diagnostics software, where AI was included in all or a few of their products. The final interviewee was a decision maker at a Swedish hospital with more than two decades of experience in radiology. The interviews were mainly exploratory to get a wider understanding of the relations among the physicians, decision makers and suppliers, as well as to get a sense of potential areas of interest during the subsequent interviews. The pre-study interviews were open to their character and participants were asked to talk about implementation of AI and areas that could be important for acceptance. Areas such as trust and technological knowledge was emphasized, leading us to focus more specific on the attitudes of physicians and decision makers.

Table 4.1. *List of participants in pre-study interviews.*

Pre-study interviews			
Participant	Position	Interview type	Date
Participant X	Supplier	Face-to-face	12/02/19
Participant Y	Decision maker	Face-to-face	19/02/19
Participant Z	Supplier	Face-to-face	20/02/19

4.2 Research design

4.2.1 Research method

An interpretivist standpoint

Since this study focused on understanding the reasoning behind the factors that affect acceptance, the research question was approached from an interpretivist point of view. Bryman and Bell (2015) describe the interpretivist paradigm as focused on "*[...] understanding human actions rather than the forces that act on it*" (Bryman & Bell, 2015, p. 28), which the authors believe to be in line with the aim of this study.

Qualitative design

As the purpose of this study is to explore what factors affect the acceptance of AI among radiologists, an understanding of physicians' and decision makers' worldview is important, in order to understand why they end up with certain attitudes. Furthermore, the authors want to see the challenges of AI through the eyes of the participants. In cases such as these, Bryman & Bell (2015) suggest the use of a qualitative study design.

As earlier mentioned in 3.2.3, TAM has mostly been applied to quantitative studies historically. Nevertheless, our choice of a qualitative design was based on the findings of studies such as that of Vogelsang et al. (2013) as well as Ouadahi (2008). Vogelsang et al. (2013) argue that to acquire a deeper understanding of TAM and increase the likelihood of finding new acceptance factors, one has to approach it differently, either through mixed-methods or with qualitative measures. Similarly, Ouadahi (2008) argues that his study goes beyond "what" can predict employees' acceptance, an argument which is in line with that of Vogelsang et al. (2013). Furthermore, studies have proposed that the context of the healthcare sector differs a lot from other industries (Holden & Karsh, 2010). Drawing from the conclusion of these studies, we want to take contextual influences into consideration. For this purpose, Bryman and Bell (2015) recommend the use of a qualitative design.

Abductive approach

Using an abductive approach, we start with both the empirical context and theoretical rules (Mantere & Ketokivi, 2013). The abductive approach allowed us to continuously explore the empirical context as well as adapting the theoretical framework and interview questions simultaneously throughout the whole research process (Bryman & Bell, 2015). Given the fact that the research field within acceptance of AI in radiology is scarce, the abductive approach gave us an opportunity to both assess existing theory and potentially add our insights to create an extended TAM2 model, building on prior theoretical frameworks.

Further, the study included an abductive data analysis where we initially used an inductive approach, seeking to understand the empirical settings of the participants. Subsequently, a deductive approach was used in order to assess the fit of our chosen theoretical framework in this nascent context (see further discussion under 4.2.3 Data analysis). By applying the theoretical rules on the empirical findings, an inference to explanation became possible.

4.2.2 Data collection

Interviews

Semi-structured interviews served as a main source of data in this study. In order to capture thoughts about acceptance of AI, interviews were deemed as the most suitable qualitative method to use. While using TAM in a traditional way, with surveys, might provide the researcher with easily interpretable and comparable results (Vogelsang et al., 2013), our interview approach could capture unexpected issues of acceptance that a survey would not. Nevertheless, interviewing is a time-consuming endeavor and therefore we could not have as large of a sample size as if we had used surveys. As a result, this approach may lead to a deeper understanding of a few, but the findings are less generalizable than that of a quantitative study (Bryman & Bell, 2015). Another alternative would be to use a mixed-method approach, with both surveys and interviews, to verify the qualitative findings with quantitative measures. However, we argued that it was best to focus entirely on interviews in order to fulfill our study's purpose and explore the factors of acceptance rather than to statistically assess them. Lastly, one could argue that we would have gotten a larger sample size if we had used focus groups, while still reaching a deeper understanding of acceptance and exploring unexpected issues. Yet, in focus groups people might be afraid to express beliefs which are contradictory to those of the group (Halcomb, Gholizadeh, DiGiacomo, Phillips & Davidson 2007). In addition, physicians have a very busy schedule and it would be difficult to plan and coordinate such an approach. With all of these considerations in mind, we found that it was reasonable to conduct semi-structured interviews, an approach which will be further discussed below.

In a semi-structured interview, researchers have an interview guide with predetermined questions available (Bryman & Bell, 2015). This gives them a structure to follow, but also provides opportunities to ask additional questions as a response to answers by the interviewees that seems significantly interesting (Bryman & Bell, 2015). An interview guide was created by us (see appendix B), based on the theoretical framework of TAM2, covering the determinants of technology acceptance. This process could make our findings biased towards finding and validating acceptance factors that are already included in the theory. However, the interview guide served mainly as a tool to spark the discussion regarding aspects of acceptance, not as a tool to validate the framework. Furthermore, the interview guide included some initial questions regarding the interviewees background and experiences of AI as well. These questions were asked in order to make the participants comfortable with the interview setting before moving on to more difficult questions. Following these questions, the interviewees were asked about topics related to their attitude about, and acceptance of, AI. One important thing to consider is that the interviewees were not given a definition of AI, but were asked to speak freely about the topic. This was done in order to not put any pressure on participants with less technical knowledge. Additionally, our purpose with not providing a definition, was to capture a wide variety of views on AI and ideas about what opportunities comes with using it. However, if asked for a definition or clarification, we used the following definition from Kaplan & Haenlein (2018, p. 17): "*a system's ability to interpret external data correctly, to learn from such data, and to use those learnings to achieve specific goals and tasks through flexible adaptation*". Moreover, we also stated that we focused on image recognition and machine learning, if asked by the participants to be more specific on what kind of AI we researched.

Participant sampling

The data was collected from 18 in-depth, semi-structured interviews with physicians and decision makers within radiology as well as neurology. The distribution in terms of gender among the participants was 11 male and 7 female.

Radiologists today mainly serve as a paraclinical profession, meaning that they do not primarily meet the patients, but mostly provide clinical physicians with expert knowledge within radiology. Clinical physicians serve as internal customers to radiologists and sometimes cooperate closely together with them. The relation between neurologists and radiologists is an example of such close collaboration. Neurologists are usually dependent on results of brain scans as part of their diagnosis and evaluation, often leading to a proficiency among neurologists in analyzing medical images as well. We chose to interview decision makers as well as physicians from other fields, such as neurologists, in order to triangulate the answers that had been given, during both the pre-study as well as the main study. However, one has to bear in mind that the results could be leaning toward a more positive attitude. The participants voluntarily answered our request, and sacrificed time in their schedule. This fact could be interpreted as an inclination among the participants to be more interested and eager to accept AI than the average radiologist.

In order to address the research question of this study, a purposive sampling was conducted on the basis of role and profession (Bryman & Bell, 2015). Prior knowledge of AI was not concerned in the sampling process. Physicians within the fields of radiology and neurology as well as decision makers at major hospitals all around Sweden were contacted. Their contact information was collected from the registers of several professional associations within these fields, associations in which the participants served as board members during the time of this study.

In total, 48 physicians (radiologists, neurologists) and decision makers were invited to participate in the study, either through purposive sampling by the authors themselves or by a snowball sampling procedure, in which the physicians and decision makers referred to others that had more time or knowledge in the area. Table 4.2 provides an overview of the participants that agreed to participate in the study. In total, 18 participants were interviewed. We started to see recurring topics and themes around the time when 13-15 participants had been interviewed. Very few new thoughts or ideas, if any, related to acceptance were discovered after this point. Francis et al. (2010) propose that if no ideas emerge after a certain number of interviews, one could use that as a decision point for when saturation has been reached. Similarly, we believe that we reached a sufficient level of saturation, especially when considering our time restriction and available resources. Yet, in future studies we believe that one might be able to get a richer description of acceptance by using a larger sample size, adding a wider variety of characteristics among the participants.

Table 4.2. *List of participants in main study interviews.*

Main study interviews			
Participant	Position	Interview type	Date
Participant 1	Decision maker	Skype call	28/02/19
Participant 2	Decision maker	Face-to-face	04/03/19
Participant 3	Decision maker	Phone	05/03/19
Participant 4	Radiologist	Phone	06/03/19
Participant 5	Radiologist	Skype call	07/03/19
Participant 6	Radiologist	Skype call	08/03/19
Participant 7	Radiologist	Skype call	18/03/19
Participant 8	Radiologist	Phone	20/03/19
Participant 9	Radiologist	Phone	20/03/19
Participant 10	Neurologist	Phone	21/03/19
Participant 11	Decision maker	Phone	22/03/19
Participant 12	Radiologist	Phone	26/03/19
Participant 13	Decision maker	Phone	27/03/19
Participant 14	Decision maker	Skype call	28/03/19
Participant 15	Radiologist	Phone	28/03/19
Participant 16	Neurologist	Face-to-face	28/03/19
Participant 17	Radiologist	Face-to-face	29/03/19
Participant 18	Radiologist	Face-to-face	29/03/19

Interview settings

The interviews ranged between 35 to 60 minutes and were conducted in February and March 2019. Due to time constraints and the distribution of participants all over Sweden, we decided to mix face-to-face interviews with skype calls as well as phone interviews. Even though Sturges and Hanrahan (2004) argues that face-to-face interviews in some cases might be favorable, the authors considered the cost of not getting in contact with highly relevant interviewees to be higher than the cost of lacking visibility of facial expressions, a consideration also highlighted by Bryman and Bell (2015). The major challenge of using calls instead of face-to-face interviews, was the risk of having a bad connection, resulting in words disappearing or being misinterpreted. During the interviews only minor problems that were considered to affect the quality of the interviews negatively occured. However, we could not be certain if this loss of information altered the final results, but we tried to minimize this effect by encouraging the participants to repeat their statements when in doubt about what was said.

As preparation, an information leaflet (see Appendix C) was sent to all participants through email, describing the purpose of the study as well as the data collection process and recording of the interviews. However, to make sure that the participants were informed, each interview session started with the authors repeating the purpose briefly. Also, after the brief information was provided, the participants were provided the opportunity to consent to being recorded for data processing purposes. Each respondent was granted anonymity in the study and were informed that they could discontinue their participation at any time.

