Artificial Intelligence in Radiology: Promises and Pitfalls

A cross-sectional study of Norwegian radiologists' knowledge and attitudes

Karoline A. Nyberg Lippert

University of Oslo

Faculty of Medicine

Institute of Health and Society

Department of Interdisciplinary Health Science

Thesis submitted as part of the Master of Philosophy degree in Interdisciplinary Health Sciences

June 2020

UiO : Institute of Health and Society
University of Oslo

Artificial Intelligence in Radiology: Promises and Pitfalls

A cross-sectional study of Norwegian radiologists' knowledge and attitudes

Karoline A. Nyberg Lippert

Master of Philosophy Degree in Interdisciplinary Health Sciences
Institute of Health and Society
Department of Interdisciplinary Health Science
Faculty of Medicine

University of Oslo

June 2020

June 2020

Artificial Intelligence in Radiology: Promises and Pitfalls
A cross-sectional study of Norwegian radiologists' knowledge and attitudes

http://www.duo.uio.no

University Print, University of Oslo

Abstract

Background

Considering the rapid developments in artificial intelligence (AI), machine learning (ML) and the pressure on radiology services, AI is predicted to transform radiology and improve diagnostic and treatment accuracy. Investigating radiologists' knowledge of and attitudes toward AI is important in order to adopt AI in radiology. Radiologists are the end-users of this technology and responsible for patients' safety.

Objectives

The main objective of this study was to investigate the characteristics of Norwegian radiologists' knowledge of and attitudes toward AI. In addition, to examine whether the number of radiological examinations undertaken per day and radiologists' age could serve as predictors for knowledge levels and attitudes.

Methods

Radiologists and radiology residents working in Norwegian hospitals were invited to complete an anonymous electronic survey published on the Facebook page of the Norwegian society of radiology (*Norwegian: Norsk radiologisk forening*) and distributed by email to contacts at radiology departments in South-Eastern Norway. The survey included 13 questions (excluding demographics) focusing on knowledge of and attitudes toward AI in radiology. The data was collected in two phases between December 2018 and March 2019. Data from 31 respondents were included in the statistical analyses. SPSS was used for statistical analyses. A histogram, skewness and the Kolmogorov-Smirnov test were used to evaluate normality. Frequencies and percentages were calculated for categorical data. Associations between groups were investigated by using the Fisher's exact test. A p-value of 0.05 was used to determine statistically significant associations. The few free-text answers and elaborations were analysed through a simple content analysis in Excel.

Results

31 participants completed the survey (3.1% of the Norwegian radiologists). Most respondents stated that AI was a computer programme/ aiding system (55%) and two thirds had not attended courses or seminars in terms of AI/ ML in radiology (66.7%). Whether AI would improve radiological examinations and diagnostic-and treatment accuracy was questionable.

55% believed AI would improve the quality of the radiological examinations compared to 42% who did not know. 58% believed AI would increase accuracy in diagnosis and treatment compared to the 32% who did not know. Respondents were not convinced that AI would replace them or take over most of their tasks. About 70% did not know compared to the nearly 23% who believed it would to a small/ to a very small extent. Some areas to apply AI were more favourable than others; on top lesion tracking (97%) followed by pathology (94%) and prediction (68%). The same applied to areas to financially invest with diagnostics (90%) and treatments (71%) being most popular. The majority had concerns regarding data privacy and security (65%); however, under half (40%) did not believe that patients would refuse radiological examinations because of data concerns if AI-based solutions were being used. There was found to be no statistically significant associations.

Conclusion

Respondents knowledge of AI was low and prior course and seminar attendance reflected this result. They were not convinced that AI would improve radiological examinations and diagnostic-and treatment accuracy. The number of radiological examinations undertaken per day and radiologists' age was not predictors for respondents' low level of knowledge and attitudes. An adoption of AI by Norwegian public and private hospitals is not immediate, as neither the technology nor radiology sector is ready for its integration.

Keywords

Artificial Intelligence (AI), machine Learning (ML), radiologists, knowledge, attitudes

Sammendrag

Bakgrunn

Med tanke på den raske utviklingen innen kunstig intelligens (KI) og det økende presset på helsevesenet har industrien og enkelte forskere forutsett at KI vil forandre og revolusjonere radiologien. Radiologer kan ved hjelp av KI-basert teknologi foreta bedre og mer informerte valg om diagnostikk og behandling, enn det som er mulig i Norge i dag. Radiologer er sluttbrukere av denne avanserte teknologien og en utforskning av deres kunnskap om KI og holdninger tilknyttet implementering, kan bidra til verdifull informasjon om hva som skal til og hvordan implementering av KI kan gjennomføres på best mulig måte i fremtiden.

Formål

Hovedformålet til denne studien var å utforske radiologers kunnskap om KI i radiologi og deres holdninger tilknyttet en mulig implementering. I tillegg, så var det ønskelig å undersøke om det fantes noen sammenhenger mellom antall radiologiske undersøkelser utført per dag og alder, sett i lys av kunnskap om - og holdninger tilknyttet KI.

Metode

Radiologer ansatt ved norske offentlig og private sykehus ble invitert til å delta i den anonymiserte elektroniske spørreundersøkelsen publisert på Facebook-siden til Norsk radiologisk forening. Det ble også sendt ut en epost til kontakter tilknyttet radiologiske avdelinger i Sørøst-Norge. Datainnsamlingen foregikk i to faser mellom desember 2018 og mars 2019. Data fra 31 respondenter ble inkludert i analysene som ble gjennomført. SPSS ble brukt til å analysere data. Et histogram og skjevhet, samt Kolmogorov-Smirnov testen ble brukt for å undersøke om dataen var normalfordelt. Deskriptiv statistikk ble også brukt til å analysere data. Fisher's exact testen ble brukt for å undersøke om det fantes mulige sammenhenger. Signifikansnivået var $p=0.05$. De få fritekstsvarene inkludert i spørreundersøkelsen ble analysert ved hjelp av en enkel innholdsanalyse utført i Excel.

Resultat

31 respondenter fullførte spørreundersøkelsen og dette tilsvarte 3.1% av de registrerte radiologene. De fleste beskrev KI som et dataprogram eller støttesystem (55%) og flertallet hadde ikke vært tilstede under en forelesning eller et seminar som omhandlet KI i radiologi.

Respondentene var også usikre på om KI ville forbedre de radiologiske undersøkelsene, samt forbedre diagnostikk og behandling. 55% mente KI kunne forbedre kvaliteten på de radiologiske undersøkelsene sammenliknet med de 42% som ikke visste. 58% mente KI kunne bidra til økt presisjon i diagnose og behandling sammenlignet med 32% som ikke visste. Respondentene var usikre på om KI ville avløse eller ta over de fleste arbeidsoppgavene deres i fremtiden. Cirka 70% visste ikke, sammenliknet med de 23% mente at KI ville til en liten grad overta arbeidsoppgavene deres i fremtiden. Lesion tracking (97%) etterfulgt av patologi (94%) og prediksjon av utfall (68%) var de mest populære områdene hvor respondentene kunne tenke seg å bruke KI. Populære områder hvor det ble ment at det bør investeres finansielt var diagnostikk (90%) og behandling (71%). De fleste mente at det fantes utfordringer tilknyttet datafortrolighet og sikkerhet (65%), mens litt under halvparten (40%) mente at pasienter ikke ville motsi seg radiologiske undersøkelser dersom KI-baserte systemer ble brukt. Det ble heller ikke funnet noen sammenhenger mellom antall radiologiske undersøkelser utført per dag eller alder, og kunnskap om AI og holdninger.

Konklusjon

Respondentene hadde lite kunnskap om KI i radiologi og få hadde vært tilstede ved en forelesning eller et seminar om KI i radiologi. Respondentene var heller ikke overbevist om at KI kunne forbedre de radiologiske undersøkelsene eller øke presisjonen i diagnostikk og behandling. Antall radiologiske undersøkelser per dag og alder var heller ikke medvirkende faktorer til respondentenes kunnskapsnivå og holdninger. Implementering av KI i norske offentlige og private sykehus er ikke nært forstående. Teknologien er ikke klar for implementering og det er heller ikke radiologien.

Nøkkelord

Kunstig intelligens (KI), maskinlæring (ML), radiologer, kunnskap, holdninger

Acknowledgements

First, I would like to express my gratitude to my supervisor Anne Catrine T. Martinsen, professor at OsloMET. Thank you for your guidance through all of the stages of this project and thank you for all of your support and encouragement. Your input and enthusiasm are much appreciated, and you have introduced me to an area of great interest.

I would also want to thank my secondary supervisor Morten Magelssen, associate professor at the University of Oslo. Thank you for your valuable guidance through all of the stages of this project and much support and help in solving practical problems.

My sincere thanks to Helga Brøgger, President of the Norwegian Society of radiology, for your valuable input and help by distributing the questionnaire on the Facebook page of the Norwegian Society of radiology.

I would also like to thank Cathrine Brunborg, statistician at Oslo Centre of Biostatistics and Epidemiology. Thank you for patiently guiding me through the statistics and analysis of this project.

A special thanks to friends and family for your endless support. A special thanks to my friends Blue Ryan and Sara Hardy, for your valuable input regarding the final stages of this thesis. A very special thanks to Eran Cutliffe for your endless support and for always believing in me.

Thank you, Simon Ringrose, for your comments and feedback in the final stages of this thesis.

I would like to dedicate this work to my late father, Kai Otto Lippert, who never saw the beginning of this project nor got the opportunity to see it finalised.

Abbreviations and acronyms

AI	Artificial intelligence
ANN	Artificial neural network
CAD	Computer-aided-detection
CT	Computed tomography
DL	Deep learning
EC	European Commission
ESR	European society of radiology
EU	European Union
FDA	Food and Drug Administration
ML	Machine Learning
MRI	Magnetic resonance imaging
NAV	Norwegian Labour and Welfare Administration
PET	Positron emission tomography
RSNA	Radiological society of North America
UK	United Kingdom
US	United States

Table of Contents

List of figures

List of tables

List of appendices

1. Introduction

1.1 Background of the study

Artificial intelligence in radiology has recently gained a lot of attention. The availability of large data sets, advances in computing power and new deep learning algorithms, has led to the potential use of artificial intelligence and machine learning in various radiological imaging tasks (1). Research has suggested that machine learning – a subset of artificial intelligence can be programmed to improve medical image interpretation, providing substantial clinical impact. However, the process of its implementation has been shown to be complicated and poses a number of challenges (2). Firstly, the knowledge base for artificial intelligence in radiology is not as transparent as suggested (3). Secondly, the implementation of artificial intelligence is influenced by other factors, such as characteristics of the users, external influences, policies and in which settings it is applied (4). Thirdly, it is difficult to predict all of the consequences of implementing artificial intelligence in radiology. Its adoption could possibly compromise medical ethics and healthcare policies along its way to success (5). Finally, new advanced healthcare technologies have a tendency to cost more than existing technologies which they seek to replace and the success is not certain (6). The success of AI could be measured by the value it is creating such as increased diagnostic certainty, faster turnaround, better outcomes for patients, and better quality work life for radiologists (7).

2. Theory

In this section, diagnostic imaging and artificial intelligence will be briefly introduced. Areas of applications where research on artificial intelligence have been conducted will be set out, as will whether these applications have been tested and/or adopted successfully. There will also be an outline of factors such as knowledge and attitudes that may have an impact on if and how artificial intelligence is adopted by Norwegian public and private hospitals.

2.1 Diagnostic imaging

The purpose of diagnostic images is to provide enough relevant information relevant for detection, diagnoses and localisation and reduction in diagnostic uncertainty (8, 9). Advances have made it possible to acquire high-resolution images of human anatomy and function by using different imaging modalities such as: x-ray, computed tomography (CT), magnetic resonance imaging (MRI), positron emission tomography (PET) and ultrasound (10). The interpretation of diagnostic images is a very complex task since the images are individual, numerous and not self-explanatory (11, 12). Diagnostic accuracy is critical to ensure optimal patient care and radiological interpretation is influenced by clinical circumstances, clinical context, previous diagnostic history and various biases (13).

A growing challenge for the radiological services is the growing workload due to the increasing number of radiological examinations, resulting in tremendous pressure to be more efficient while maintaining and improving accuracy (14). In Europe the number of radiological examinations has increased over the past years due to the availability of advanced technology (15). The number of MRI, CT and /or PET scans were relatively high in relation to population numbers in various countries in 2017 (15). Similar trends were found in Norway as the number of MRI and CT examinations increased between 2011 and 2015 (16). Despite the rapid increase of radiological examinations, a shortfall of radiologists has been predicted in years to come and the majority of the current workforce is getting older (17-22). To ease the pressure on the radiological services, researchers and the industry are continuously aspiring to develop and test new technology (23, 24).