Both authors were present at the interviews, however, one was leading the interview, setting the frame of each interview. The second author had a more observing role, taking notes and adding questions in the end of each session in order to cover areas of interest that had not yet been addressed or clarified. The interviews were conducted in Swedish, as all participants were native or fluent in the language and had a preference to use it in the interview situation. All interviews were recorded with an Olympus © VN-541 PC dictaphone and transcribed within a week.

To make the interviewees comfortable, the authors had pre-interview conversations (off the record) to build trust. We made it clear that we were interested in getting a broader picture of potential benefits and challenges of technological implementations, as well as used our prior experiences from the industry to show that we understood the challenges that comes with implementations.

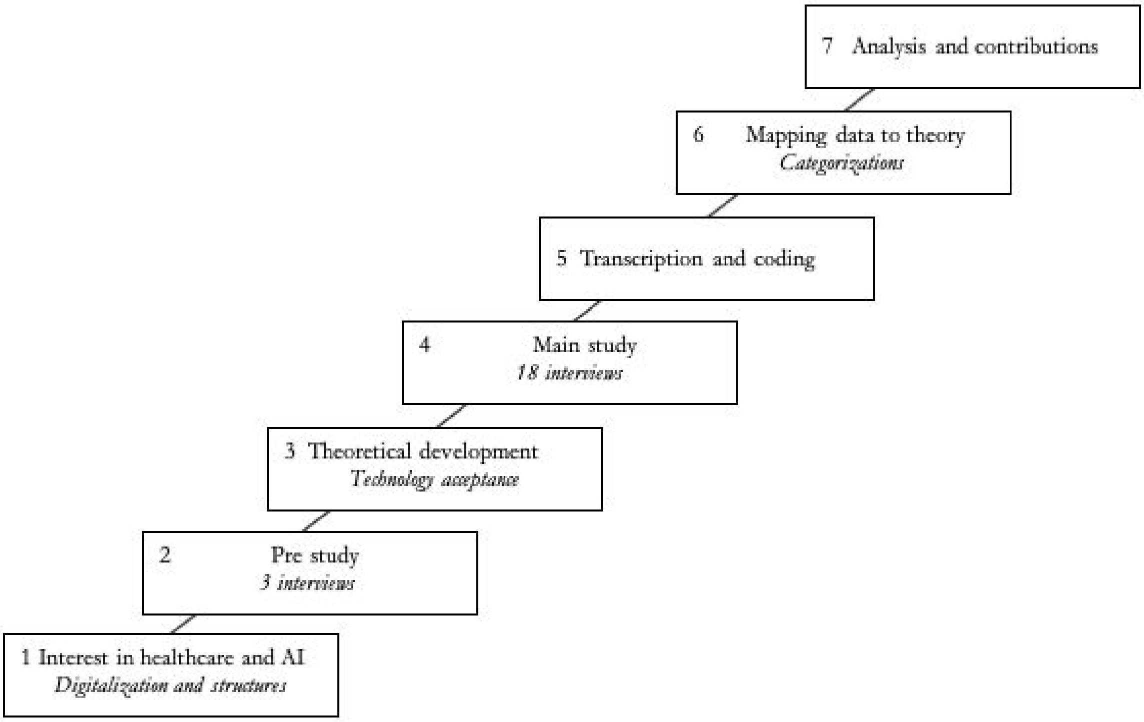
4.2.3 Data analysis

We chose to follow the principles of qualitative data analysis as described by Braun and Clarke (2006), focusing on the use of inductive thematic analysis, as it would allow us to make a detailed analysis on the data. All transcribed interviews were read, analyzed and coded individually by each author, highlighting recurring trends and interesting sections. Then, the individual findings were compared and discussed (if any disagreements would occur). Due to the study's methodological choices and time constraints, the data was analyzed through semantic themes, where the focus was to describe and interpret patterns rather than seeking to explain underlying assumptions (Braun & Clarke, 2006). The process had an open coding approach (Corbin & Strauss, 1990), which is beneficial in order to recognize concepts that can be grouped and categorized in the end.

As the process of coding included several challenges of deciding how to categorize the data, all categories and themes were given individual definitions (see 5. Empirical findings), which allowed us to be more consistent throughout the whole process of categorization. When the themes had been categorized, they were reviewed and updated in order to assure a logical division and inclusion of each theme in the proper category. After the initial categorization was done, the subsequent analysis had a more deductive approach, as we assessed the fit of our empirical findings to the existing TAM2 framework (see table 6.1 and the section following the table for a detailed discussion). We chose this division of inductive and deductive approaches in order to let our empirical findings guide the research process and assess the existing theoretical framework. In contrast, starting with the theoretical framework could have made us jump to premature conclusions in order to validate the theory.

For an overview of the research process that has been described in this section, see figure 4.1 below.

Figure 4.1. The research process of this study.



4.3 Quality considerations

4.3.1 Authors' position

In order to make this study as transparent and reliable as possible we want to consider possible personal biases. Both authors have an interest in technological transformation as well as experience from working in healthcare. Martin, has a degree within medical science and work experience as a physiotherapist, while Felix has experience as an organizational consultant within healthcare consulting. Additionally, Felix has worked for a global information technology company that develops AI applications for healthcare. However, no one had any major experiences from radiology, even though a pre-understanding of the Swedish healthcare system existed.

No one, besides one of the participants in the pre-study and one in the main study, had a personal connection to the authors. The participant in the pre-study was a former colleague to one of the authors and the participant in the main study was a friend of the family of an author.

4.3.2 Quality of research

The concepts of reliability and validity are important in order to value the quality of academic research (Bryman & Bell, 2015). However, the before-mentioned concepts are closely related to quantitative research and connected to measurement (Bryman & Bell, 2015). Lincoln, Lynham and Guba (2005) instead propose that quality assurance within qualitative research should focus on *trustworthiness* and *authenticity*.

Trustworthiness

Trustworthiness consist of four different criteria, *credibility, transferability, dependability* and *confirmability* (Bryman & Bell, 2015).

Through *credibility* the authors ensure that research has been conducted through good practice and that through confirmation from the social world, the authors have correctly understood the area of study (Bryman & Bell, 2015). We tried to validate responses from the interviewees by using triangulation of sources, speaking to important stakeholders with close relations to the radiologists, such as decision makers and neurologists. Furthermore, by using respondent validation (Bryman & Bell, 2015), ideas and concepts expressed through one or a few concepts could be tested and asked about in following interviews. For example, the influence of organizational demands on AI acceptance were found and then validated in subsequent interviews. As a result, this allowed us to identify more distinct themes covering AI acceptance among radiologists. In addition, we separately coded the data as a first step of analysis (analyst triangulation).

Our study examined the attitudes toward the wider concept of AI, a complex (and sometimes self-learning) technology, still mostly in a pre-implementation phase. As a result, our findings might not be *transferable* to other technologies which have less complexity. Additionally, the findings might not provide the same results if a study is conducted in an implementation or post-implementation phase. Furthermore, the authors are aware that the healthcare industry is a sector that is different from most other industries. With this in mind, the *transferability* outside of the industry is limited. However, some aspects of acceptance might be transferable to other professional workers when accepting AI.

In order to ensure *dependability* in the process, meaning to show that findings are consistent and could be repeated (Bryman & Bell, 2015), records from all steps of the research process have been saved; from development of research question to selection of participants, interview recordings and transcripts. This has been done in order to allow external control to be done as well as helping the authors to distance themselves from adding personal opinions when possible, allowing *confirmability*. However, we were aware that our positive attitude towards AI might influence our interpretations. Given this circumstance, we used a journal for the research process and repeatedly discussed our personal feelings and ideas about the study, to be aware of potential pitfalls during the process.

Authenticity

To assess the wider impact of the research, Lincoln et al. (2005) calls for a criterion they call *authenticity*. In this criterion, we focused on evaluating *fairness* (Bryman & Bell, 2015), which means that the research fairly represents viewpoints in the overall social setting you study. In our initial categorization and analysis, all of the participants but one were quoted. A majority of the quotes will be presented in section 5, Empirical findings, while additional ones can be seen in Appendix D. The authors have tried to take into account the views of decision makers as well as physicians from other fields, in order to give the reader some additional insight. However, the authors have not had the time nor resources to study the complete ecosystem of important stakeholders when accepting AI in radiology.

5. Empirical findings

Overall, our findings show mostly positive attitudes toward AI within radiology, thereby showing indications of acceptance among radiologists. However, the participants sometimes referred to specific areas of concern for acceptance, such as lack of control. Generally, the understanding of AI was fragmented among the participants, some stating that they had almost no knowledge at all, while others came across as more confident about their level of knowledge. Furthermore, most of the discussions covered machine learning (especially supervised learning, see figure 3.1) and opportunities as well as challenges within this area.

Our thematic analysis resulted in 15 separate antecedents that were categorized into the areas of user experience, external influence, system performance, personal experience and uncertainty, which will be presented in this section along with their definitions.

5.1 User experience

"The degree to which a user experiences the program as easy to use"

The user experience among physicians and decision makers within radiology could be viewed from two different angles, simplicity and integration. Simplicity is focused on the importance of the program or application running smoothly, independently from other systems, while integration concerns the relation between new and existing systems.

5.1.1 Simplicity

"The degree to which a user experiences the program as easy to use independently from other systems"

Radiologists experience a high volume of patients to examine and diagnose every day, which could explain why time management seems to be a major concern for them. As a result, radiologists find it important for AI to be user-friendly. Furthermore, interviewees emphasize that in order to find AI usable, the factor of time cannot be down-prioritized.

"[...] it is important when AI is coming that, regardless how good it is in diagnosing, it will not be too slow... then you will not manage to do anything."

- Participant 4, Radiologist

Some of the interviewees had tried AI applications in their department and addressed the low work required and user friendliness as a major strength.

"Yes, it has been very easy, you could say... it has only been in the background and sorting... so it has been none... no work effort at all really... which is very important as well."

- Participant 1, Decision maker

5.1.2 Integration

"The degree to which a user experiences the program as easy to integrate with other systems"

It is not only the application itself that seems to be of importance when radiologists are considering the user experience. In today's healthcare, there are plenty of different programs, machines and applications that cause integration issues. Therefore, it was a common subject when the radiologists discussed acceptance of AI.

"[...] the major problem is to fit it into the workflow... a regular clinical workflow. You cannot run between different computers, different programs [...]"

- Participant 4, Radiologist

The integration issues that the interviewees had experienced did not only seem to affect the user experience negatively, but also seemed to cause a heightened state of concern about risks in the daily routines.

"[...] if it is not working, it is tricky, as you then have to open up two things, and you do not do that... then you have to transfer the information from one system to the other, and that can be to cut and paste and that could be a risk... so, no... the user friendliness has not been that good [...]"

- Participant 6, Radiologist

One factor that was highlighted as a problem, by some participants, was that AI requires large amount of data from various departments to reach full capacity. This integration factor was perceived as influential in the acceptance of AI.

"What is needed to be done, is to connect various diagnostic silos. We got radiology, we got pathology, we got genomics, we got... You need to combine... to make a really good AI-system for diagnostics. It is a lot of work to be done before we are getting there and have what we really want. And it will take some time, it is not done... in a year."

- Participant 5, Radiologist

Here, the participant highlights the necessity of working together and that an organizational shift is needed in order to integrate AI. These challenges cause radiologists and decision makers to raise concerns regarding the efficiency of using an AI system. Furthermore, these concerns also relate to the supply of AI applications.

"[...] because it is one diagnose... one specific software for one diagnose and then we have five thousand other diagnoses... so the scalability is non-existent... it is not possible... we cannot integrate five hundred software, we cannot integrate 50 software... we might be able to integrate two, three or four [...]"

- Participant 1, Decision maker

Based on this, it seems like radiologists' acceptance towards AI is partly driven by organizational concerns, that the limited and narrow supply of applications will bring only minor value among a small set of diagnoses.

5.2 External influence

"The degree to which external parties influence the acceptance of AI"

Throughout the interviews, the influence of external parties came up quite often. Besides the social pressure given by their peers, additional factors such as organizational influence or work-related aspects were brought up, which will be presented below.

5.2.1 Professional community

"The degree to which the beliefs of the professional community influence the acceptance of AI"

During the interviews, physicians and decision makers talked about the influence from various stakeholders regarding acceptance of AI in their respective field. A major influence, that was commonly brought up as a source of influence by the participants, was congresses and symposiums within the community of radiology, where physicians and medical companies from all over the world come to meet.

"[...] already at that meeting [RSNA, Chicago] you realized that it would take time before the technology progresses that much... Instead they coined the expression 'AI will not replace radiologists, but radiologists who do not use AI will be replaced by radiologists that use AI', meaning that you have to be on board and use the technology."

- Participant 7, Radiologist

The quote illustrates how the professional community might be an important influencer when it comes to shaping the opinion on AI. However, another group also seemed to have an effect on the individual perception, namely the colleagues at the local department.

"If you look at our congresses, both in Europe and US, you see that there is an enormous interest in everything that involves AI and its different varieties. When you are coming back home to the department, it is more 'yeah, yeah... we'll see... we'll see where we end up.'"

- Participant 5, Radiologist

Even though this participant described skeptical views, the influence of local colleagues might not only work as a source of negative attitude towards AI, but also as a willingness to achieve change.

"[...] what I most often face is 'What the hell? Why is nothing happening!? Why don't we already have these things in our systems?! It has been a hot topic for five to ten years and we have not come further, why is nothing happening?', that is the attitude that I mostly face."

- Participant 14, Decision maker

What could be seen in this section is how persons of importance might influence the individual radiologist's attitude towards AI on different levels. Researchers and companies seem to push for a change in the field, while radiologists are more ambiguous in their beliefs.

5.2.2 Capacity

"The degree to which perceived current and/or future workload influences the acceptance of AI"

Several of the radiologists talked about the need to use AI simply due to the fact that the workload has become too much to handle for them.

"*The number of radiologists are not increasing, so to be able to handle this we need help from the computers too. Therefore, I believe... otherwise... we can't work in the same manner as today, it is not sustainable, if we continue like this then we can't cope with the current production that we have.*"

- Participant 14, Decision maker

As seen above, some participants declared a sense of urgency in the way that they addressed this issue. It became clear that they needed some kind of help, and if AI could provide that help they were positive to the new technology. In addition, the participant in the example above did not seem to believe that there was a choice between using AI or not. In contrast to this, some radiologists talked about a choice: either increasing the workforce or using AI (or a combination of both).

"*It is our dilemma, that we struggle and struggle and they just pile images on to us [laughter]. It is increasing all the time, we can't keep up with it and it is frustrating for the patients and clinicians [...] The question is: what should we replace... should we train more radiologists? I think that is done to some extent. Or should we bring in AI as support?*"

- Participant 12, Radiologist

In this example, the participant argues that radiologists still have a choice if they want to introduce AI or not into the workforce, at least partly. However, the participant shared the same feelings of having a heavy workload that was not sustainable in the long run, with the first interviewee that was presented in this section.

5.2.3 Organizational demands

"The degree to which perceived demands from parties outside of the radiology department influence the acceptance of AI"

Since the radiologists are a part of the hospital system, we found that they could feel pressured to use AI when considering how stakeholders outside the radiology department might affect them if they avoided using it. One major concern was that if they did not start using AI, their "clients" (the referring clinicians) would bypass them and purchase AI radiology applications for themselves.

"*In order to remain a specialty, we must be involved and design how one should use these things. If we turn obstinate like that... then the clinicians - we call our referring clinicians for clinicians - will set up these systems on their own.*"

- Participant 7, Radiologist

However, some argued that even though this could be a threat, it could be avoided with improved communication.

"However, I believe that if we get stuck crosswise and say 'no, we do not want that', then it will get in by itself... it gets into our department anyway [...] but if you have a good dialogue with the referring clinicians and work together, then I believe that... then you avoid this..."

- Participant 3, Decision maker

5.2.4 Professional status

"The degree to which users believe that accepting AI will improve their status in the community"

The current discussion about the future demand of radiologists has raised questions among stakeholders in the field about how to approach AI. Further, some participants described how this could have an effect on the image and status of the radiologist as a professional worker in the clinical setting.

"[...] about three, four years ago you were convinced that AI would take away our jobs within five years, and you should absolutely not begin a specialization within radiology... that view has disappeared completely, instead now you see that we will have a job that both allows and demands more contact with referring clinicians and more contact with patients as well..."

- Participant 4, Radiologist

The quote highlights how the common view of radiologists has changed recently; an opportunity to leverage the status of the profession has occurred, instead of a fear of losing one's job.

Some participants emphasize how radiologists could develop a competitive advantage and climb in healthcare's pecking order. One participant develops this argument below.

"[...] to put image diagnostics in relation to the patient and what problem the patient has in communication with the clinicians... that is what is going to become a more important aspect as well, thus... if that happens, which I hope and believe, then the status of radiologists will not decrease, but more likely the opposite. Then you become even more of a partner, and less of a pure service discipline that only execute an order..."

- Participant 14, Decision maker

Even though the future remains ambiguous, most participants express AI as a positive influence on their status. However, one participant described a reluctance to change in his team, which was related to the image of themselves.

"[...] I have tried here, in region X, a system that finds dots in the lungs during CT-scans, and I first though, a bit stupid as I have been around for quite a while, that my colleagues would cheer. That 'now when this system is implemented, you do not need to search for dots, as it is quite time consuming and boring' [...] but it almost backfired, there were many that did not want it...it might have threatened the vocational pride a bit. During decades, they have learnt to become good at finding the dots by themselves, they do not want a system that outperforms them."

- Participant 7, Radiologist

5.3 System performance

"The degree to which the performance of the system influences acceptance of AI"

The importance of the applications to have a high performance was highly emphasized by most of the interviewees. In order for AI to be considered, the radiologists most often set high demands in that it should be adding value to their daily tasks. Different aspects were mentioned to influence acceptance, such as how well AI could be applied to one's job, the mismatch between expectations built up by the suppliers versus reality, the ability to exert control, as well as the accuracy of the AI technology.

5.3.1 Applicability

"The degree to which the AI system is perceived to be applicable to one's job"

The applicability was one of the most frequently discussed topics throughout the interviews, where many of the participants believed that AI was well suited to their job tasks.

"[...] that standard analysis, where you see, for example, that the ventricles are expanded, that the brain volume has increased or decreased and so on. AI is very well suited for that..."

- Participant 15, Radiologist

As earlier presented, radiologists experience, on average, a high demand of their services, making them eager to accept solutions that can reduce their workload. However, the use of AI could not only be used to increase the quality of the assessment, but also to increase efficiency.

"[...] to get support for things that manually takes long time to do, for example to measure different [pathological] changes that a computer can do quickly... It is quantification and then detection, where you can get support by an AI-system, which makes it easier... it makes it faster, and also lowers the margin of error."

- Participant 17, Radiologist

However, even though the participants could understand the benefits from having the AI, some expressed the reality to be far more troublesome and questioned the applicability to a clinical setting.

"AI is pretty bad at saying that 'there is nothing else'. Every answer that you want from an AI, you must ask a question that it has to... then it has to have all the information about everything... and that is... that type of information is... it is extremely substantial in this kind of picture..."

- Participant 11, Decision maker

What is expressed in this quote is the difficulties to make AI relevant when working with complex image recognition, such as recognition of the human body. What makes it even more complicated is the large variation in the appearance of a healthy and well-functioning body. Consequently, the AI is running the risk of providing false positives or false negatives.

"I think that you could say that there is a risk... there is too much individual variation, it needs to be a human eye that can discover these variations, which a machine would not be able to do..."

- Participant 16, Neurologist

The individual variation makes the question of "what does healthy look like?" more complicated, raising concerns whether a machine would be able to see these delicate distinctions. It seems like the participants believed that, in order for radiologists to trust the algorithms, the computers need proper training from highly skilled experts. This suggests that the participants mainly think of algorithms based on supervised learning when discussing AI.

"[...] someone has to train it and that is a thing that becomes even more important. I do not think that anyone can train an algorithm... that is why I do not believe in all these applications. They might work in one place, but to create an algorithm that can do everything... everywhere... that will take a while..."

- Participant 2, Decision maker

5.3.2 Expectations

"The effect that the perceived gap between what was promised about AI, and what was delivered, has on applicability and accuracy"

The aspect of expectations is mainly related to hyped sales pitches by companies, perceived by some participants to cause a gap between pre-set expectations and experienced reality. This gap is described below to be something of a frustration to the participant, affecting the perception of the application negatively.

" [...] they are trying to give a, in my eyes, false picture of straightforwardness... it always sounds very fancy, but when you are looking closer at it there is a lot of 'but and aber and maybe and that it does not really work'... that is something that I have experienced... the way they are presenting AI to the profession might not always make us feel that we have been given what has been promised... there are for sure better as well, as they sometimes actually can hold their promises"

- Participant 6, Radiologist

The feeling described above, that the radiologists have not been given what was promised, might indicate that this is related to the capabilities or performance of the application.

5.3.3 Control

"The degree to which the perceived degree of control of the system influences acceptance of AI"

If AI applications would take over some tasks from radiologists, there would be a decreased control over the diagnostic process, requiring a high amount of trust in AI. In a field such as radiology, which is associated with high responsibility and reliance on making correct decisions, the feeling of losing control was a major concern to the participants.