It is suggested in literature that technology such as teleradiology, workflow orchestration and artificial intelligence can resolve the growing challenges listed above for the radiological services (25-27). The World Health Organization (WHO) defined telemedicine as "*healing at* *a distance*" (28). It is understood by this researcher as remotely caring for patients when the consultant is not present with the patients. Siemens Healthcare has termed workflow orchestration as a tool that enables productivity and efficiency of radiologists by organising and optimising their workflow in a clinical environment (29). A definition of artificial intelligence will be presented in the next section.

2.2 Artificial intelligence

In literature and in the media the terms artificial intelligence (AI) and machine learning (ML) are being used interchangeably which may lead to some confusion (30). However, Oxford Learner's Dictionary defines AI as: "*…the study and development of systems that can copy intelligent human behaviour*" (31), whereas, Cambridge Dictionary defines ML as: "*… the process of computers changing the way they carry out tasks by learning form new data, without a human being needing to give instructions in form of a program*" (32). AI serves as a collective term in computer science where ML is identified as a subclassification with deep learning (DL) as a subclassification of ML (33, 34). See **Figure 1** for an adapted Venn diagram (35, 36).

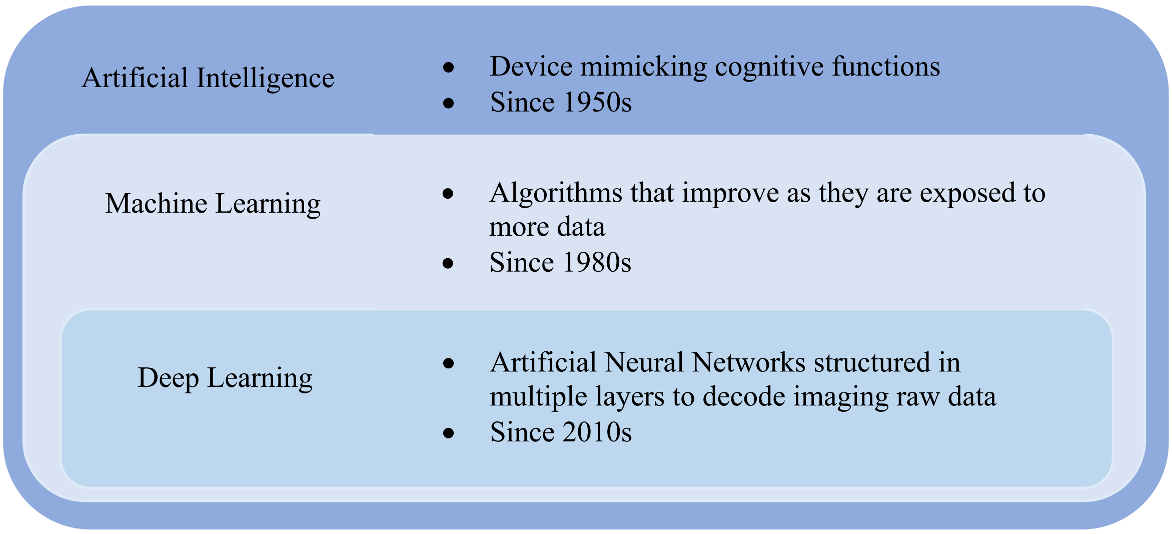

Figure 1: Adapted Venn diagram of the hierarchy of artificial intelligence

2.2.1 Machine Learning

Traditionally ML enables the creation of statistical algorithms that can learn and make predictions by identifying patterns that are present in training sets (33, 37, 38). An algorithm is defined as a mathematical procedure for solving a particular problem (39). The methods of learning used by ML are subclassified into categories such as supervised deep learning (SDL) and unsupervised deep learning (UDL)(40). To predict a given output from an input, SDL algorithms are trained on fully labelled datasets, whereas UDL algorithms are trained on unlabelled datasets and have no specified training in order to predict outcomes (41).

It is argued by some that recent advancements in DL are driven by breakthroughs in artificial neural networks (ANN) (42). These powerful algorithms enable complicated pattern recognition in datasets and are inspired by the structure and function of the human brain (42-44). In order to emulate the neural process the network consists of one input layer of neurons, one or more hidden layer(s) and an output layer, where each hidden layer is made up of a set of neurons each connected to the previous layer (33). These neurons are arranged in rows and multiple connections exist between the constructing layers strengthening the network (45). An example is found in **Figure 2** which illustrates thee input nodes, two hidden layers (each four nodes) and two output nodes (35).

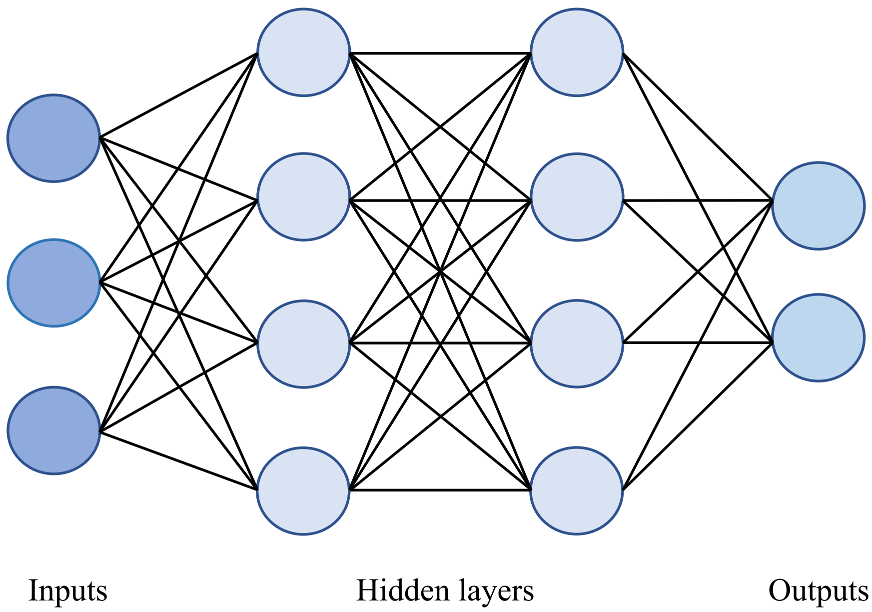

Figure 2: Illustration of a deep learning network

In radiology DL can be applied to find patterns in diagnostic images (46). This process or objective typically commences with a set of available inputs (i.e. diagnostic image data) and finishes when a desired output consists of a set of conditions and associated probabilities (38). Research suggests that DL has the potential to increase the output quality of imaging support systems (47, 48). AI based systems may also play an important role in the development of personalised medicine due to their ability to sort, aggregate, access and integrate the data they generate (49). However, concerns have been raised in terms of patient privacy, ownership, data protection and bias (27, 50).

2.2.2 Artificial intelligence in radiology

Radiology is not new to the idea of using AI based systems to support clinical decision making, considering computers have played an important role in diagnostic imaging analysis for years (51). One example is computer-aided detection (CAD). It was first introduced in the late 1980s/early 1990s to decrease observational oversights by consultants in their investigation of mammograms (52, 53). CAD has also been applied to other areas of cancer detection such as detection of lung nodules, breast lesions and colon polyps (54). The term CAD refers to pattern recognition software that identifies suspicious features in a diagnostic image and brings it to attention (55). Observational oversight is defined in this context as false negatives made by the investigating consultant (56). A false negative can be described as a false test result that does not detect the condition when it is present (57). Based on recent research, a CAD algorithm constructed by ANN goes through several steps (image processing, image feature analysis and data classifications) in order to generate one single output (58). However, its success is limited to high sensitivity, reasonable specificity and the consultant's ability to interpret the computer-generated outputs (59).

Another example is the emerging research field of radiomics. Radiomics is defined as "*the quantification of phenotypic traits of a lesion from diagnostic images (i.e., CT, PET, MRI, ultrasound)*" (60). Phenotypic traits of a lesion are described as the characteristics of an area of abnormal tissue (61, 62). In cancer research lesions can either be benign (non-cancerous) or malignant (cancerous) (63). Radiomics creates mineable databases in order to reveal quantitative predictions or prognostic associations between medical images and medical outcomes (64, 65). A radiomic workflow is based on four successive processing tasks: image acquisition/ reconstruction, image segmentation, feature extraction and quantification, and feature selection/ statistical analyses (66).

The ANN (and/or DL) can be applied to any aspect of the workflow, but current research has applied ANN to automatically identify and extract features or in terms of feature selection (67). It is only recently that radiomics has been applied to areas other than cancer precision medicine, in order to potentially aid diagnosis, predict response to treatment, monitor disease status and assess prognosis (68, 69). However, clinical success in radiomics depends on good predictive performance potentially leading to improved decision making and predicting the patient's response to treatment (70, 71). Furthermore, DL has been introduced to radiological image reconstruction by two CT manufacturers: Canon and General Electric Company (GE) Healthcare (72, 73).

2.2.3 Overview of areas of application of deep learning in radiology

AI is expected to play a key role in automating clinical tasks completed by radiology consultants (74). DL applications have led to a rapid advancement in computing analysis of diagnostic images (75). AI development has relied on large data sets being available through PACS (Picture Archiving and Communication System) and DICOM (Digital Imaging and Communications in Medicine) (76-78). Classification, detection, segmentation, and registration are popular areas of research where DL has been tested successfully in diagnostic imaging analysis (79). Other favourable areas detected in Litjens et al's (2017) survey on deep learning in image analysis were content-based image referral, image generation and enhancement and combining image data with reports (79). In general terms, classification refers to the categorisation of a specific group or type of lesions such as binary (i.e. benign or malignant) or multi-class lesions (various subtypes of lesions) (80). In addition, detection refers to highlighting specific subregions in a diagnostic image likely to contain abnormalities (79). Whilst segmentation refers to the identification of meaningful structures and regions within an image (81).

Research suggests that DL based image processing has been successful in the reconstruction (image pre-processing) of mammograms (82), the reconstruction of CT images (83), and identifying kidney stones in CT scans (84) and breast lesions in ultrasound (85). Whereas, DL based computer-based detection has been applied to the detection of pneumonia and wrist fractures in chest x-rays (86, 87) and brain metastasis in MRI scans (88). In addition, DL based segmentation has been successful in analysing CT images of the liver (89), CT urography of the bladder (90) and brain metastasis in MRI images (91). DL based classification has been successful in identifying emphysema patterns in CT images (92) and pulmonary tuberculosis in chest x-rays (93).

2.2.4 Ongoing initiative

There is a growing trend in the development of image interpretation algorithms and the Food and Drug Administration (FDA) in the United States (US) has approved a number of proprietary algorithms, see **Table 1**; however, few applications have been peer- reviewed (94).

Table 1: Approved image interpretation algorithms by the FDA as of 2018

Company	FDA Approval	Indication
Apple	September 2018	Atrial fibrillation detection
Aidoc	August 2018	CT brain bleed diagnosis
iCAD	August 2018	Breast density via mammography
Zebra Medical	July 2018	Coronary calcium scoring
Bay Labs	June 2018	Echocardiogram EF determination
Neural Analytics	May 2018	Device for paramedic stroke diagnosis
IDx	April 2018	Diabetic retinopathy diagnosis
Icometrix	April 2018	MRI brain interpretation
Imagen	March 2018	X-ray wrist fracture diagnosis
Viz.ai	February 2018	CT stroke diagnosis
Arterys	February 2018	Liver and lung cancer (MRI, CT) diagnosis
MaxQ-AI	January 2018	CT brain bleed diagnosis
Alivecor	November 2017	Atrial fibrillation detection via Apple Watch
Arterys	January 2017	MRI heart interpretation

To date this researcher has not been able to locate a list from the European Medicines Agency (EMA) including approved AI applications. In Europe medical devices and/or equipment have to undergo a conformity assessment in order to demonstrate that they meet the legal requirements to ensure they are safe and perform as intended (95). When approved, manufacturers can place a CE (Conformité Européenne) mark on the medical device (95).

However, in the United Kingdom (UK) The artificial intelligence company DeepMind Technologies has collaborated with Moorfields Eye Hospital NHS Foundation Trust since 2016, in order to analyse eye scans for signs of disease in order to prevent blindness (96, 97).

DeepMind has also collaborated with University College London (UCL) Hospital in London in order to develop an ML algorithm aspiring to diagnose head and neck cancer from CT and MRI scans (98). In contrast, International Business Machines (IBM) has in recent years bought up a variety of imaging databases and used DL based technology in order to help consultants diagnose more efficiently and accurately (99).

Norwegian scientists and researchers have to date not developed an AI solution in radiology for testing or adoption to this researcher's knowledge.