"[...] there might be a fear that AI can become too much of a 'black-box'... you go too far in the process and that you then do not know... what is happening... what is the actual basis for the decision for the individual patient... I think that some are afraid that they then need to handle data that they do not understand or that you just get the output... 'well, and how did it come to this output?'... and to

understand how this work, no one does... I mean, in deep learning you cannot understand what the computer did..."

- Participant 6, Radiologist

The participant highlights how the feeling of a black-box raises doubts of using AI. This might reflect that if the radiologist cannot follow the logical steps of reaching the conclusion, it will be easy, for both physicians as well as patients, to question diagnoses and treatment proposals, making AI difficult to accept.

"[...] it can become dangerous if you assign that to AI... then you have to be sure that... AI is good enough for it. There might be ethical problems and doubts whether the final decisions and treatments and stuff, that will remain in the hands of humans for quite some time, I think."

- Participant 15, Radiologist

The quote captures the concern of how the lack of control could lead to misdiagnosis and mistreatments that in the end would affect the patients. A lack of control seems to lead to mistrust in the algorithms' ability to make correct diagnoses. The fact that it is done by computer, and not a human, adds an additional layer of the control aspect.

"We believe that it is okay to drive into a ditch once in a while, we are still allowed to drive a car. But if an automatic, AI-driven car would crash once, it is over. That is not allowed to happen..."

- Participant 5, Radiologist

"Would you dare to go with a car on autopilot, 120 kilometers, on the German autobahn? Or fly an airplane without a pilot? Would you like a machine to diagnose you?"

- Participant 18, Radiologist

The participants used examples such as cars and planes to describe how exposed you could feel when you put your safety in the hands of a computer. Furthermore, the participants emphasized the use of AI from a broader perspective, where it is not only related to them and their work, but also to the end users. This might propose that the reluctance among patients to be diagnosed by a computer, instead of a human, could be a factor considered by radiologists when accepting AI.

5.3.4 Accuracy

"The degree to which the perceived accuracy of the system influences acceptance of AI"

A final area of concern regarding the system performance was the importance of accuracy. The participants described the need to be able to trust that the algorithm delivered the results in an "accurate enough" way. In contrast to other antecedents within system performance, this antecedent is solely focusing on the technological limitations that AI still brings, regardless of influence from applicability or control.

"[...] that is what I believe is the biggest problem with what we call artificial intelligence and machine learning, that when we are... when the machine is examining images, there are actually some differences in voxel intensity [...] sometimes, in the voxel, one millimeter is quite large... pictorial. If the distinction between brain and liquid goes in the middle of the voxel, the machine has difficulties in deciding what it is. It can include too much brain or too little brain..."

- Participant 18, Radiologist

The participant explains how AI might have limited accuracy within specific areas and even anatomical structures. As anatomical structures within the body have different sizes, the accepted margin of error will vary. The smaller the structure, the more important the accuracy of AI is. Furthermore, another aspect of accuracy might be the contribution of AI when highlighting pathological changes.

"Things that are not good enough have been tried, yes. It highlights a lot of things that is nothing. You call that false positive and, of course, if it becomes too much false positives... that is a lot to sort... Yes, we have seen that. We had a CAD-system for the colon. It was a lot of false positives, you got fed up with it..."

- Participant 7, Radiologist

The quote shows how the level of accuracy in detection needs to be high, even in those cases when the system is merely assisting the physicians, otherwise they will not use it. Not least because it will not save time, but rather the opposite. The importance of this aspect was shown in section 5.1.1 Simplicity.

5.4 Personal experience

"The degree to which a user's knowledge and previous experiences influence acceptance of AI"

When talking about the acceptance of AI, the participants often described their technological understanding as well as prior implementations that they had heard of or participated in. Therefore, experience was divided into two categories; technological understanding of AI and prior implementations.

5.4.1 Technological understanding of AI

"The degree to which knowledge of AI influences acceptance of AI"

Many radiologists felt unsure about what AI really means, and what different types of AI there are. The level of knowledge was fragmented among the participants, which was shown in several statements that were made in the interviews (e.g. see participant 6 below).

"*I think it varies a lot… there are people who… principally you can say that the level of knowledge is really low among radiologists when it comes to what AI really means, what Deep Learning is and so on… I can not say that I know a lot about it… as a result, it may be difficult to embrace and adopt something we do not know that much about.*"

- Participant 6, Radiologist

This participant was hesitant about accepting the technology due to a lack of understanding. It was also the participant's belief that the level of knowledge among radiologists were generally quite low. However, there were participants that did not believe that they needed to understand the technology to accept it.

"*And then I can not reason that AI is the most complicated part there, I have to say, because if you take into consideration all of the enormous [emphasized] technology that surrounds a magnetic* *camera, then it is so tremendously many things that one, as a radiologist, absolutely [emphasized] does not have any detailed knowledge about.*"

- Participant 14, Decision maker

Participant 14 compared the use of a magnetic resonance camera to AI when asked about if the level of complexity of AI might be higher than that of previous technology.

Some of the participants were more nuanced in the need for technological understanding of AI. One participant described how some degree of black-boxing was not perceived as an impediment for acceptance.

"*One probably needs to have at least some degree of insight in order to grasp what it is about... otherwise I mostly believe that you... have some opinion that is biased. But then I do not believe that one should have a detailed knowledge in any way, rather knowing basically: 'this is the limitations, this is the system and this is how it works'.*"

- Participant 13, Decision maker

When asked about AI, some of the participants also wanted a definition of AI while others didn't react at all to the use of the term AI.

"[...] we are talking about the technology in singular here, but this is actually a very broad technology with a lot of applications and the like, so I mean, then we have to define a bit more clearly what we mean by AI if we should be able to say that we understand the technology [laughter]."

- Participant 14, Decision maker

5.4.2 Prior implementations

"The degree to which results of previous (non-AI) technology implementations influence the acceptance of AI"

Radiology is a highly technical field and senior radiologists has seen a lot of technology development throughout the years. When talking about acceptance of AI, they often come to think of their past experiences and some explain that they feel a bit skeptical towards system implementations because of these experiences.

"*Many believe that you buy a complete and finished solution, but that is something I have learned through the years, that you never do...*"

- Participant 3, Decision maker

"[...] someone talked a lot about a machine that could... well... measure something or do something and then it was purchased and cost a fortune, but then people realized that 'no, it was not that great' and became left standing in someone's closet."

- Participant 12, Radiologist

Some participants specifically addressed the issue of making the same mistakes over and over again, not learning from prior implementations. This might have a cumulative effect on accepting new technology, such as AI, in the future.

"You repeat the mistakes over and over again and then you have to handle... and there is... sometimes you have a tendency to not include the users in the procurement process and then... there are a lot of examples when the technology actually isn't that helpful. Or makes a mess... makes the work less efficient."

- Participant 9, Radiologist

5.5 Uncertainty

"The degree to which an individual is uncertain about how the use of AI might influence his or her future"

A recurring theme among the participants in this study, is that there is a lot of uncertainty surrounding the use of AI in radiology and how it could come to affect work and processes. Specifically, most of the radiologists talked about uncertainty of their future work content, responsibilities and how AI could be implemented in a relatively ambiguous legal environment.

5.5.1 Future work content

"The degree to which an individual is uncertain about how the use of AI might influence his or her future work content"

There is a lot of uncertainty about the future work in radiology when discussing AI. Many are talking about the potential of AI and how it might affect radiologists' working conditions positively or negatively. Some have had first-hand experience with AI systems while others have heard or read about it, which might increase the uncertainty.

"As stated before, if the artificial intelligence can handle almost anything that we are doing right now we will become somewhat redundant. And if the artificial intelligence can help us with finding things that we later can proceed with and demonstrate and develop, then I think it becomes the other way around. And I think it is quite uncertain in which direction we are heading."

- Participant 9, Radiologist

One radiologist even went so far as to say that this uncertainty is creating a psycho-social problem among radiologists.

"It is a relatively high workload a lot of the time [...] we don't have any idea of what is to be expected, and I have told you this before, that it is a psycho-social problem as well, that we don't really know what we have to prepare for... I think many suffer from this... that it feels really tough for many."

- Participant 6, Radiologist

It is evident from these statements, that the uncertainty of what AI could achieve is of importance to the radiologists and could influence the acceptance of AI.

5.5.2 Responsibility

"The degree to which an individual is uncertain about how the use of AI might influence his or her future responsibilities"

In a world where machines are able to make diagnoses and work more human-like, ethical and moral dilemmas become more common. The participants described different situations where they thought about a shift from man to machine and who should be held responsible for the result that the machine produces. In order to accept AI, participants stressed the need to have a clear division of responsibility.

"Well, there are a lot of feelings involved when... people make mistakes and then those people are responsible, but who is responsible when machines fail? [...] You know, up until that moment when the radiologist is involved, then we are responsible, my word is the last. But when the time has come to only machines... that I don't really know. I don't know."

- Participant 18, Radiologist

While the overall responsibility was discussed, there were also some thoughts about letting the referring clinicians take on some responsibility.

"So, if you leave the opinion to the computer then it is some other human being that should be responsible and that is the referring clinician. And so far, the referring clinicians have been pretty unwilling to be held responsible for what is on the x-rays, they really want a radiologist's opinion even for rather simple examinations which one would think that 'this might the referring clinician handle'..."

- Participant 5, Radiologist

5.5.3 Legal

"The degree to which an individual is uncertain about how the use of AI might be influenced by legislation"

In addition to the questions raised about responsibility, a lot of the participants talked about legal uncertainty. There were many question marks regarding the use of AI with current legislation and if/how it could be changed to accommodate the technology.

"A third challenge, frustration for me is… the law behind and… the companies that work with this, they need data to move forward and we in healthcare don't have any good ways to provide this information… approve that it is released…"

- Participant 1, Decision maker

GDPR was mentioned as something that had become an issue for them already, and could be even more troublesome if AI would be introduced into practice. Some participants specifically brought up the issue of what data they were allowed to share in order to develop and use AI.

"It is a lot of this with GDPR and where you can store patient data and stuff like that, which you have to have decided on before moving on to something like that."

- Participant 13, Decision maker

6. Analysis & Discussion

This study is among the first to apply TAM2 through a qualitative method on acceptance of AI among radiologists. This section is divided into two parts. First, we will begin with an assessment of the theoretical fit of the antecedents, found in the empirical data, to TAM2. Second, we will use our findings to analyze how determinants within both social influence processes (subjective norm, voluntariness and image) as well as cognitive instrumental processes (job relevance, output quality, result demonstrability and perceived ease of use) could serve as a first step towards understanding how acceptance of AI is shaped within radiology. Here, our findings will be compared to previous acceptance literature. Lastly, we will present our suggestion to an extended model of TAM2.

6.1 Fit between TAM2 determinants and empirically found antecedents

As a first step in our analysis, each of the antecedents were evaluated for their fit in the TAM2 framework in order to get an overall understanding of the model's applicability to the empirical data. Table 6.1 gives an overview of this process, where each empirically found antecedent (as described in section 5) has been placed on the horizontal axis and each determinant of TAM2 (see table 3.1) on the vertical axis. For the purpose of matching antecedents with determinants of TAM2, we used the definitions provided in table 3.1. In the event that we saw an overlap between an antecedent and a determinant, partly or fully, an "X" was placed in the table. On the following pages, we will describe the relationships that we have found (displayed in table 6.1) and explore how well they fit into the TAM2 framework. Then, in order to simplify this process, we will use our definitions of the empirically found antecedents and match them, one-by-one, with the most relevant determinant of TAM2 (see table 6.2).

Table 6.1. *Fit between discovered antecedents to acceptance and the determinants of TAM2.*

		SI	IN	PC	CA	OD	PS	AP	EX	CO	AC	TU	PI	FW	RE	LE
	EXP	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
Social influence processes	SN	-	-	X	-	X	-	-	-	-	-	-	-	-	-	-
	VLN	-	-	X	X	X	-	-	-	-	-	-	-	-	-	-
	IMG	-	-	X	-	X	X	-	-	-	-	-	-	X	-	-
Cognitive instrumental processes	JR	-	X	-	-	-	-	X	X	-	-	-	-	-	-	-
	OQ	-	-	-	-	-	-	X	X	X	X	-	-	-	-	-
	RD	X	-	-	-	-	-	-	-	X	-	-	-	-	-	-
	PEU	X	X	-	-	-	-	-	-	-	-	X	X	-	-	-

Table 6.1 list of abbreviations

Horizontal (empirical findings): Simplicity (SI), Integration (IN), Professional community (PC), Capacity (CA), Organizational demands (OD), Professional status (PS), Applicability (AP), Expectations (EX), Control (CO), Accuracy (AC), Technological understanding (TU), Prior implementations (PI), Future work content (FW), Responsibility (RE), Legal (LE).

Vertical (TAM2): Experience (EXP), Subjective norm (SN), Voluntariness (VLN), Image (IMG), Job relevance (JR), Output quality (OQ), Result demonstrability (RD), Perceived ease of use (PEU).

For experience, a moderating variable of subjective norm (as it is defined in TAM2, see table 3.1), we could not find anything in our empirical data that pointed towards that the effect of subjective norm will subside, increase or stay the same over time. Even though this effect might be present, this did not seem to be a top of mind subject to the participants.

6.1.1 Social influence processes

When it comes to subjective norm, we believe that it is highly related to *professional community* and *organizational demands*. In our findings, the professional community (see 5.2.1) seems important to the radiologists as it influences their perceptions about AI through events such as conferences. Another important group is the referring clinicians and other partners in the hospital, who may have a lot to say about the use of technology since they are the "clients" of the radiology department. They influence subjective norm through organizational demands.

Concerning the influence of voluntariness, the participants have stated that they hear a lot about AI in their *professional community*, with several of them citing a quotation about the replacement of radiologists that do not use AI. Our conclusion of this reasoning is that the use of AI is in fact mandatory and thereby affect the determinant of voluntariness. In addition, most of the radiologists' themselves do not believe in a sustainable future without AI, since they do not have the *capacity* to handle the workload and believe that they could be circumvented by their referring clinicians, which influence voluntariness through *organizational demands*.

Also, we found several antecedents that affects the image of a radiologist in our interviews. It is clearly an important part of the *professional status* and *professional community*, as well as it has some association with *organizational demand* and *future work content*. The professional status was found to be directly applicable to image. In addition, the professional community is an important part of the radiologist's immediate social system. However, the professional community is mainly comprised by radiologists, which is why we argue that parts of organizational demand is related to image through its influence in a wider social system and, by that, affecting the pecking order of physicians. Furthermore, when the participants talk about their future work situation, they describe situations where their importance might increase or decrease in this system.

6.1.2 Cognitive instrumental processes

For job relevance, we found a significant overlap with *applicability*. The participants often came back to the subject of how well-suited AI was to their job tasks. A connection was also visible in the *expectations* of the technology, since the radiologists' expectations of the applicability was not often met from the suppliers. Lastly, we found a minor influence from *integration* on job relevance. The statements of the participants often covered how well or bad the system would fit into their work processes as a result of how easy or difficult it was to integrate.

In this study, output quality was highly associated with *accuracy* as well as *control*. The radiologists stressed the importance of accuracy in the output of the system and also showed a strong will to be included in the evaluation, and having control over the output, of the new technology. When talking about the *applicability*, it was easy for the participants to touch upon issues of quality as well, but this antecedent does not seem to be as influential on output quality, as accuracy and control. Additionally, the *expectations* of AI seemed to influence output quality to some extent. Naturally, when suppliers and others are setting expectations, they are addressing both the relevance and quality of their products. As a result, we see some overlap between antecedents to output quality and job relevance.

The radiologists didn't cover that many subjects which could be related to result demonstrability, however, we found support for a relation to both *simplicity* and *control*; some participants reported experiences of systems that where easy to use and that provided easily-interpreted results. In contrast, others expressed negative feelings towards the lack of control and "black-box"-experience of AI, which made the reasoning behind the output difficult to understand.

We experienced that several of the participants touched upon subjects related to perceived ease of use. A significant overlap seemed to exist with the antecedents *simplicity* and *integration*, in which radiologists talked about speed and reliability of the system. While these two seemed directly linked to perceived ease of use, the link to system performance antecedents were not as obvious. Furthermore, our study indicated that *technological understanding of AI* and *prior implementations* had some cumulative effects on the perceived ease of use of future technology. A higher level of technological understanding as well as a positive experience with prior implementations seemed to increase perceived ease of use. However, these two antecedents were experienced to have a minor overlap with perceived ease of use and therefore was not finally matched to that determinant.

6.1.3 Concluding remarks and final matching of antecedents

Some areas are more or less a perfect match, such as applicability and job relevance. This could potentially be explained by the fact that this area is such a top-of-mind subject among most professional workers. Interestingly, it has also been proven to be one of the most significant determinants in previous studies, when assessing the acceptance of technology (Chismar & Wiley-Patton, 2003; Nadri et al., 2018).

Based on this thematic analysis above, we have made suggestions of where the empirically found antecedents seems to best fit into the TAM2 model, using the definitions in table 3.1. These suggestions are presented in table 6.2 where the first column shows the determinants of TAM2, the second, our empirically found antecedents, while the third column includes a definition which has been inductively derived from our empirical findings.

Table 6.2. *Definitions of antecedents and best fit to determinants.*

Determinant	Antecedent	Definition
Experience	-	-
Subjective Norm	The professional community	*The degree to which the beliefs of the professional community influence the acceptance of AI.*
Voluntariness	Capacity	*The degree to which perceived current and/or future workload influences the acceptance of AI.*
	Organizational demands	*The degree to which perceived demands from parties outside of the radiology department influence the acceptance of AI.*
Image	Professional status	*The degree to which users believe that accepting AI will improve their status in the community.*
Job relevance	Applicability	*The degree to which the AI system is perceived to be applicable to one's job.*
Output quality	Control	*The degree to which the perceived degree of control of the system influences acceptance of AI.*
	Accuracy	*The degree to which the perceived accuracy of the system influences acceptance of AI.*
Result demonstrability	-	-
Perceived ease of use	Simplicity	*The degree to which a user experiences the program as easy to use independently from other systems.*
	Integration	*The degree to which a user experiences the program as easy to integrate with other systems.*

As seen in the table above, quite a few of our antecedents could be applied to fit the theoretical framework of TAM2. However, given the fact that a number of important antecedents to technology acceptance among our participants were not, or only partly, covered by the existing theoretical framework, we have chosen to propose two additional determinants, *uncertainty* and *personal experience*, in order to increase the understanding of what factors affect acceptance of AI among radiologists. Furthermore, expectations were argued to moderate applicability and accuracy and was therefore not included above (see further discussion in section 6.2.3). Table 6.3 below provides an overview of additional antecedents and determinants.

Table 6.3. *Definition of additional determinants and antecedents which are not included in TAM2.*

Determinant	Antecedent	Definition
Uncertainty		*The degree to which an individual is uncertain about how the use of AI might influence his or her future.*
	Future work content	*The degree to which an individual is uncertain about how the use of AI might influence his or her future work content.*
	Legal	*The degree to which an individual is uncertain about how the use of AI might be influenced by legislation.*
	Responsibility	*The degree to which an individual is uncertain about how the use of AI might influence his or her future responsibilities.*
Personal experience		*The degree to which a user's knowledge and previous experiences influence acceptance of AI.*
	Technological understanding of AI	*The degree to which knowledge of AI influences acceptance of AI.*
	Prior implementations	*The degree to which results of previous (non-AI) technology implementations influence the acceptance of AI.*
N/A (Moderating effects)	Expectations	*The effect that the perceived gap between what was promised about AI, and what was delivered, has on applicability and accuracy.*

6.2 Towards an understanding of acceptance of AI

Our findings both confirm and challenge previous insights in the literature about acceptance of new technology. Further, it adds insights about AI to the acceptance literature.

In line with Ouadahi (2008), this qualitative approach focused on moving beyond *what* can predict acceptance, and instead tried to explain *how* endorsement or rejection of AI is formed among the users. As seen in previous sections, this approach has allowed us to get a more fundamental understanding of how and why specific determinants might be considered as more important than others when accepting AI.

From a more general point of view, our findings seem to strengthen the hypothesis set out by Hu et al. (1999) that professional workers consider perceived ease of use as less important than non-professionals when accepting new technology. Based on our interviews, perceived ease of use seems to be regarded as merely a hygiene factor. Participants often related it to issues that concerned organizational and IT constraints (see 5.1), rather than bringing up the importance of a simple program to use, a connotation that is in line with the arguments by Gagnon et al. (2012). The reason to why this could be the case is not fully discovered in our study, however, based on existing data, physicians seem to relate simplicity and well integrated systems to efficiency in their complicated work processes, rather than to make their work less complicated. This goes in line with Chismar and Wiley-Patton's (2003) argument that physicians might be more willing than the average person to use a program even though it is not easy to use, if it is considered to bring additional value.