2.2.5 Implications of AI in diagnostic imaging

The potential of AI has been recognised for some time. It is only in recent years that modern AI solutions have been approved and adopted in radiology (100-102). Modern AI also poses a complex series of social, political and economic challenges (103, 104). A series of ethical, legal and social implications have been listed by Carter et. al. (2020). Those of relevance to the discussion section of this thesis are summarised and commented on below:

Data ownership, confidentiality and consent – AI systems require large quantities of data for training and validation (105). Ownership and consent for data and protection of the data are considered as critical issues, since misuse of such data can threaten personal privacy (105). Patients should not trade away their health data without knowing and/or considering the potential risks and issues first (106).

Legal risk and responsibility – No courts have developed standards specifically addressing who should be held legally responsible if AI causes harm (105). For personal data and privacy protection, the European Union (EU) suggests possible adjustments to the existing legislative framework relating to AI (107). EU Safety legislation has to date only focused on placing AI based products on the market and principally not the services employing this technology (i.e. healthcare services and transport services) (107). In addition, the Norwegian government has acknowledged the need to develop a regulatory framework for health-related areas before AI methods can be tested and adopted (108).

Medical moral and professional responsibility - It is suggested that consultants will face challenges in respect to their moral and legal responsibility if their decisions depend on non-explainable AI recommendations (105). Clinicians should be trained or take an interest in learning how to avoid machine bias as AI/ML could affect their human decision making (105). In addition, it is important to maintain transparency in order to maintain the doctor-patient relationship (109).

Patient knowledge, experience and trust - Public engagement with eHealth technology depend on: the characteristics of the users, technological issues, characteristics of eHealth services, social aspects of use and eHealth services in use (110). It can also contribute to the legitimacy and trust in AI solutions in radiology and healthcare services (105).

The pressure to implement AI – There is currently a great deal of momentum towards implementing AI in radiology and general healthcare (111). AI is being sold as something ground-breaking, but evidence suggests that these promises may not be realised, and that they are not authentic but merely powerful imaginings developed to inspire us to commit to the uncertain future of AI (112). Rapid advances in medical imaging technology and very high expectations related to AI have contributed to this hype (113). A hype can be defined as: "*a situation in which something is advertised and discussed in newspapers, on television, etc. a lot in order to attract everyone's interest*" or " *to make something seem more exciting or important than it is*" (114).

2.3 Knowledge of and attitudes toward artificial intelligence

The general public's knowledge of AI is limited and the majority understand only a fraction of the benefits and risks of how AI may operate in clinical settings (115).
The European Union Commission (EC) has identified the lack of AI knowledge and skills as the most important barrier to its adoption in Europe (116). It is therefore surprising that the knowledge level and attitudes of radiologists in relation to AI is a relatively unexplored research area.

2.3.1 Relevant empirical studies

Few studies have investigated these characteristics in terms of the nature of AI and radiologists. The empirical studies of relevance for this study are reviewed below and included only cross-sectional studies (See **Table 2)**. Of note, studies with medical students, radiology residents and radiologists were included in this review, as the number of studies with only radiology residents and radiologists were limited.

2.3.1.1 Studies including radiology residents and radiologists

A limited number of studies have investigated radiology residents and/or radiologists in settings such as education, perception, knowledge, attitudes and expectations in terms of AI. Collado-Mesa et al. (2017) sought to develop educational resources to help and prepare radiologists for the development and implementation of AI in diagnostic radiology.
Two years later, Waymel et al. (2019) investigated factors such as perception, knowledge, wishes and expectations towards the rise of AI with a sample of radiology residents and radiologists in France. The future of radiology was investigated by Hoek et al. (2019) through opinions and assessments of radiologists, surgeons and medical students in Switzerland. In another study, including members of the European Society of Radiologists (ESR), Codari et al. (2019) sought to determine radiology residents and radiologists' positions toward new innovative technology that may affect their specialty. A few technologists such as physicists and computer scientists were also included in their multi-national study. In addition, advantages and disadvantages of AI implementation and radiologists' general opinion toward AI in radiology was investigated by Coppola et al (2020) in their national survey of Italian radiologists.

Table 2: Overview of prior survey studies including radiology residents, radiologists, medical students and others

Author, country	**Respondents**	**Methods and Statistical analyses**	**Response rate**
Collado-Mesa et al. (2017), *United States*	34 radiology residents 35 residents	Online survey using SurveyMonkey, Pearson's Chi-square test, Wilcoxon rank sum test	Response rate 66% (69 of 104).
Waymel et al. (2019), *France*	70 radiology residents 200 residents	Online survey using Google Forms, Mann-Whitney rank sum test, Kruskal-Wallis test one-way analysis of variance (ANOVA), Dunn's multiple comparison test	Response rate 43.8 % (270 of 617).
Hoek et al. (2019), *Switzerland*	59 radiologists 56 surgeons 55 medical students	Online survey using SurveyMonkey, Kruskal-Wallis test one-way analysis of variance (ANOVA), Dunn's multiple comparison test,	Response rate unknown. 170 were included in statistical analyses.
Codari et al. (2019), *Multi-national*	675 radiologists	Online survey using SurveyMonkey, Spearman's correlation coefficient	Response rate 3.4% (822 of 24.000).
Coppola et al. (2020), *Italy*	1032 radiologists	Online survey using SurveyMonkey, Chi-square test, Spearman rank test.	Response rate 9.5 % (1032 of approximately 11.000).
Gong et al. (2018), *Canada*	322 medical students	Online survey using the institutional Qualtrics website, Chi-square test, Mann-Whitney rank sum test, Kruskal-Wallis test one-way analysis of variance (ANOVA)	Response rate 2.9% (322 of 11.444).
Pinto dos Santos et al. (2019), *Germany*	263 medical students	Online survey using SurveyMonkey, Wilcoxon singed rank test	Response rate unknown. 263 was included in statistical analyses.
Sit et al. (2020), *United Kingdom*	484 medical students	Online survey using Google Forms, Wilcoxon rank sum test	Response rate unknown. 484 were included in statistical analyses.

*Wilcoxon rank sum test is also termed in this table as the Mann-Whitney rank sum test by some authors

2.3.1.2 Studies including medical students

As with studies in relation radiology residents and radiologists, few studies have investigated medical students' perception, attitudes, understanding. For instance, Gong et al. (2019) investigated Canadian medical students' perception of AI, AI's impact on radiology and their preference of radiology based on more recent developments in AI. In contrast, Pinto dos Santos et al. (2019) assessed German medical students' attitudes toward AI in radiology and medicine. More recently, Sit et al. (2020) investigated in their multi-centre survey the attitudes and perceptions of UK medical students toward AI, as well as evaluating the current climate of education related to AI.

2.3.2 Knowledge of artificial intelligence

Most clinicians (i.e. paramedics, specialty doctors, radiologists) are likely to use DL based AI in the future (94). Topol (2019) emphasises the importance of arming the current and future workforce with the necessary skill to work critically with novel AI based solutions (94). It is increasingly apparent that AI education for clinicians and medical students is needed as the lack of AI skills is an important barrier for its adoption. The term knowledge refers to: "*the understanding of or information about a subject that you get by experience or study*" (117).

To date, AI is not incorporated as part of the typical medical education curriculum or the radiology residency programme to this researcher's knowledge. From this, it would seem that radiologists are responsible for their own understanding of AI as they are learning–by–doing and/or have a personal interest in learning about it. It is appreciated that a limited number of learning opportunities and educational platforms may contribute to the lack of knowledge and information in respect of AI systems and ML algorithms.

Prior research suggests that residents, radiologists and medical students all in general have a limited understanding of the terms of AI and ML algorithms (118-123). For instance, when US radiology residents and or/ radiologists were asked "*Are you familiar with big data analytics"* over half of the radiologists answered "no", compared to half of the radiology residents (118). Most Italian radiologists responded that AI was "*an aid to daily working practice*" when asked about the most suitable definition (122). Their response suggests they know what it can do, but not the underlying mechanics. Jointly, most French radiologists reported they had received insufficient prior information about AI (119). In terms of medical students, approximately 31% of German students answered “yes” when asked: “*Do you personally have a basic understanding of the technologies used in these topics?*” (121). In contrast, approximately half of the UK students indicated that they had an understanding of basic AI computational principles. The confidence was higher among Canadian students in terms of self-reporting knowledge however, only a small percentage answered all 5 questions correctly when knowledge was objectively assessed (120).

Encouragingly, radiology residents, radiologists and medical students reported positive willingness to attend courses and/or training programmes in terms of AI (118, 119, 123, 124). It was also reported in Callado-Mesa et. al (2018) and Gong et. al (2019) that the majority of respondents believed that AI/ML should also be a part of the basic medical education and training (121, 123). An overwhelming majority of ESR members believed radiologists should take part in AI development, but only a fraction reported current involvement in developing projects (125).

2.3.3 Attitudes toward artificial intelligence

An attitude is defined as “a *feeling or opinion about something or someone, or a way of behaving that is caused by this*” (126). Radiologists’ attitudes, behaviour and cognition could have an impact of how AI is adopted and implemented in clinical practice. Prior research suggests that residents, radiologists, medical students, and surgeons believe that AI systems would impact their job in the foreseeable future both positively and negatively (118-125).

When asked: “*Which techniques do you foresee will be the most important fields of AI-applications in the next 5-10 years?*” members of the ESR responded “*detection of disease*” (61.1%), “*staging/ restaging in oncology*” (46.5%), “*quantitative image biomarkers*” (37.9%) and “*imaging processing*” (35.9%) (125). In comparison, the majority of Italian radiologists believed AI would aid detection and characterisations, which were considered as easier tasks (122). Similar results were reported by Gong et al (2019) and respondents believed AI could potentially detect pathologies (121). However, half of them believed AI was not capable of establish a definite diagnosis. Conversely, the majority of respondents from the Swiss study believed that “*Artificial intelligence should be used as support for evaluating radiological images”* (124). This concurs with the majority of French radiologists who believed AI would contribute to the reduction of image-related medical errors (119).

The future of radiologists was also an area of interest investigated in few of the studies included in this literature review. Thus, while Swiss respondents believed AI should be used as support, the majority was not confident about the future of radiologists (124). In contrast, the minority of respondents in Gong et al., Coppola et al., Pinto dos Santos et al. and Sit et al. believed AI would replace radiologists in the future. However, there was some agreement that AI would affect job opportunities in the future and AI has, in fact, affected some respondents in their choice of specialty (118, 123-125).

Even with an uncertain future, some radiologists believed AI would reduce the time of examinations and increase the time spent with patients (119). However, it was questioned whether AI should be used alone for image evaluations (124, 125). Respondents also believed that AI would to some extent: make radiologists more clinical, change the doctor-patient relationship and save time to enable more peer interaction (125). One study reported shared responsibility between radiologists and developers if AI caused error or harm (125). This concurred with the Swiss study, where respondents questioned AI's liability (124). Only in two studies were specific patient privacy and data security questions included. Among the Swiss respondents, over half believed that data should be stored locally in hospitals (118). Whereas, the majority of Italian radiologists denied ethical concerns over AI and believed AI should be regulated by specific policies (122).

2.3.4 Summary of current literature

Based on the current climate of knowledge and attitudes toward AI found in this review, it was apparent that the knowledge of AI was limited among radiology residents, radiologists, medical students and others. Equally, not all of the included studies reported findings of knowledge or included similar topics in terms of attitudes. However, areas to apply AI, employment status and impact, and expectations were reoccurring topics in included studies. The attitudes in these studies were divided and due to the limited number of similar studies it is important to gain more knowledge of these topics through further research.

2.4 Study rationale

The review of previous studies indicated that knowledge of and attitudes toward AI are under- researched areas. However, the baseline generated from these studies could serve as an indicator of the current landscape. Conceivably, these results may not serve as generalisations because of the small sample size, low response rate and sample variations. In addition, knowledge of and attitudes toward AI may differ between countries, based on general knowledge, interest, the educational system, training and own work experience.

As knowledge was limited and areas of attitudes varied in the relevant studies included, it is important to establish a baseline of Norwegian radiologist's knowledge of and attitudes toward AI. It is believed by this researcher that these factors could provide an indication in relation to *if* and/or *how* AI should be implemented in the Norwegian radiological services in the future, as radiologists are considered end-users of this developing technology. It is also hoped that researchers and scientists will include radiologists, or at least seek their knowledge or opinion, when developing AI education and training, as well as the legislative framework for a safe adoption by radiology and- healthcare services.

2.5 ABC model of attitudes and conceptual framework

2.5.1 ABC-model of attitudes

The Affective, Behavioural and Cognitive model, also known as the ABC – model of attitudes, may add valuable information to the connection between knowledge and attitudes recorded in this study. The ABC-model was traditionally aimed at users' attitudes toward a new product(s) or tool(s) and consists of 1) affect (how he/she feels about it), 2) behaviour (intention to take action about it, e.g. use/ not use/ or accept/not accept) and 3) cognition (what is believed to be true about it) (127). See **Figure 3** for ABC – model of attitudes.