6.2.1 Social influence processes might matter for acceptance

However, in contrast to the work of Chismar and Wiley-Patton (2003), we found indications that social influences could be a factor in accepting AI. Based on the nascent stage of AI within radiology, many of the interviewees referred to collegial congresses or symposiums when quoting the situation or picturing the future for radiologists. This could, however, follow the pattern shown by Venkatesh and Davis (2000) where influences such as subjective norms can be more impactful before implementation, but decrease in importance over time. Given the fact that the field of AI within healthcare is nascent, the social influence should, with the reasoning of Venkatesh and Davis (2000), be greater than in more established technologies. Furthermore, the participants in this study were all board members of professional associations within the community. This might have resulted in more significance being given to subjective norms by them, as they are actively participating and leading the community. However, as AI serves on different premises than previous technologies, we believe that since the nature of the technology is different, social influence could have a larger impact over time than experienced before.

Our hypothesis is that because AI is more human-like than previous technologies, with self-learning capabilities as well as a feeling of 'black-box'-thinking and losing control (as argued in 5.3.3), it could even come to challenge the status or existence of radiologists. This might evoke emotional responses, like feeling threatened, which could be further influenced by social influence processes. Even though further studies are needed to develop this hypothesis, it is clear, based on our data, that the interviewees experience several external forces that influence how radiologists are approaching the future use of AI. This goes in line with the findings of Buckley et al. (2018), who suggested that automation of tasks prior done by humans would be likely to address the psycho-social factors more than before, indicating that subjective norms could be important when accepting AI.

What might be the most surprising finding in this study was how the arrival of AI has influenced the belief of a gain in social status among radiologists. Based on headlines about AI replacing radiologists a few years back (e.g. Chockley & Emanuel, 2016), one could assume that radiologists would expect a negative effect on their image when AI is introduced. Opposite to this notion, our findings suggest that some radiologists and decision makers within the field see an opportunity to strengthen the image of the profession. There seems to be a belief among the participants that an increase in technological complexity strengthens the position of the radiologist. Similar to previous discussion concerning factors that impact subjective norms, we cannot say how many of the responses related to image that are based on the individuals own belief of an increase or decrease in status, from introducing AI, or if it is a reproduction of a collegial mantra in order to keep the profession aligned and calm.

The expressed feeling of a mandatory implementation of AI in the healthcare system, seems to be one of the major factors that is impacting the effect of subjective norms. Venkatesh and Davis (2000) showed that in mandatory settings, subjective norms explain the intention to use the technology more than in voluntary settings. Among our participants, we could see a similar pattern, where radiologists emphasized that they do not have a choice whether to accept AI or not, if they want to keep up with the demand of healthcare. What this study can contribute with further, is the division of voluntariness between capacity and organizational demands. The latter brings forward an aspect that partly is connected to both control of output, but also to a question of image. The profession might not only accept and adopt AI based on the fact that it is necessary due to increasing volumes, but also to secure the radiologist's position as an expert in, and quality assurer of, images within healthcare. There seems to be a concern about who is setting the agenda, and a concern that the existing status and relevance of the radiologist could be lost or downplayed. Similar findings have been made by Barley (1986), who found that an introduction of CT scanners caused a redefinition of the relationship between radiologists and radiological technologists, leading to structural changes.

6.2.2 Cognitive instrumental processes as the main concern for acceptance

The thematic analysis shows both a quantitative as well as contextual overrepresentation of data relating to cognitive instrumental processes. This result is in line with previous studies, both inside and outside the healthcare sector, in which the determinants job relevance and output quality have been statistically deduced to be major determinants of technology acceptance (Venkatesh & Davis, 2000), suggesting that there might exist an overlap between the characteristics of prior technology acceptance and the acceptance of AI.

As earlier mentioned, in line with the findings of Chismar and Wiley-Patton (2003), the participants were concerned about the relevance of the technology, rather than user experience. The question of relevance could be seen from different perspectives. The first part is closely related to the applicability of the application to the daily routines. Most of the interviewees stressed that a well-tailored software, rather than one that is easy to use, is the first crucial step in order for them to begin the process of accepting AI. However, what makes the determinant of job relevance difficult to assess individually is that it seems to be influenced by other factors as well. A common problem brought up by the participants was the lack of well-tailored software today, which also was manifested in a frustration about the lack of understanding from external stakeholders about what was relevant to the radiologists. As an effect, in order to fulfill the job relevance aspects, some radiologists expressed a need of influence and control in the development and validation process. Venkatesh and Davis (2000) suggest that there is an interaction between output quality and job relevance on technology acceptance. We can see similar patterns in our data, where the concerns regarding quality aspects are influencing the discussion of job relevance. In a highly specialized and complicated occupation, such as that of a radiologist, quality in one's examinations could be seen as an important part of the occupational pride. This might explain why radiologists to such an extent believe that they have to be highly participative in the development of the applications.

Even though several studies have shown that AI could be applied to today's radiology (Choy et al., 2018; Lakhani et al., 2018), our study shows a trust issue concerning the output quality of such applications. This is in line with the findings of Tulio Ribeiro et al. (2016), where trust was highlighted as a major factor in acceptance of AI. The concerns of output quality are multi-layered, however, it is strongly influenced by the fear of losing control. Even though earlier studies have shown that output quality is a major factor among physicians' technology acceptance (Chismar & Wiley-Patton, 2003), our findings suggest that the feeling of a "black-box" and not being able to trace the logic behind the decision, differs from what radiologists have encountered before. On one hand, losing control is related to being able to follow the process clearly, on the other, it is also related to the question of responsibility. Today, being in control means that you have the responsibility of that part of the patient's care, where a misconduct could lead to legal consequences. We believe that the uncertainty of the future is influencing technology acceptance among radiologists to such an extent that we have chosen to keep it separate from the existing determinants of TAM2 and introduce it as a suggested extension of the model, which will be displayed in section 6.2.3.

6.2.3 Towards an extended TAM2 model

To begin with, as briefly mentioned when discussing the impact of output quality, uncertainty of the future is a recurring theme among many of the participants. Therefore, we want to include *uncertainty* as a determinant in our extended model. This uncertainty could be seen from multiple perspectives. The most fundamental part is the uncertainty of how AI will change the role of the radiologist. As recent studies have highlighted (Choy et al., 2018; Yu, Beam & Kohane, 2018), the future role of radiologists is ambiguous and dependent on many stakeholders. Drawing from this uncertainty, it is difficult for the radiologists to decide whether they should embrace the technology or not. Will AI only become a support tool within image recognition? Will it draw only some conclusions on its own? Or will it replace them entirely?

However, the uncertainty of future work content did not only occur as a topic in relation to expressions of negative emotions. With increasing use of technology, the possibility of becoming more of an integrated team member in the interdisciplinary team has increased. Radiology is considered a para-clinical specialization and several of the participants even referred to it as a "service specialty". AI might come to change that, as well as increase job satisfaction for those that prefer a more visible role and frequent team work. Additionally, uncertainty of future work brings opportunities for structural changes in the social order. Specifically, on that matter, Barley (1986) propose a model, where social structures are more likely to be redefined by exogenous shocks, like technological disruptions. However, uncertainty of the future also includes the risk that other stakeholders circumvent the radiology department. For example, in a future where referring clinicians could turn directly to AI for answers, the demand of a radiologist's services would decrease.

Furthermore, an additional significant aspect of uncertainty is related to future legislation and responsibilities. Our findings, in line with current research (Lee et al., 2017), suggest that legal liabilities as well as individual responsibilities in case of mistreatment or other errors are of great concern to physicians. What most participants agree on is that even a computer will fail someday, but what happens then? As physicians are expected to make life-or-death decisions on a daily basis, their focus is that the division of responsibility is clearly stated beforehand. Furthermore, as this legal responsibility exists, the need for understanding the underlying mechanisms of the AI software might be greater for physicians, in comparison to professionals in occupations where an error might not result in human suffering or legal action. In a future where AI serves as support in the decision-making process and where the final responsibility still remains with a radiologist, it is likely that radiologists ask for either more involvement and knowledge about how the technology works, or that the current system of responsibility is modified. This is still a topic that needs to be addressed in order to increase acceptance from radiologists. Yet, based on our study, most radiologists are not likely to accept and bear the responsibility of an outcome that they have not quality-controlled themselves.

The second determinant that we would like to include in our extended version of the model is what we have chosen to call *personal experience*. Looking at TAM2, one would realize that the model already includes a determinant called experience, however, it addresses how the influence of subjective norms will decrease over time as a function of system experience (Venkatesh & Davis, 2000). In our study, with a low number of participants with actual user experience of AI, we did not find any clear support of such influence. However, we found influence from experience in the pre-implementation phase instead. To begin with, what became clear throughout the study was that the level of knowledge of AI was fragmented among the participants. We also found indications of a relationship between the level of knowledge and several of the other determinants. Higher level of knowledge seems to reduce the level of uncertainty in the future work division between man and machine as well as influence radiologists to provide a more nuanced picture of the capabilities of the technology, which seemed to be tied to a higher degree of acceptance of AI.

Furthermore, this higher level of knowledge also resulted in more detailed opinions of what to expect from the application.

The second aspect of personal experience was found to be related to prior implementations. The radiologists experienced that they had been put through plenty of system implementations, with systems of doubtful efficiency, throughout the years. Even if they are presented with a new technology targeting a different area, previous experiences seem to mitigate the acceptance and project negative feelings onto future expectations. We believe that TAM2 does not fully take into consideration the cumulative effect of multiple technology implementations as a contributing factor towards technology acceptance. Experience, as defined in TAM2, is mainly forward looking and does not account for the personal history of the user.

Lastly, we found expectations to be closely related to applicability and accuracy, moderating the effects of these antecedents. As job relevance and output quality are of major concern to physicians when assessing a new program, a significant influence is given to the expectations that precede the implementation. The hype and promises built up by decision makers and suppliers failed to deliver on some radiologists' expectations when tested in reality. The giant leap between promises and reality could decrease acceptance of AI. Earlier studies, like Boehm et al. (2008), as well as our participants, have stressed the problematic nature of false positive findings and how time consuming they can become. We found support in the interviews for an experienced mismatch between what is seen as "good enough" among suppliers of AI and "good enough" among radiologists. We believe that a gap between expectations and reality indirectly leads to a decreased level of acceptance. This gap is not addressed by the theoretical framework of TAM2, therefore, it was also included in our extended model.

Based on our findings and analyses presented in this section we will provide an extended model of TAM2 in figure 6.1 below.