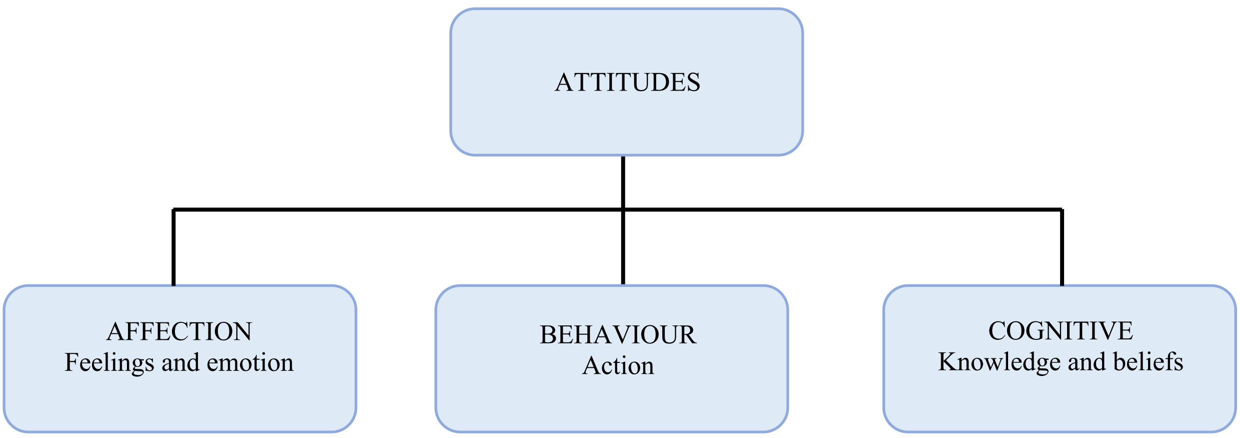

Figure 3: Illustration of the ABC- model of attitudes

2.5.2 Conceptual framework

The conceptual framework for this study is presented below:

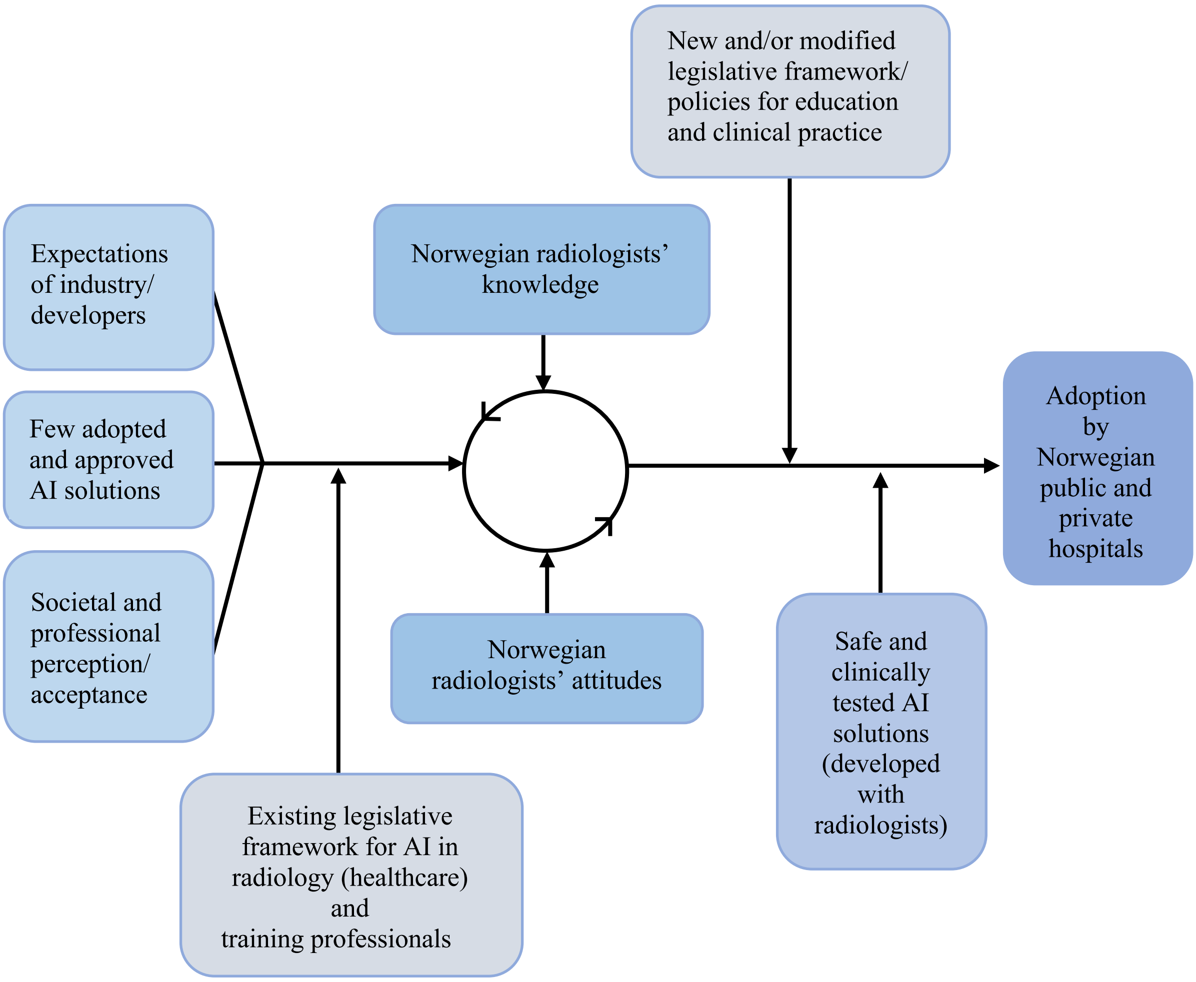

Figure 4: Conceptual framework of AI adoption by Norwegian public and private hospitals

Three domains of barriers possibly affecting a new/ and modified legislative framework or policies for education and clinical practice, as well as developing safe and clinically tested AI solutions (with inputs from radiologists) are found far left. However, it is too demanding for this small-scale study to explain the possible pathway for a safe adoption of AI. That is an area for further research. This researcher still hopes to collect and investigate current knowledge of and attitudes toward AI by Norwegian radiologists. This will be for others to build on and finalise in order ensure a safe and accepted adoption of AI by Norwegian public and private hospitals in the future. It is believed that the current legislative framework and policies need to be modified and or/ developed for a safe adoption and necessary training of professionals to take place.

2.6 Research questions and hypotheses

The questions that informed this research were:

What factors characterise Norwegian Radiologists' knowledge and attitudes toward artificial intelligence?

a) To what level do Norwegian radiologists self-report their own knowledge of artificial intelligence?
b) Have Norwegian radiologists attended courses/ lectures/ seminars in artificial intelligence in radiology?
c) How do Norwegian radiologists think AI will impact radiology?
d) What are the attitudes among Norwegian radiologists toward artificial intelligence in radiology?

The working hypotheses that informed this research were:

Hypothesis 1 Older radiologists have limited knowledge of AI

Hypothesis 2 Radiologists undertaking 20 or more examinations per day know more about AI

Hypothesis 3 Younger radiologists will endorse more positive attitudes in general towards AI in radiology

Hypothesis 4 Radiologists undertaking under 20 examinations per day demonstrate fewer positive attitudes toward AI in radiology

3. Method

3.1 Study design

This is a quantitative cross-sectional survey undertaken in Norway. Data collection consisted of a web-based questionnaire using *Nettskjema*. The data was collected anonymously, and 31 radiology residents and radiologists participated in the study. Data collection was conducted between December 2018 to March 2019.

3.2 Inclusion of respondents

3.2.1 Radiologists in Norway

The sample was based on the 990 registered radiologists in Norway in 2017 (128). The inclusion criteria included radiology residents undertaking training in Norway and radiologists employed at Norwegian public or private hospitals. Other categories such as radiographers and orthopaedics were excluded together with those no longer practising as radiologists.

3.2.2 Recruitment procedure

The recruitment of participants was split into two phases: 1) through Facebook and 2) email invitations sent to contacts in the field of radiology. In the initial phase, the link to the web-based questionnaire, supplemented with the information letter, was published on the Facebook page of Norsk radiologisk forening (*Eng: Norwegian Radiology Society*) in December 2018. Only 13 participants responded. In order to increase the number of respondents, an email was distributed early in March 2019 to contacts in 6 radiology departments in South-Eastern Norway: Vestre Viken, Østfold, Akershus, Ullevåll, Rikshospitalet and Radiumhospitalet. The email included the information letter and link to the web-based questionnaire. It was also requested that the invitation to participate in this study was further distributed to other colleagues in order to recruit more participants to this study. An additional 20 participants responded.

3.2.3 Total sample

In total, the two phases of recruitment generated 33 out of 990 possible respondents. This was a lower number than expected. Out of these 33 only 31 could be used for statistical analyses due to missing important variables.

3.3 Background characteristics and questionnaire development

3.3.1 Background characteristics

Demographic information was only sought for age (groups) and sex (male/ female) to secure radiologists' anonymity as the field of radiology is small in Norway. Individuals are easy to identify on the basis of exact age, education and experience and employment location (in either four of the regional health authorities) and status (radiology resident or certified radiologist). These variables were therefore excluded.

3.3.2 Questionnaire development

The 13 questions developed for this study were modified and translated into Norwegian. Some questions were taken from *The Role of Artificial Intelligence in Diagnostic Radiology: A Survey at a Single Radiology Residency Training Program* (118) and an early stage pilot study by graduate students at the University of Porto (129) and then translated and adapted, whereas other questions were created anew for the questionnaire. The justification for this method is that according to literature, using or adapting existing questionnaires is productive (130). However, supervisors and an attending radiologist were still asked to review the initial questionnaire before it was published online on Nettskjema. *Nettskjema* is an online tool used for designing and conducting online surveys and is operated by the University Information Technology Center (USIT) at the University Oslo (UiO) (131). An overview of the questions in English with answers can be found in **Table 3** or in full, in Norwegian in **Appendix 2**.

3.3.3 Responses

The responses were scored either by categorical yes/ no responses or a five-point Likert scale varying from: *very high* to *very low*, *strongly agree* to *strongly disagree* or *to a very large extent* to, *to a very small extent.* Open-ended questions were included, allowing the respondents to elaborate on their answers through free-text. In addition, a number of questions allowed respondents to elaborate on their answer if they answered *to a very large extent* or *to a very small extent* and *strongly agree* or *strongly disagree*.

Table 3: Overview of survey questions translated into English, including answers, used for statistical analyses

Question/ statement	Answer
Q1 - What is artificial intelligence in radiology?	Free-text
Q2 - In what way do you think AI could impact radiology?	Free-text
Q3 - To what level do you evaluate your own knowledge of AI in radiology?	Five-point Likert-scale
Q4 - In what area(s) would you like to apply AI?	Yes/ No
Q5 - Have you attended lectures/ seminars in respect to AI in radiology?	Yes/ No
Q6 - AI will improve the quality of radiological examinations	Five-point Likert-scale
Q7 - AI will take over the radiologists' work tasks in the future	Five-point Likert-scale
Q8 - AI will contribute to increased accuracy in diagnostics and treatment in the future	Five-point Likert-scale
Q9 - In which area(s) do you think financial investment in AI is required?	Yes/No
Q10 a - The use of AI raises concerns related to privacy and data security	Five-point Likert-scale
Q10 b - The use of AI makes patient refuse radiological examinations due to data security concerns	Five-point Likert-scale
Q 12 - How many radiological examinations are you undertaking per day?	Numeric response

*Q5 and Q9 included alternatives where Yes/ No is applicable

* Q11 and Q13 was not included in this table as and responses were not included in statistical analyses

* Q7 and Q8 allowed respondents to elaborate on their answer if answering *to a very large extent* or *to a very small extent*

* Q10a and Q10b allowed respondents to elaborate their answer if answering *strongly agree* or *strongly disagree*

3.4 Ethical considerations

3.4.1 Ethics

The National Committee for Research Ethics in the Social Sciences and the Humanities (NESH) is clear that participation can only be undertaken by competent individuals; who understand the project, choose to participate after considering the information provided and who have not experienced any inappropriate pressure or disadvantages in the process (132). Participants were informed of the potential risks and benefits of participating in this research (See **appendix 1: Information letter**), enabling them to make an informed choice on whether to take part in this study. The risks associated with the participation in this study are considered to be low because their responses cannot be identified, nor does it affect current clinical practice.

3.4.2 Confidentiality

In the case of this self-administered web-based questionnaire, various measures were taken to ensure the participants' confidentiality. Firstly, *age* was divided into categories and information of hospital regions and years of practice was not sought as the combination of specific information might enable specific participants to be identified.

Secondly, all participants were informed that the study was voluntary and anonymous. The participants were also informed that they could not withdraw from the study once the questionnaire was completed since *Nettskjema* automatically made all the responses anonymous and therefore impossible to trace back to a specific participant. Lastly, data was processed anonymously without any identifiable information and was only used for the purpose of this study.

The purpose of the study was not to expose gaps in radiologists' understanding of AI, but to examine their general knowledge, perception and attitude toward AI applications in radiology accurately.

3.4.3 Reflexivity

The background of the researcher plays an important role in the construction of this study. Who she is and her relationship to the research, can both positively and negatively influence how the research is constructed and conducted, as well as the analysis of the related findings.

My background is in sports and exercise science with additional courses in engineering. As a graduate student at the faculty of Medicine at the University of Oslo, I have been introduced to different areas of medicine and healthcare, including growing challenges, such as the medical information explosion and navigating technology, confidentiality and ethics.

My interest in this study arose from a course in medical physics which introduced me to the physics of advanced healthcare technology. The motivation to study radiologists' perception, knowledge level and attitudes was a result of the current ongoing talk of robot-assisted surgery, 3D-printing of organs, e-health and application of artificial intelligence diagnostic radiology. From the available studies found in **Table 2**, it was evident that there is a gap in research in terms of knowledge of, and attitudes toward, AI end-users in radiology.

3.4.4 Financing and conflict of interest

There are no costs associated with this study. The researcher and the supervisors have no conflict of interest related to this research.

3.5 Statistical analyses

The data was processed both in Excel (Office 365) and the Statistical Package of Social Science (SPSS version 25 and 26). Raw data generated from *Nettskjema* was processed in Excel before final analyses in SPSS. Missing data was discussed with supervisors and excluded for further analyses. Normal distribution was assessed following inspection of skewness, histograms and Kolmogorov-Smirnov test for normal distribution. Based on this assessment the criteria for normal distribution was not met as the p-value was listed as $p=0.000$. Therefore, in respect of the small sample and non-normal distribution, a statistician was consulted for recommendations for further statistical non-parametric analyses. The Fisher's Exact test ($p=0.05$) was then used as an alternative test for associations, since the Chi-Square test (X^2) was deemed invalid due to the low number of expected frequencies.

3.6 Free-text answers

The free-text answers constitute a modes qualitative material. Due to the material's limited scope and depth, a simplified qualitative analysis approach was deemed appropriate and sufficient. The free-text answers were categorised through a simple approach which involved inductive construction of categories – content analysis. First, the free-text answers were read several times. Then, categories thought to fit the spectrum of answers were constructed. Next, each answer was placed in the category judged most appropriate and the number of responses in each category was counted.

4. Results

4.1 Respondents

The number of respondents included in the statistical analyses were 31. **Table 4** describes the sample of this study in terms of age and number of examinations undertaken per day. As can be seen in the table, most respondents were under the age of 50 and most undertook 20 or more examinations per day.

Table 4: Background characteristics of respondents (n (%))

Scale, N = 31	Male (n=26)	Female (n=5)
Age range in years		
Under 50	17 (65%)	4 (80%)
50 and above	9 (35%)	1 (20%)
*Number of examinations undertaken per day**		
Under 20	11 (42%)	3 (60%)
20 and above	15 (58%)	4 (40%)

*Q12 - How many radiological examinations are you undertaking per day?

4.2 Knowledge

When asked "*What is artificial intelligence in radiology?*" many of the respondents self-reported that AI was a "computer programme/ aiding system" (55%). Only 3 % provided a labelled application (IBM Watson) with no further explanation. Approximately 20% did not provide a definition of AI and was considered "*N/A*" (Not Applicable). One respondent seemed to have copied and pasted their answer directly from Google (web-based search engine) and was therefore treated as N/A in this study. Approximately 25% included keywords such as "*machine learning/ algorithms*" in their free-text answer. See **Figure 5** (see **Appendix 3** for content analysis).

In response to "*In what way do you think artificial intelligence could impact radiology?*" the majority (55%) answered a "*decision support system/ second opinion*". 16% thought it would improve "*detection/ classification/ diagnosis*". Few (6%) thought AI would reduce the radiological workforce. Nearly 25% of the responses fell into the category "*N/A*". See **Figure 6** (see **Appendix 4** for content analysis).

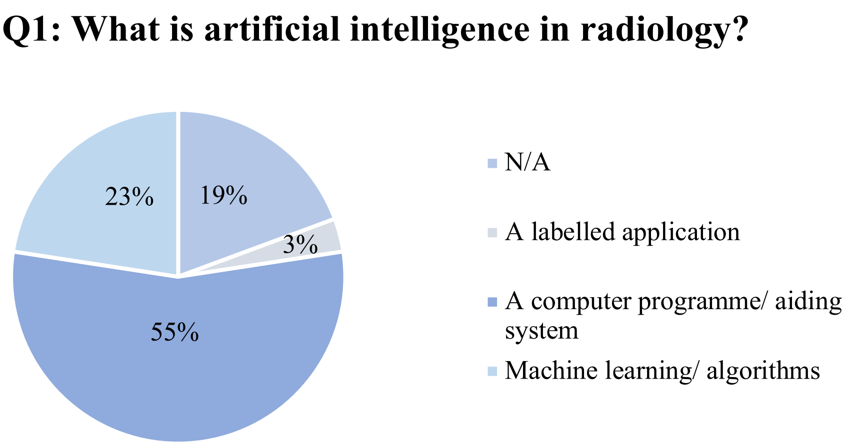

Figure 5: Respondents' self-reported knowledge of AI, free-text answers

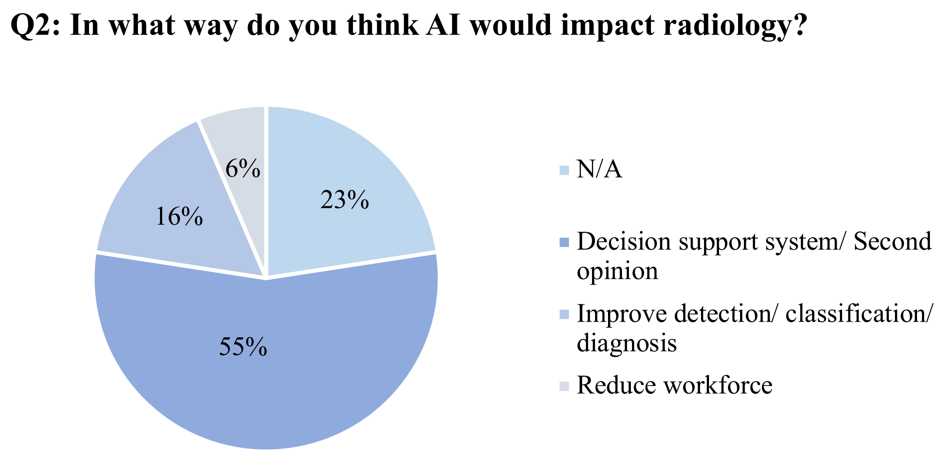

Figure 6: Reported areas in radiology where AI could make an impact

Approximately 39% of the respondents reported "*average*", when asked about their knowledge of AI in radiology, whereas, nearly 23% thought they had good knowledge of AI (including answers such as *Very good* and *Good*), with 39% reporting they had low knowledge of AI (including *Low* and *Very low*). 32% had attended lectures/ seminars related to AI in radiology in comparison to the 68% who had not. See **Table 5**.

Table 5: Self-reported level of knowledge and lecture and/or seminar attendance

Question/ statement	N	Frequency (%)
Q3 - To what level do you evaluate your own knowledge of AI in radiology?		
Very good	3	9.7
Good	4	12.9
Average	12	38.7
Low	9	29
Very low	3	9.7
Q5 - Have you attended lectures/ seminars in respect to AI in radiology?		
Yes	10	32
No	21	68

4.3 Attitudes

The responses for "*In what areas would you like to apply AI?*" varied and not all respondents answered *Yes* and/or *No* to this question. Most respondents who replied were in favour of applying AI to *Lesion tracking* (97%) and *Pathology* (94%). *Prediction* and *Teaching* were less favourable areas of those replying, with approximately 68 % responding yes and about 25% responding *No* to apply AI in these two areas. Nearly 50 % thought AI should be applied to *Other areas* (not specified) compared to the 25% of respondents who disagreed it should be applied to *Other areas*. See **Figure 7**.

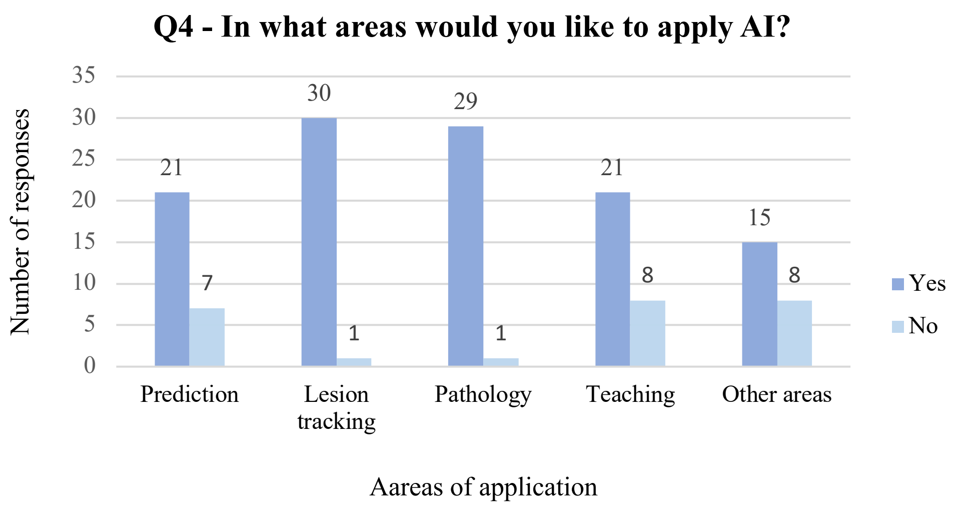

Figure 7: Reported areas to apply AI

Reported attitudes in relation to the quality of radiological examinations, workforce and privacy and data security results are found below in **Table 6**.

Table 6: Reported attitudes toward AI

Question/ statement	**N**	**Frequency (%)**
Q6 - AI will improve the quality of radiological examinations		
To a very large extent	7	22.6
To an extent	10	32.3
Do not know	13	41.9
To a small extent	1	3.2
To a very small extent		
Q7 - AI will take over the radiologists' work tasks in the future		
To a very large extent		
To an extent	3	9.7
Do not know	21	67.7
To a small extent	6	19.4
To a very small extent	1	3.2
Q8 - AI will contribute to increased accuracy in diagnostics and treatment in the future		
To a very large extent	4	12.9
To an extent	14	45.2
Do not know	10	32.3
To a small extent	3	9.7
To a very small extent		
Q10 a - The use of AI raises concerns related to privacy and data security		
Strongly agree	9	29
Agree	11	35.5
Do not know	7	22.6
Disagree	4	12.9
Strongly disagree		
Q10 b - The use of AI makes patients refuse radiological examinations due to data security concerns		
Strongly agree	2	6.5
Agree	6	19.4
Do not know	8	25.8
Disagree	12	38.7
Strongly disagree	3	9.7

About half (55%) thought AI would improve the quality of radiological examinations (including answers: *To a very large extent* and *To an extent*). Nearly 70% responded *Do not know* to whether AI would replace radiologists' tasks in the future. Only one respondent elaborated on their response *to a very small extent* to *Q7 - AI will take over the radiologists' work tasks in the future*. Translated from Norwegian the response read as: "*Radiology is too complex to be run by machines.*"

To *Q8 - AI will contribute to increased accuracy in diagnostics and treatment in the future* four respondents provided information explaining the reason behind their answer *to a very large extent.* One elaboration read as: *"… AI will be able to make probability calculations … with greater precision from a database…and will be able to contribute greatly to improved and targeted diagnosis and treatment in the future*." While another read: "*…better sensitivity* …." Whilst the third read: "*…opportunities for utilising image data beyond the purely visual impression and gaining experience from large databases.*" Last, the fourth, read: "*Efficient operation and exploit greater potential of image information*."