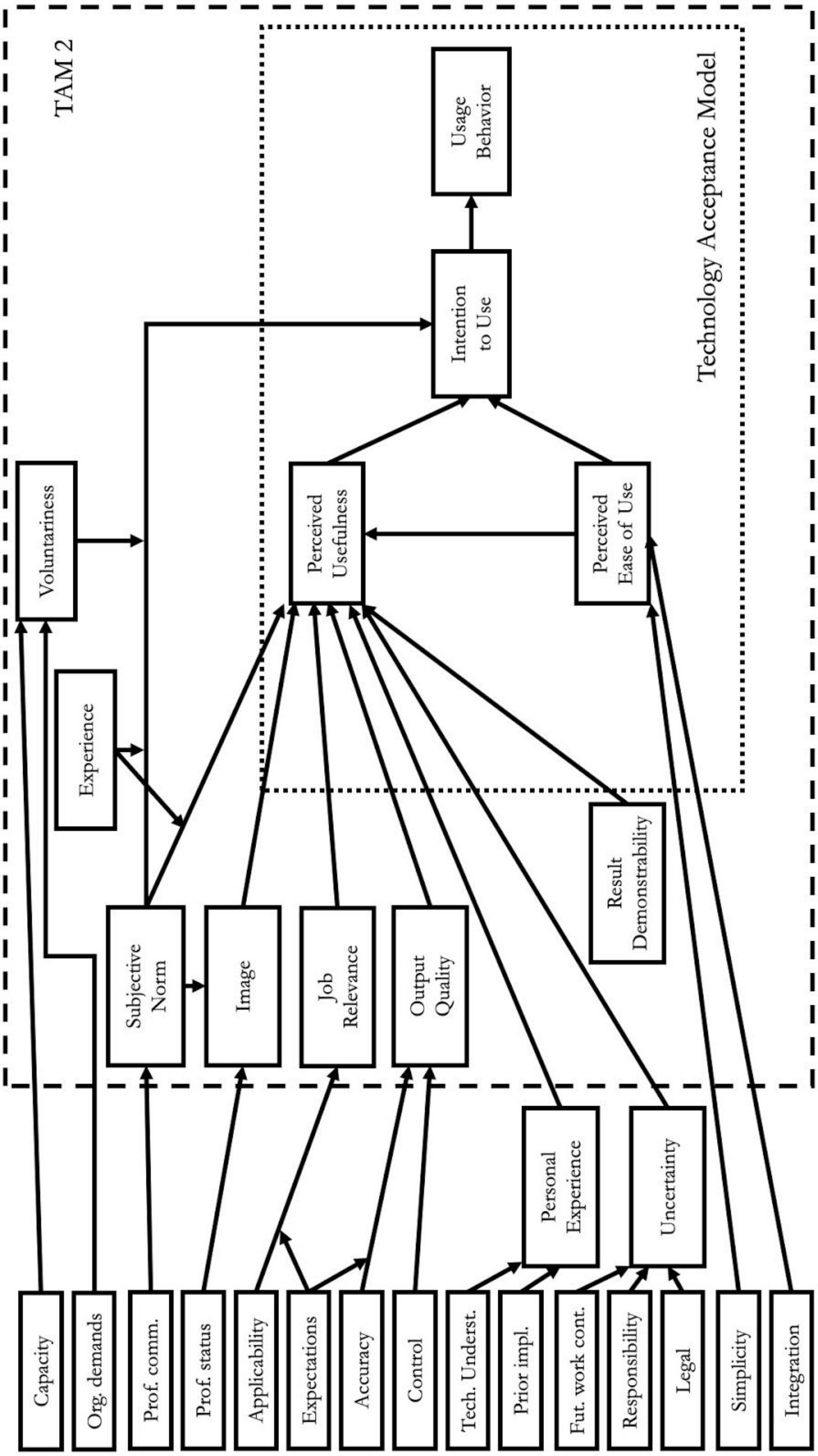


Figure 6.1. Extended TAM2 model based on the findings of this study.

7. Conclusion

The purpose of this study was to investigate what factors affect acceptance of artificial intelligence among radiologists. As a result of our analysis, we believe that acceptance among radiologists rely on several different factors that are related to TAM2, hence, the empirical findings seem to have a fairly good fit to the existing theoretical framework. Based on this study, we can conclude that there are indications that TAM2, with some additions, and possibly reductions, could be suitable when assessing acceptance of AI within radiology.

Additionally, the authors found how concerns of job relevance and output quality, as well as a new determinant called “uncertainty”, seemed to have a major impact on the radiologists’ acceptance of AI. Specifically, the study’s antecedents of control and applicability were experienced as important. In addition, the findings support how subjective norm and image may affect acceptance of AI to a greater extent than they have affected acceptance of previous technologies.

7.1 Theoretical contribution

Our study provides an additional layer compared to quantitative studies, as several antecedents to the determinants of acceptance could be found, suggesting that qualitative methods could serve the purpose that Vogelsang et al. (2013) propose, and lead to researchers finding new constructs as well as developing a deeper understanding of existing ones. Further, this study contributes to the literature on technology acceptance in two additional ways.

First, we are widening the sparse field of literature within acceptance of AI. The findings expose how the nature of AI might call for a revision in previous theory regarding what determinants influence acceptance as well as why they are considered important.

Second, this study resulted in empirical findings that led to the introduction of two additional determinants and one moderating variable, not included in the original TAM2 theoretical framework. The introduction of forward-looking as well as backward-looking determinants gives the theory a more longitudinal aspect, offering a wider ground for explaining how determinants are functioning over time.

7.2 Practical implications

Although one can question whether or not AI should be implemented at all, we discuss what our findings suggest regarding how acceptance of AI could be increased and sustainable implementation facilitated.

We find our results to have four different major practical implications. First, it shows the need for information about AI (e.g. answering the questions: how is it trained? by whom?) as well as participation of radiologists in deciding how it is to be integrated into processes. The lack of knowledge creates uncertainty and a risk of making decisions based on incomplete information.

Second, it exposes the feeling of different views and expectations between physicians and software suppliers, for instance, the view of what a "good enough" product is, might differ. In order to make high quality programs, that will be used in the clinic, suppliers and users must align in matter of content and quality.

Third, information regarding future opportunities and challenges to physicians might be best communicated through the professional community. Even though international differences exist between radiologists, their community seems to be the main source of external influence. In order for management to communicate more efficiently with radiologists, inspiration from, and/or collaboration with, the community could be of interest, allowing radiologists to feel that they too set the agenda rather than being subject to external agendas.

Fourth, the introduction of AI within healthcare will put new demands on the legal environment, both concerning responsibilities of treatment decisions as well as patient data protection. Clear guidelines and legislation, that evolves along with the technological development, might be needed in order to achieve acceptance as well as to have a functioning healthcare in the future.

7.3 Limitations

This study comes with several limitations to keep in mind. To begin with, most of the participants were board members in different professional associations. Participation of more radiologists with no active participation within the professional community could have provided a wider picture of acceptance.

Furthermore, this study did not examine in depth how the professional community is influencing and controlling stakeholders within radiology as well as between specializations. We have seen some indications of its importance, however, the data gives insufficient answers to this question.

Finally, the primary purpose of this study was not to investigate which role the overall organizational structures have in influencing attitudes and acceptance. In order to get a fuller understanding of individual acceptance, one would have to study, to a wider extent, what role the organization has.

7.4 Future research

Even though this study has provided the literature with suggestions of additional determinants to complement the existing theoretical framework, it further opens up questions for future research. The acceptance of AI is still a nascent field of study. Future studies will be needed in order to fully understand how trust and control influence the relationship between man and machine, not least longitudinal studies illustrating how attitudes may change over time as more experience is gained.

Also, future research could investigate how acceptance (and later adoption) of AI might impact organizations. The changing use of data and work tasks might call for changes in the organizational structures.

Lastly, the reasoning of different stakeholders in this transformation could be an area of interest. A future researcher might benefit from studying how different world views and logics might create tensions between management, suppliers, physicians and the public.

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9. Appendices

Appendix A - Subcategories of AI

In figure A.1 below, AI-techniques are put into context by a vertical axis (problem domains) and a horizontal axis (paradigms). The problem domains are defined as "[...] historically the type of problems AI can solve" and the paradigms as "[...] the approaches used by AI researchers to solve specific AI-related problems" (Corea, 2019). In addition, Corea (2019) color-codes the different categories to show a division of macro-approaches. These are symbolic, subsymbolic and statistical approaches. The symbolic approach argues that human intelligence could boil down to symbol manipulation and an intelligent system should be based on pre-known sets of rules and knowledge (Corea, 2019). Meanwhile, the subsymbolic approach states that no specific knowledge should be provided beforehand, the system should function more "like a human brain" and figure out how to solve problems along the way (e.g. neural networks or deep learning) (Corea, 2019. Furthermore, a statistical approach is recognized by its use of mathematical tools as well as probability theory to solve problems (Corea, 2019). Lastly, the AI types are categorized by narrow or general application. This means that they either can be used to solve specific problems/tasks (narrow) or can be used in a wider sense today or in future applications (general) (Corea, 2019).

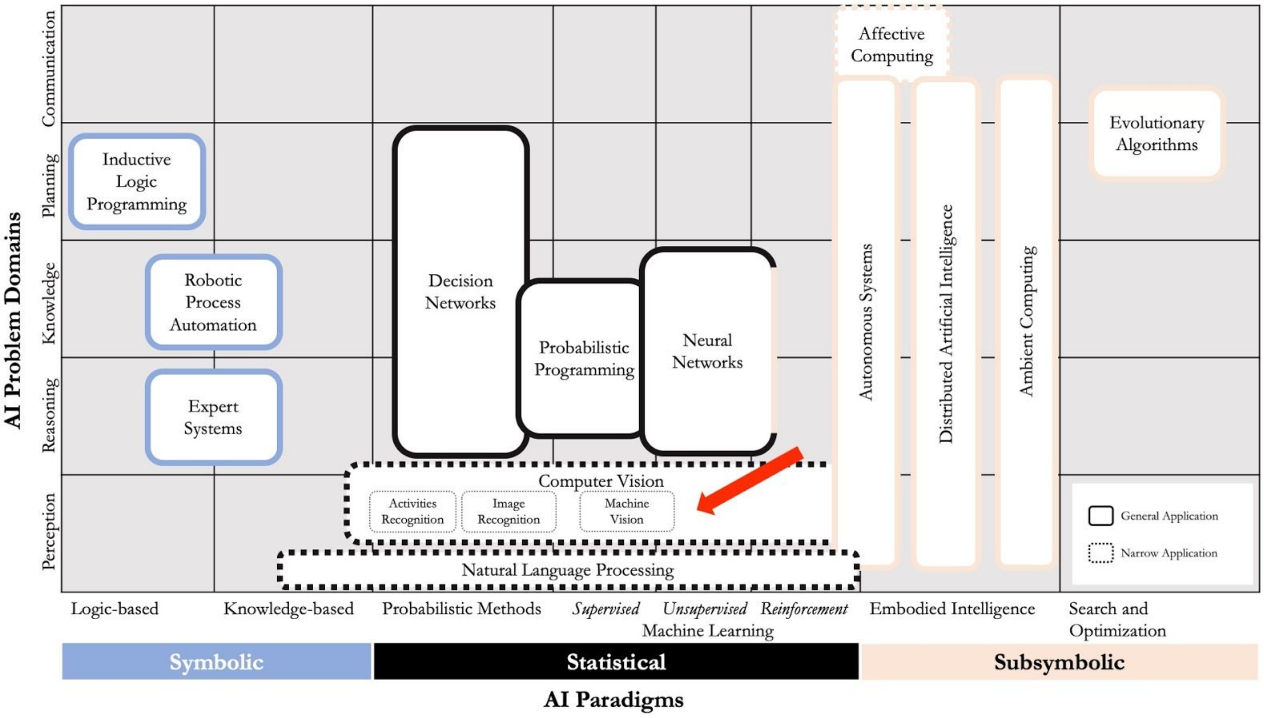

Figure A.1. Classification of AI, figure based on the work of Corea (2019). The arrow marks the area of focus for this study.