Approximately 65% thought AI would raise concerns in respect to personal privacy. Seven out of nine respondents provided an explanation to their answer *strongly agree* to *Q10 a - The use of AI raises concerns related to privacy and data security*. Reoccurring themes from their elaborations were:

Table 7 – Summary of free-text elaboration, privacy and data security

-	Scepticism toward third party private organisations and data handling and/or access
-	Doubts concerning present legislative framework in respect of data privacy and patient safety
-	Concerns related to patients' involvement in terms of allowing access to data for examinations/ treatment
-	Concerns related to data access and whether it is actually possible to fully anonymise data generated form examinations, procedures and treatments used in AI development and training

For instance, one respondent asked questions back: "*Who should store patient data? Who should have access to data (other doctors, insurance companies, employers, NAV)? To what extent should data be available across hospitals / health agencies / countries?*" Another respondent replied "*… it is uncertain whether current solutions are secure enough in terms of data privacy…*" In contrast, about 40 % of the respondents did not believe patients would refuse radiological examinations because of data security concerns related to the use of AI.

Elaborations were not provided for *Q10b - The use of AI makes patients refuse radiological examinations due to data security concerns* by any respondents and most respondents disagreed with the statement; 38.7% *disagreed* and 9.7% *strongly disagreed*.

When asked "*In which area(s) do you think financial investment in AI is required?*" the majority (90.3%) of those who responded thought there should be financial investment in diagnostics, compared to the lower response rate for treatment (71%). Surprisingly, only 54.8% thought there should be investment in teaching/ educating the radiological workforce in AI. See **Figure 8**.

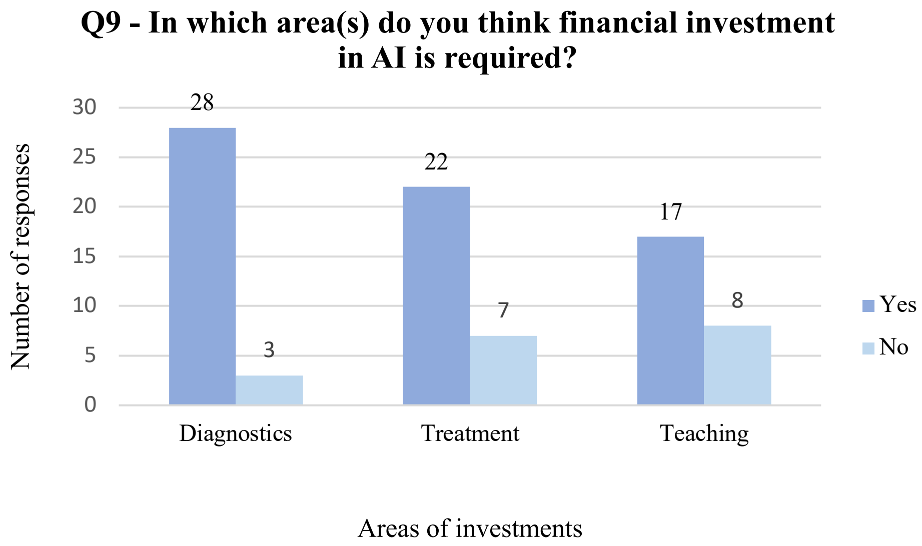

Figure 8: Reported areas financially invest in AI

4.4 Associations

The study also sought to investigate associations, if any, between the *age* of radiologists and the *number of examinations undertaken per day*. *Age* was chosen based on the stereotype that older people, in this case radiologists, struggle with new technology. Number of *examinations undertaken per day* was chosen because it could influence radiologists' attitudes based on their current workload and expectations.

4.4.1 Knowledge

There was found to be no statistically significant association between the *self-reported knowledge* and *number of examinations undertaken per day*. Nor was there found to be a statistically significant association between the *self-reported knowledge* and *age*. There is also no statistically significant association between *course participation* and *number of examinations undertaken per day* and between *course participation* and *age*. See **Table 8**.

Table 8: Associations between the number of examinations and between age, and self-reported knowledge and course participation (n (%))

	Number of examinations undertaken per day			Age range in years		
Scale, N = 31	Under 20 (n =14)	20 and above (n = 17)	p-value	Under 50 (n =21)	50 and above (n = 10)	p-value
Self-reported Knowledge						
Good	3 (21)	4 (24)	0.999	6 (28)	1 (10)	0.077
Average	6 (43)	6 (35)		5 (24)	7 (70)	
Low	5 (36)	7 (41)		10 (48)	2 (20)	
Course participation			0.497			0.148
Yes	4 (29)	6 (35)		5 (24)	5 (50)	
No	10 (71)	11 (65)		16 (76)	5 (50)	

These results **do not support working hypothesis 1** that older radiologists have limited knowledge of AI. Therefore, is not possible to reject the null hypothesis of no statistically significant association between *knowledge level* and *course participation* in respect of *age* and *number of examinations undertaken per day*. Although these findings should be interpreted within the context of statistical limitations: this study's relatively small sample size.

4.4.2 Attitudes

Overall, no statistically significant associations between *areas of application* and *number of examinations undertaken per day* were found or between *areas of application* and *age*. There was also found to be no statistically significant association between *areas to invest* and *number of examinations undertaken per day*. Nor was there found any statistical association between *areas of application* and *age*. See **Table 9**.

Table 9: Associations between the number of examinations and between age, and areas to apply AI and areas of financial investments (n (%))

	Number of examinations undertaken per day					Age range in years				
	Under 20		20 and more			Under 50		50 and above		
Scale, N = 31	(n=14)	Missing, n	(n=17)	Missing, n	p-value	(n=21)	Missing	(n=10)	Missing	p-value
Areas to apply AI										
Prediction	12 (86)		9/14(64)	3	0.385	14/19 (74)	2	7/9 (78)	1	0.999
Lesion tracking	13/14 (93)		17 (100)		0.452	20 (95)		10 (100)		0.999
Pathology	13/14 (93)		16/16 (100)	1	0.467	20 (95)		9/9 (100)	1	0.999
Teaching	9/12 (75)	2	12 (71)		0.999	13/19 (68)	2	8 (80)		0.657
Other areas	5/ 10 (50)	4	10/13 (77)	4	0.221	11/18 (61)	3	4/5 (80)	5	0.621
Areas to invest										
Diagnostics	12 (86)		16 (94)		0.576	18 (86)		10 (100)		0.533
Treatment	11 (79)		11/15 (73)	2	0.999	13/14 (93)	1	9/9 (100)	1	0.066
Teaching	9/12(75)	2	8/13 (62)	4	0.673	11/ 17 (65)	4	7/8 (88)	2	0.205

These results **do not support working hypothesis 2** that younger radiologists endorse more positive attitudes towards AI in radiology. Therefore, it is not possible to reject the null hypothesis of no significant difference between *areas of application* and *areas to invest* in respect of age and number of examinations undertaken per day. Again, these findings should be interpreted within the context of statistical limitations: this study's relatively small sample size.

In sum, no statistically significant association was found between the *attitudes toward AI* and *number of examinations undertaken per day*. Nor was there found any statistically significant association between the *attitudes toward AI* and *age*. See **Table 10**.

Table 10: Associations between the number of examinations and between age, and improvements in the quality of examinations, replacing and taking over work tasks and improving precision medicine (n (%))

	Number of examinations undertaken per day			Age range in years		
	Under 20	20 and above		Under 50	50 and above	
Scale, N = 31	(n= 14)	(n=17)	p-value	(n=21)	(n=10)	p-value
Improve quality of examinations			0.275			0.621
Agree	9 (64)	8 (47)		10 (48)	7 (70)	
To some extent	4 (29)	9 (53)		10 (48)	3 (30)	
Disagree	1 (7)	0		1 (4)	0	
Take over work tasks			0.628			0.104
Agree	1 (7)	2 (12)		2 (10)	1 (10)	
To some extent	11 (79)	10 (59)		12 (57)	9 (90)	
Disagree	2 (14)	5 (29)		7 (33)	0	
Improve precision medicine			0.760			0.543
Agree	8 (57)	10 (59)		11 (52)	7 (70)	
To some extent	4 (29)	6 (35)		7 (33)	3 (30)	
Disagree	2 (14)	1 (6)		3 (14)	0	

These results **do not support working hypothesis 3** that older radiologists will endorse more negative work-related attitudes to AI. Therefore, it is not possible to reject the null hypothesis of no statistically significant difference between *work attitudes* in respect of age and number of examinations undertaken per day.

As previously stated, these findings should be interpreted within the context of statistical limitations: this study's relatively small sample size.

5. Discussion

5.1 Discussion of the results

The most important finding in this study was that respondents had limited knowledge of AI. Respondents were not convinced AI would improve radiological examinations, however lesion tracking and pathology detection were favourable areas for its application, reflecting the desired areas of financial investments. Interestingly, the respondents did not believe AI would replace radiologists in the future. Only a few had attended a course or a seminar in terms of AI in radiology. It was therefore not surprising that teaching (learning/ educating radiologists in AI) was an area where approximately half believed financial investments should be made. Personal privacy and data security were areas of concerns in this study which reflects the ongoing debate about privacy and data protection in the age of AI.

Interestingly, there was no statistically significant association between *number of examinations undertaken per day* and *age* and the respondents' knowledge of and attitudes towards AI.

5.2 Knowledge

5.2.1 Self-reported knowledge of artificial intelligence

The main finding of this study was that respondents had limited knowledge of AI (**Table 5**). It was found no association between self-reported knowledge and *number of examinations undertaken per day* and *age* in this study. The result of limited knowledge of AI is consistent with findings from previous literature (118-123). For example, one study did not find any association between radiology residents and attending radiologists in terms of knowledge of big data analytics (118). Based on this finding it is suggested here that age is not a factor affecting knowledge of AI as it is believed that radiology residents are younger than radiologists due to the number of years of completed training. Of note, this could be a deceptive result due to this study's limited sample as well as the sample in the comparing study (See **Table 4** and **Table 2**).

It is universally accepted that knowledge is power. As AI is predicted to have a bright future in radiology, literature has revived the debate on whether radiologists should know basic theoretical concepts of AI/ML in order to understand the technology. Levey and Hessel (133) suggested already back in 1982; that computer science should become a part of the radiology-residency curriculum in order to understand the technology they will be using on a daily basis. Supporters of this idea believe that because of the fact that radiologists are the professionals who will be using this technology, make decisions in terms of diagnosis, and treat patients, they should know the basic principles of AI/ML (36). Without an understanding of basic concepts, the ability to detect false positives and false negatives generated by the AI-based system is limited. This runs the risk of possibly endangering the patients in terms of wrong diagnosis and/or wrong treatment, and the public trust in the radiologists becomes conditioned (74).

In reality, it is the radiologists who are fully responsible for the overall radiological decision making and not the AI-based solution used (even though it assisted in the decision making). The AI-based solution used is not held accountable for any errors generated in terms of misdiagnosis and/or treatments to date. Additionally, it is believed that knowing the basic principles about AI will encourage radiologists to embrace the technology when it is adopted in full-scale and make them more prepared and confident in using such tools (27). According to some, the use of AI is inevitable, and they urge radiologists to work with it and not against it, as it is likely to be of help by reducing their workload and improve diagnostic accuracy (134-136).

On one hand, well-informed radiologists could educate hospital management, consultants and other clinicians, patients and others about the benefits and limitations of AI in clinical settings. In addition, the terms AI and ML are used interchangeably in literature, media and social media and it was reported in a survey that most medical students had acquired knowledge of AI through newspaper articles and/or social media, instead of lectures or seminars in terms of radiology (121). Moreover, acquiring knowledge about AI/ML through newspapers and social media could be misleading and damaging in terms of public opinion and the adoption of AI in the radiology services, as most articles do not provide enough scientific evidence and theoretical information. Through basic knowledge of AI principles and communicating this information, typical misconceptions of AI such as that AI will replace radiologists and decisions and/or treatments will only rely on AI based outputs and not radiologists, could be eradicated. This researcher acknowledges the fact that basic knowledge of AI/ML could also lead to misconceptions as this technology is very complex and not easily explained.

On the other hand, those professionals who are not informed of AI could believe such knowledge is not essential to their profession, as current AI – based solutions are not widely adopted in clinical practice. It could seem pointless to develop an understanding of AI due to its continuous fast-growing development, the increasing number of new scientific articles published monthly, and the number of successful theoretical solutions. Furthermore, the knowledge acquired could be outdated in 6 months and by theoretical solutions, this researcher refers to AI/ML- based solutions tested in a training environment and not tested in real-time clinical settings.

Of note, knowledge of AI/ML is not enforced, or compulsory in radiology training. In addition, it could be argued that acquiring theoretical and practical knowledge about a technology not yet widely adopted is not a priority due to radiologists' high workload. Arguably, it may be that their focus should be directed to current clinical practices rather than a technology with potential to transform the sector in the future. In addition, knowledge of AI could also be interest based. If respondents have no interest in AI, it is unlikely that they would seek information and gain and understanding of the topic.

Both sides present good arguments however, a strong case can be made that knowledge of AI/ML is not essential for radiologists at the moment. Although the current workload is increasing day-by-day and AI has the potential to assist with the growing workload, spending time acquiring knowledge about a technology under constant theoretical development, without much practical training and testing using real-time environment(s) or data seems redundant. AI is not ready yet for clinical practice and therefore, it is concluded that the limited knowledge reported in this study is justified by the current experimental status of AI. Having an interest in technology one thing, working with technology is another.