As seen in figure A.1, there are a lot of subcategories in the field of AI and there might also be other categories that are not included in this rather extensive categorization.

Appendix B - Interview guide (Swedish)

- Förklara din roll och dina arbetsuppgifter idag
    - I vilken utsträckning använder du AI i ditt dagliga arbete?
- Hur mycket har du följt diskussionen om AI och ML i radiologi/neurologi?
    - Har du testat det kliniskt?
- **Om system finns:** Har du haft inflytande över implementering och utformande av detta system samt hur det ska användas?
    - Skulle du velat ha mer inflytande?

- Tycker du/Tror du att AI skulle förenkla din effektivitet på jobbet?
- Anser du att AI/ML gör det lättare för dig/läkare att ställa diagnos?
    - Varför?
- Hur användbart tycker du att AI/ML är?

- Hur enkelt anser du det är att använda de AI/ML system som finns?
    - Vad är det svåraste med att använda AI/ML inom ditt område?
- Finns den grundläggande tekniska förståelsen för hur systemet fungerar tror du?
    - **Om det finns ett system som används:**
        - Är det lätt att hitta det man söker efter?
        - Är det lätt att lära sig systemet?
        - Är det lätt att komma åt systemen/applikationerna?
- Tror du att de läkare som använder AI/ML tycker det är bekvämt att använda sig av sådana system även om resultatet/produktiviteten av deras arbete varken skulle förbättras eller försämras?

- Hur viktig är den nya tekniken för att du ska kunna utföra ditt jobb?
- Hur kommer ditt jobb förändras rent praktiskt av att använda AI/ML?

- Hur mycket litar du på att resultatet från systemet stämmer?
- Tror du att patientsäkerheten kommer att påverkas?

- Hur enkelt tror/tycker du det är att påvisa resultaten från ett AI/ML-system? Blir det en tydlig förbättring/försämring?
- Hur enkelt är det att kommunicera dessa resultat?

- Hur tycker du att andras upplevelse av AI/ML verkar vara? Negativa/positiva?
    - (Om du ser till din arbetsgrupp?)
    - Påverkar dessa åsikter dig tror du?
    - **Om ja:** Hur?

    - **Om nej:** Varför tror du inte det?
- Hur tror du att en motståndare till AI inom radiologin skulle motivera sin åsikt?

- Tror du att ditt/ert anseende kommer att förbättras eller försämras om ni använder det här systemet?
    - Hur tror du att andra skulle beskriva denna förändring i anseende?

Appendix C - Information leaflet (Swedish)

Till dig som är läkare, sjuksköterska, beslutsfattare eller leverantör av system i hälso- och sjukvården.

Information och förfrågan om deltagande i intervjustudie.

Utvecklingen av teknologi inom sjukvården ger nya möjligheter till hur hälso- och sjukvård kan bedrivas. Den skapar också nya frågeställningar kring hur teknologi ska användas och hur man effektivt kan implementera nya lösningar.

De senaste åren har speciellt Artificiell Intelligens (AI) och Maskininlärning (MI) utvecklats i hög takt. Dessa teknologiska tillämpningar kan användas inom till exempel bilddiagnostik för att hjälpa till att diagnosticera olika sjukdomar.

Vi vill därför genomföra en intervjustudie med förhoppningen att resultatet kan leda till ökad förståelse för de faktorer som bidrar till en ökad adoption av AI/MI-lösningar i sjukvården.

Syftet med studien är att undersöka betydelsen av sociala faktorer och normer för att ta till sig, samt använda, den nya teknologin.

Sjuksköterskor, läkare, beslutsfattare och leverantörer av system i sjukvården i området kommer att tillfrågas om deltagande i denna intervjustudie. Om du har erfarenhet av AI/MI inom sjukvården eller har tankar kring ett eventuellt införande av sådana system, skulle vi vilja att du som är intresserad av att delta i vår studie kontaktar någon av oss via e-post eller telefon.

Det är helt frivilligt att delta i studien och du kan när som helst avbryta din medverkan. Intervjuerna kommer att genomföras på din arbetsplats eller annan avskild plats som du väljer. Vi beräknar att intervjuerna kommer att ta 45-60 min. Förutsatt ditt godkännande kommer intervjuerna att spelas in för att förenkla analysprocessen.

Allt material som samlas in kommer att behandlas och hanteras konfidentiellt. Det kommer också att förvaras så att ingen obehörig kommer åt materialet. Inga enskilda personer kommer att kunna identifieras i examensarbetet.

Vi heter Felix Lernfelt och Martin Albrecht och läser Master i Business Management på Handelshögskolan i Stockholm. I vår utbildning ingår ett examensarbete om 30 högskolepoäng, vilket är anledningen till att denna intervjustudie kommer att genomföras. Har du några frågor är du välkommen att höra av dig.

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Appendix D - Supporting interview quotes

Simplicity

"I just put images in the machine which calculates and [poff] a whole table containing volumes and I only check afterwards that the machine has done the correct measurements."

- Participant 18, Radiologist

"And AI does it like, well, yes... it calculates the volume and then you go to a standard model and you can... you get a precise value, so then you don't have to guess... then... well... things like that for example."

- Participant 15, Radiologist

"[...] then it has to be able to work in real time... it cannot be that it takes time... because... it is right now that I am handling a patient, you want everything, you do not want to wait for it, because then it will fail, that is how it is today... that the system is so slow, that sometimes you have to wait and go back to the previous patient, because it takes time [...]"

- Participant 3, Decision maker

Professional community

"I just went to ECR, European Congress of Radiology, in Vienna and it almost felt like AI...everyone wants AI... Everyone had something that covers AI on everything... it was almost ridiculous [...] it is a lot of hype around it."

- Participant 2, Decision maker

Capacity

"If we see an increase of work into the radiology workflow, we 'on the other side' have to be prepared for this and find time to take and write. And then I believe that AI will be needed, otherwise we won't cope."

- Participant 8, Radiologist

"[...] it has been like an exponential explosion of imaging data during recent years and the number of images double almost every other year or so, or right now it is yearly... and someone need to look at all these images, even if only for milliseconds or a couple of seconds per image. Someone has done it and

then people might start to think that: 'okay, it might not be terribly bad to use AI if we can replace some parts'."

- Participant 2, Decision maker

"You can save time in the tasks that you are running and might be able to read more cases, which is necessary, as we get faster and faster sequences and more and more patients to examine in shorter time periods..."

- Participant 8, Radiologist

Organizational demands

"[...] my greatest concern might be that if radiology as a field or specialty does not handle it, then the suppliers will turn directly to our referring clinicians and offer solutions that are somewhat half-baked [...]"

- Participant 2, Decision maker

Professional status

"I do not think that anyone is afraid, actually... sometimes it is said that 'oh, radiologists are afraid of losing their jobs'... I can say one thing, there are very few that I know who feel that way..."

- Participant 6, Radiologist

"I believe that radiologists will become even more important. Because, it will still in the end be the radiologist that decides if the red dot is a node or if it is only an artefact, as an example. AI cannot do that..."

- Participant 8, Radiologist

"If AI develops fast, we will become more of a conductor that says, 'in this examination, we are running the pictures through those and those programs and you will get that result' and you supervise when they are signing."

- Participant 7, Radiologist

Applicability

"[...] the companies have some problems to assess and they can... well, they have a hard time to assess the needs and by that also difficulties to really understand what could be of commercial interest in the long run. There, you have to have a very frequent contact with healthcare, as I see it, and that we discuss what solutions might be interesting..."

- Participant 14, Decision maker

"We are not satisfied with that they are coming with a final product, because often it is not good enough for what we intend to use it for... we actually want to give more input on what we wish for..."

- Participant 3, Radiologist

"[...] but I do not have too high expectations if I would expect it to give me proposals of diagnoses... but if I tell it to measure some things, as an example to measure a surface or area or measure some else, then I will have higher expectations, because I believe that a computer of course has to do it better than when I am guessing it..."

- Participant 6, Radiologist

Expectations

"[...] and they are of course selling their product and 'this is really good and it can do this and this and this', but it later shows that it was not as developed as they said..."

- Participant 12, Radiologist

Control

"It is that... you do not really have control of the technology and that is the great danger, that we let go too early, too much. That we do not really know how much we can trust it. That we will make severe mistakes, where patients will die in vain..."

- Participant 14, Decision maker

Accuracy

"If we, as humans, are 85% then we should be satisfied, but machine 90%, they need to be a bit better than us... but that is quite much a discussion and ethical positions... before we reach a conclusion there... that is something we need to do within a few years. That is partly one of the weaknesses with AI... meaning when they are making an error, they are doing it drastically... but on the other hand, so are we..."

- Participant 1, Decision maker

"We have already had AI for, so to speak, a couple of decades in radiology as a helpful tool in screening within mammography [...] then you have been able to exchange one of the radiologists for a computer program... but it has been to slow and provided too many false positives that you have to click away, so it hasn't been that helpful."

- Participant 4, Radiologist

Technological understanding of AI

“[...] the level of knowledge is pretty low as of today... I have to say, when it comes to... what really means... there are not many that have... well, there is not anyone who has a high degree of knowledge of it and least of all me... but the majority really does not have a clue about what it is [...]”

- Participant 1, Decision maker

Prior implementations

“Many of the older are a bit hardened by one hype at a time that comes and wonder if this is one of those that will also pass by...”

- Participant 1, Decision maker

Future work content

“So, I have thought for a long time that ‘within 5 years the computers will do a lot of the work that I am doing today’ and I have so far been wrong, so I don’t know. But if we say within a reasonable time horizon, maybe before I retire, then I count on the computers to help us with these ‘find five faults’-things by then.”

- Participant 14, Decision maker

Responsibility

“Who is responsible? Hardly the device, I almost said... it is hardly the software. There is an insecurity that might need to be discussed even if it is difficult.”

- Participant 8, Radiologist