5.2.2 Course and lectures attendance

Not surprisingly, few respondents reported course and/or lectures attendance (**Table 5**). It was revealed in this study that neither *number of examinations* or *ag*e was associated with their low course or lecture attendance. In contrast, one study demonstrates an association between the willingness to learn about AI and age, as residents are more likely to learn about AI compared to radiologists (118). A possible explanation for this diverse result is that this study did not specifically ask if respondents would consider attending a course or a seminar in respect of AI in radiology, it primarily asked if they had previously attended a course or a seminar. With hindsight, this study should have asked if respondents are considering attending courses or seminars in order to collect as much data possible in terms of respondents' attitudes and willingness to learn about AI/ML.

As knowledge of AI is not mandatory in radiology and AI still finds itself in a developmental phase, radiologists' willingness to attend courses and seminars could be questioned based on the findings in this study.

An interest in new technology could serve as a predictor for course and/or seminar attendance however, knowledge of AI is not mandatory, and radiologists are not required to attend such events. It is believed here that attendance is voluntary and grounded in their own interest, knowledge level and/or curiosity. Additionally, availability of courses, peer influence and/or work environment could also be among reasons for respondents to attend course or seminars.

It could be argued that those with greater interest in new technology would want to attend courses or seminars related to AI for self-development and education. Keeping up to date with the rapid developments of theoretical and practical AI/ML and meeting others sharing the same interest and/or view(s) could be beneficial and possibly prepare them for the future. Of note, the information acquired, and research presented in these events, may not be relevant in 6 months due to rapid developments fuelled by the increasing funding. Peer influence and work environment could encourage course and/or seminar attendance, as well as participation in research related activities.

Those professionals who have not attended a course and/or seminar are possibly not interested and may share the view that AI is not imminent, and course and/or seminar attendance is not necessary. Traveling and spending time out the office to attend costly events, that are currently not relevant to clinical practice would seem nonessential. It could be argued that time (and resources) should be spent on inpatients and other research, rather than something that is still in its developing stages and not adopted clinically.

If not the lack of interest, the availability of events could determine respondent's attendance, as the AI in radiology community in Norway is small to date. Radiologists who want to attend courses and/or seminars are required to travel, either domestic or internationally, which could be costly and time consuming. These costs could be covered by radiologists' affiliated institution/ employers and/or grants however, if their possible sponsor(s) shares the view presented in *section 5.2.1 Self-reported knowledge of AI*: that AI knowledge is not a requirement for radiologists, attendance could be proven difficult.

The arguments for both sides are well grounded however, course and/or seminar attendance is not currently vital for further professional development, as few practical AI solutions have been adopted, let alone in Norway. Although the availability of AI/ML in radiology courses and seminars are increasing abroad, the technology is still under development and the subject(s) and/or content presented might become outdated before clinical applications are implemented in a daily practice.

The required clinical testing of these models will still be suppressed according to this researcher, as the legislative framework concerning such testing is still not in place (e.g. data handling, patient safety, societal acceptance etc.). As AI knowledge is not mandatory, the limited course and/or seminar attendance reported in this study could, therefore, be grounded in respondents lack of interest of AI, cost of traveling and the presented assumption; that AI is developmental only.

5.3 Attitudes

The following part of the discussion will be based on the ABC-model of attitudes and working under the assumption that attitudes toward AI are founded in respondents' knowledge of AI.

5.3.1 Areas where AI could impact on radiology

It is not surprising that the majority of respondents believed AI would impact on decision support systems/ second opinions (**Figure 6**). As their workload is increasing and the radiology services are under tremendous pressure, radiologists may dream of an assisting tool with the ability relieve the current pressure.

Supporters of this idea believe that AI may offer a paradigm shift in how clinicians work assisting with workflow efficiency, while at the same time improving care and patient throughput (137). In addition, AI could improve patient outcomes and could possibly boost the productivity of human experts without removing control (138). Not losing control is an important factor as radiology is more than image interpretation. Moreover, it could be argued that AI could result in more work as radiologists need to proofread the outcome generated by the AI-based solutions (139).

AI is still in a developmental phase and it is likely that it will take more time to develop and adopt safe AI-based solutions for radiology in a wider scale.

5.3.2 Improve radiological examinations

A surprising finding in this study was that respondents were not entirely convinced that AI would in general improve the radiological examinations (**Table 6**). There is no association between *number of examinations undertaken per day* and *age* in terms of improvement of radiological examinations. The uncertainty among respondents is not consistent with findings from previous literature. In prior research radiological residents and radiologists more strongly believed AI would improve radiological examinations as an adoption of AI in radiology was considered favourable (119, 122, 124). In addition, studies have reported positive attitudes toward whether AI can reduce image and diagnostic related errors (119, 120, 125). One study has found radiologists with prior knowledge of AI to be more positive toward AI in radiology than radiologists with limited knowledge (119).

Considering the increasing workload and recent advancement, it is believed that AI will improve various aspects of radiological examinations. As recent AI/ML developments have been successful and research has confirmed this, radiologists' attitudes on whether AI will improve radiology are still divided. On one hand, the negative attitudes of those who are not convinced AI could improve radiology may be based on the limited number of adopted AI solutions, respondents' knowledge of AI and their mistrust in the technology. Moreover, it could be argued that the limited number of AI adopted solutions questions the reliability of the technology. In addition, most research is still theoretical and not tested in a full-scale clinical environment(s). Limited knowledge and insufficient legislative framework and policies could foster a mistrust in AI solutions. The proof of AI improving radiology is minimal even with billions of dollars invested and with more to come, as the number of adopted solutions is still low.

On the other hand, those convinced AI would improve radiology could possibly have a better understanding of basic concepts and with interest of AI, be more optimistic and embrace the possibilities it creates. Moreover, it is believed that AI could support and act as a second opinion. In addition, those convinced AI would improve radiology may also believe in something that is just an illusion and will not become a reality in the nearest future. A true response from radiologists' attitudes will not be accurately sampled until more radiologists are aware of AI and more AI solutions have been adopted in clinical practice. This assumption follows in the next paragraphs as well, involving attitudes.

5.3.3 Take over most work task and replace radiologists

In this study, approximately 68% of the respondents did not know whether AI would replace radiologists in the future (**Table 6**). No association was found between AI replacing radiologists and *number of examinations undertaken per day* and *age* in this study. This finding was supported by literature in terms of age when radiologists were asked if AI/ML would influence their job over the next 10-20 years (118). Another study has pointed out that radiologists do not believe that AI would replace their role in the future however, it is suggested that AI would take over their reporting of image examinations (122). Reduced learning opportunities for radiologists and lower salaries were also perceived as issues in that same study. Likewise, radiology residents, radiologists and surgeons were not confident about the future of radiology (124). The future of diagnostic radiology was uncertain as new technological innovation could jeopardise this subspecialisation (124). In contrast, studies have also reported positive attitudes toward AI in terms of reduced time of each radiological examination enabling more time to spend with patients and consult other clinicians and peers (119, 122, 125).

The respondents' uncertainty could possibly be rooted in their lack of theoretical and practical knowledge of AI. Not experiencing the technology first-hand could lead to several misconceptions concerning what it is and what it can do. A limited theoretical and practical understanding of AI could possibly affect their workplace. Take for example individual's bias and personal perceptions. It will be similar to the ongoing hype where the media publishes or presents articles about AI without fully understanding the concepts and where it is written from a commercial standpoint. Additionally, the lack of confidence may sit in tandem with a lack of theoretical knowledge and practical experience of AI. Acquiring such experience is proven to be difficult as there are few solutions available and the current legislative framework and policies reduce available opportunities. Moreover, the lack of theoretical and practical understanding of AI may determine the willingness to adopt AI. The adoption of AI is currently administered by limited legislative framework and policies and due to the current uncertain environment, it is not possible, according to this researcher, to predict whether they will embrace modern AI when and if it is available.

5.3.4 Improve diagnostic -and treatment accuracy

In opposition to prior studies, respondents in this study were unsure as to whether AI would improve diagnostic- and treatment accuracy in radiology (**Table 6**). This finding strengthens the overall sentiment as respondents are not convinced that AI would improve radiological examinations. The opposing position believed that AI will improve diagnostic and treatment accuracy as well as turnover time and treatment response (120, 122, 125). These adverse results may originate from respondents prior theoretical and practical knowledge of AI as well as their comprehension.

Contrastingly, respondents in studies reporting more positive attitudes toward AI may have a greater comprehension and/or understanding of AI. They may see AI as a system that can copy human behaviour and as a system that may improve diagnostic-and treatment accuracy. Furthermore, they embrace the possibility of a system that can help them with their increasing workload. They are confident in their role as radiology consultants as they are aware that radiology is more than image interpretation. On the other hand, the hype around AI may be responsible for camouflaging the fact that AI has been available for some time, based on the definition presented in *section 2.2 artificial intelligence.* Radiology has used advanced computer systems to assist with image enhancement and interpretation for decades. It would seem that radiologists have been using simplistic forms of AI in daily practice without knowing it is AI.

What some may fear is actually the modern subtype of AI, the complex ML systems (with hundreds of layers) that are able to learn by itself. Nobody really knows how it acquires the knowledge and how it determines the suggested outcome(s) (i.e., it is a “black box” concept). It could be debated whether developers have pushed the innovation too far without implementing a safety mechanism.

5.3.5 Areas to apply AI

It was reported in this study that lesion tracking and pathology were more favourable areas to apply AI (**Figure 7**). This result is consistent with another study where the average radiologist *mildly agreed* that AI algorithms can reliably detect a pathological condition, whereas radiologists with prior knowledge strongly agreed (119). Another study found that radiology residents and radiologists identified detection of disease in asymptomatic subjects, staging/ restaging in oncology, quantitative imaging biomarkers and image post processing as areas of targeted application of AI systems (125).

The areas identified by other studies for the application of AI could be related to the amount of research conducted in these specific areas. Most of this research, however, is theoretical and not tested in a real-time clinical environment. Acquiring approvals for clinical testing is difficult. Moreover, these are the most well-known areas of research and therefore open for personal bias. In addition, lack of knowledge of AI and current research, may cause respondents to blindly accept these areas of adoption. Conversely, few adoptions in these areas exist, questioning whether these areas are the most suitable areas to continuously trying to develop AI based solutions for clinical practice. It could be contended that as long AI is primarily theoretical and not applied widely practical, societal and sectorial hesitations will exist, altering and undermining the development of AI.

5.3.6 Areas of financial investments

Financial investments in AI is required in diagnostics and treatments according to this study (**Figure 8**). This finding is not surprising as it reflects respondents’ belief in lesion tracking and pathology as areas to apply AI. The reported percentage by respondents in terms of financial investments in teaching or learning about AI was lower. To this researcher’s knowledge this study is the first to locate areas desirable of financial investments however, this result could be deceptive due to the small sample.

The financial investments in AI on an international level is tremendous (140). As AI is predicted to revolutionise radiology and such research and developing projects are heavily funded, the success of such projects is questionable.

The reason for why the success is questionable is primarily because of the few adopted solutions available in clinical practice. If success is measured in terms of the number of adopted solutions, opponents of AI may consider the AI initiative as a failure. Firstly, spending billions of dollars on trying to develop an AI based solution, which does not make it out on the market, could seem like a misstep. Secondly, trying to develop a solution in terms of AI, that has not got the foundation of legislative framework and solutions and public trust would seem unintelligent. On the other hand, investing in such projects may eventually result in a solution capable of delivering what is promised. Furthermore, investment should also be made in educating professionals and the public in AI, in order for solutions to be more widely accepted. From this viewpoint, it seems excessive trying to develop or spend billions of dollars on a technology that end-users do not understand or trust.

Financial investments in AI cannot be fully successful until end-users and society accepts the technology that is being developed. Therefore, resources should also be allocated to educating end-users and society of such technology. Societal acceptance, not only sectorial acceptance, is crucial for the success and adoption of AI.

5.3.7 Privacy and data security

Unsurprisingly privacy and data security were identified as areas of concern in this study (**Table 6**) and this finding reflects current literature. From an ethical viewpoint, an AI generated outcome is controversial as it is not clear how the system determines the outcome (141). In addition, radiologists should not be the only ones held responsible for the generated outcome and the responsibility should be shared between radiologists, developers, insurance companies and patients according to one study (125).

The input data is important for the training of AI/ML based solutions. Without input data, the algorithm(s) cannot learn or develop, and the use of such data has raised concerns in terms of data protection, patients' security, sharing of data and access to data. Protection of data in such settings is demanding, as the legislative framework and policies are not up to date in terms of AI in healthcare. In addition, the security of data is complex and acquiring data however, it is not difficult in the age of technology. Moreover, most individuals believe their data is anonymous when shared and stored electronically however, health data cannot fully be anonymous as it is labelled and linked to each individual. Furthermore, access to data is not only reserved for developers programming and training data sets, in most settings third parties have some sort of access (e.g. investors, component parts suppliers, manufacturers etc.). Even with legislation such as GDPR, third parties with access to data are mostly unknown to the patients the data is obtained from.

On the other side, an AI solution cannot fully succeed before it is trained on a substantial amount of data and it is argued that the AI/ML algorithm(s) needs to be tested in real-time clinical environments with continuous flowing data, and not only on data stored from medical image repositories. Moreover, such data is not accessible at the moment and it is ironically protected by an insufficient legislative framework as the current framework will not approve AI/ML based solutions that should not be deleted, trustworthy and secure (ensuring patients' safety).

It is therefore suggested by this researcher that the legislative framework needs to be in place for such training to be allowed as without such training AI will not reach its full potential. In addition, the technology will not be considered trustworthy as long as it is does not succeed in a practical clinical environment and is adopted. The end-users will not embrace or welcome this technology before it is proven safe and foremost, ensures patient safety.

5.3.8 Refusal of radiological examinations

It was reported in this study that respondents did not believe patients would refuse AI-based radiological examinations due to data security concerns (**Table 6**). Another study opposed this finding where radiologists believed patients would not accept an image report made single handed by AI (125). Their finding concurs with another study related to patients' awareness and trust in AI conducted by the British Heart Foundation (BHF) and All-Party

Parliamentary Group (APPG) where patients felt more comfortable being diagnosed by a human consultant rather that an AI solution (142).

As AI solutions are still in a developmental phase and diagnosis and/or treatment has traditionally been with the radiologists (and consultants), patients' trust in AI and their consultants is important for future adoption. Literature has suggested many ways that AI could work successfully however, if either patients' or radiologists do not trust the technology it would seem difficult to justify its adoption. Additionally, if and when the technology is adopted, with sufficient legislative framework, and in the interest of the patients, it could be argued that no one will question the systems' liablity as long as it performs and the decicion making is right. Its needs to be with hospital/ clinical ethics committee or medical negligence experts equally as with other medical malpractice conducted by the healthcare services.

The hurdle AI has to overcome is development and adoption, once adopted and accepted AI could potentially be revolutionising, as litterature has suggested. On the contrary, it could be argued that when AI is successfully adopted, basic knowledge of AI is not required by patients (the public) as long as radiology consultants are confident, specialists in using AI/ML based tools and aware of its strenghts and limitations. Radiologists are only then the specialists, similar to what they are now, and their professional opinion weighs more thant patients opinion of the technology and knowledge aquired online (e.g. social media, newspapers, medical forums etc.).

5.4 Associations

The working hypotheses outlined in section *2.6 Research question and hypotheses* can be discarded as there was found to be no statistically significant associations. However, due to the small number of respondents the study might very well have had insufficient statistical strength to establish associations. Further investigations with a greater sample are required to establish any foundations for the working hypotheses presented in this study.

5.5 Implications for AI adoption by Norwegian public and private hospitals

Through the discussion of results presented above, it is apparent that a successful adoption of AI by Norwegian public and private hospitals is dependent on a variety of factors.

Firstly, radiologists' knowledge of AI has to increase. However, their knowledge of AI cannot increase without available courses and/or seminars. These courses and/or seminars are mainly held abroad, and the cost and time spent is not justified, as AI is rapidly developing and modern AI is not widely adopted internationally, let alone, in Norway. Of note, an interest in learning and knowing about AI, together with beliefs of benefits, also has to be present.

Secondly, the above cannot occur without a legislative framework or policies in place. Structuring a learning platform in AI/ML for medical school and/or residency programmes would potentially be administrated by the Ministry of Education and Research (*Norwegian*: Kunnskapsdepartementet) and with few successfully adopted solutions the benefit is of integrating such learning is minimal at the moment. AI knowledge and practical skills is not, yet, mandatory in radiology or in medicine. The question is, will it ever be?

Thirdly, the lack of adopted solutions may alter the development of the legislative framework and policies. The lack of understanding, legislative framework and policies may also prevent the development of AI solutions as the framework does not allow for necessary testing in real time clinical environments.

It is clear for this discussion that adopting AI is not straight forward and there is an interplay of variables concerning knowledge, attitudes, societal and sectorial acceptance and legislation. As AI is still in a developmental phase, it is believed by this researcher that Norwegian public and private hospitals will not adopt AI in the nearest future because the technology is not ready, and the knowledge foundation of adopting AI is frail (143).

In order to adopt AI, the Norwegian government has to develop and/or modify its current AI legislation and policies so that necessary testing in live clinical environments can occur. Jointly, the radiology sector has to increase the current knowledge of AI in radiology within the sector in order to be prepared and aware of such technology and benefits. The awareness of the public should also be increased in order to eradicate misconceptions toward the technology and to ensure that patients know that human consultants will be present in all the decision making, diagnosis and treatment. AI will not replace radiologists, it will instead serve as a tool assisting with decision-making, diagnoses and/or treatment, just as medical technology is to date.

This researcher believes that the Norwegian government needs to find a way to balance the degree of regulation and legislation of AI in order to promote sustainable innovation, safety and trust. Only then can AI-based solutions gradually succeed by moving forward from the developmental phase proposed in this study.

5.6 Is artificial intelligence too hyped?

The industry has not yet succeeded in developing a full-scale AI-based radiology solution based on the limited number of adopted solutions. AI has been sold as something new and ground-breaking however, radiologists have had access to AI a long time before this hype; the technology was not called AI/ML – it was called CAD (113). However, the industry and media have suggested that AI will change (and possibly revolutionise) radiology because of its ability to improve efficiency and accuracy of diagnosis (144-147).

It is possible to argue that the current AI research is driven forward by the hype and promise that AI will revolutionise the pressured radiology services. AI's position in the market is currently strong and this fuels research and investments. A simple Google Scholar search from the 27th June 2020 revealed that approximately 16.600 of the 38.000 articles found were published after 2018. Meaning about 44% of all of the articles found in the Google Scholar search were published after 2018. The search included these keywords; *artificial intelligence*, *machine learning*, *radiology* and *medical imaging,* and this researcher acknowledges that more articles could have been found by using additional keywords such as artificial neural network(s) and deep learning etc.

Although most research is still theoretical and has not been tested in a full-scale clinical environment (see *section 5.3.2*), the industry, scientists, researchers, and media have fabricated an illusion of success. Take for example these two statements taken from a PowerPoint presentation held by Dr. Ranschaert in 2018 at the annual meeting of the Belgian Society of Radiologists (BSR) (148):

“Algorithms can diagnose pneumonia better than radiologists”

Or

“Algorithms can detect pneumonia from chest x-rays better than radiologists

Which of these statements are most appealing and which could serve as the headline of an article? The obvious answer according to this researcher is the first statement which demonstrates a wide-spread success. Algorithms that can diagnose pneumonia better than radiologists may nourish the idea that AI-based solutions can change and revolutionise radiology. The second statement is more moderated as the algorithms involved can detect pneumonia from chest x-rays better than radiologists. It does not imply that the algorithms can universally detect pneumonia better than radiologists.

The two statements listed above originated form an article published online on Stanford Medicine news centre in 2017. The original heading of the article was (149):

“Algorithm better at diagnosing pneumonia than radiologists”,

and the subheading read as:

“Stanford researchers have developed a deep-learning algorithm that evaluates chest x-rays for signs of disease.”

By reading through the article this researcher discovered that the tone of the article was positive and that the results from the study were described as somewhat groundbreaking;

“Within a week, the researchers had an algorithm that diagnosed 10 of the pathologies labelled in the X-rays more accurately than previous state-of-the-arts results. In just over a month, their algorithm could beat these standards in all 14 identification tasks. In that short time span, CheXNet also outperformed the four Stanford radiologists in diagnosing pneumonia accurately.”

From this paragraph it is apparent in that specific study that AI/ML in radiology could possibly detect pathologies better than previous state-of-the arts results. However, the headline implied that radiologists were outperformed in diagnosing pneumonia by an algorithm. Whereas further down in the article, it was stated that four Stanford radiologists were outperformed. The result is not convincing from a critical perspective and it is therefore important to evaluate what you read in order to judge if it is trustworthy, and its value and relevance in that particular context (150). There are countless of articles published annually which may build on prior theoretical research form interdisciplinary collaborations. The amount of varying literature available and few adopted AI-based solutions to date could also perhaps, be one of the reasons why most respondents in this study had not attended a course or a seminar related to AI. They may question the material, as well as the speakers, and nobody really knows how successful a full-scale AI-based solution will be in the future.

The illusion of success attracts further research and additional investments. However, there is a deepening gap between profit and funding. A report by Signify Research: *Machine Learning in Medical Imaging-World-2018* illustrated the magnitude of the speculation around AI in medical imaging (151). Approximately 90% of the listed companies registered less than 500K in sales in 2017 and many had received over $30M in funding (151, 152). It is appreciated that additional funding and research can lead to gradual development by this researcher and new small-scale solutions are more than welcomed, however the industry and the media have promoted a revolution that is yet to come.

Based on the fabricated illusion of success and the deepening gap between profit and funding this researcher believes it is important to question and evaluate the validity of the available information and literature on AI/ML. An algorithm can be successful in detecting lung nodules but only in theory, as it has not been tested in a full-scale clinical environment. In addition, there is a mass of information and research available on AI/ ML in radiology, but much of it could possibly be commercially sponsored and/or potentially biased. Conversely, further research may build on the theoretical success however, it is less likely that a significant progress will happen as long as the algorithm(s) is not tested and/or challenged in real-time environments.

A strong case can therefore be made, that AI/ ML in radiology is to date promoted heavily by the industry due to the multi-billion investments and the current buzz. The illusion of success has contributed to further excitement among researchers and others who genuinely believes that AI/ML will change and revolutionise radiology in the nearest future. To date there is no wide-scale AI-based solution in radiology and it may not be developed in the future either.

The current expectations are far greater than the actual results. It could be argued that the industry and researchers have to take a step back and focus on a small-scale solution rather than a full-scale solution in order to succeed and harvest the trust required for adoption. In sum, on one side, hype is good as it helps drive research, bring investments and create competition (153). On the other side, hype could also be lead to over-promising, lack of investments in improving current practice, and rushed unscientific approaches to complex problems (153).

5.7 Strengths and limitations

5.7.1 Cross-sectional design

This was a cross-sectional study and variables were therefore recorded at one point of time. Based on this causality cannot be examined or inferred from the results. It is possible that associations between variables may vary over time, and cross-sectional studies may only provide a glimpse of the association(s) at the time of their data collection. Due to the study design it was impossible to provide evidence for the mechanisms connecting these variables. For example: 1) whether having limited knowledge and AI skills can cause radiologists (younger and/or older) to seek information or attend seminars or lectures on AI or ML in radiology and/or healthcare, or 2) whether having negative attitudes could actually cause radiologists (younger and/or older) to avoid using related technology in clinical settings if possible.

5.7.2 Questionnaire

The questionnaire was developed based on prior studies and this research's objective. In light of this study's findings and hindsight, a greater number of multiple-choice questions could have been included in order to collect more data for statistical analyses. Considering the small sample, it is believed that an additional number of multiple-choice questions could have strengthened the reliability of the present findings and to some extent compensate for the limited number of respondents and the rejection of generalisation.
It is also appreciated that the response rate could have been higher as well, and an addition of multiple-choice questions would still be beneficial in order to strengthen the investigation. Care was taken to ensure that the contexts of responses were not compromised in order to minimise internal validity.

Any weakness in the questionnaire can reduce reliability and validity by the introduction of random or systematic errors.

5.7.3 Recruiting issues

The overall response rate was low despite various attempts to improve the sample size. It may be that some radiologists who refused to take part in this study were influenced by personal sensitivities, objection and/or lack of knowledge to the subject area or reservations about the time it would take to complete the questionnaire (7-10 minutes). However, given the voluntary nature of participation in this study, it would be difficult to manage such factors or prevent multiple responses by a single individual due to complete anonymity being offered by *Nettskjema*. Reasons for non-participation could be demanding workloads and hours, lack of interest, forgetting to distribute the study pack (link to questionnaire and information letter) and that participation in this study was not seen as a priority due to the modest AI research in Norway.

The method of recruitment could also serve as a limitation for participating in this study. It is not a given that radiologists are active on Facebook or frequently read their e-mail. Moreover, it could be that they were receiving numerous invitations to participate in various studies. In addition, it might very well be that there was an overrepresentation of respondents with a keen interest in technology and/or technological advancements in radiology, with the ability to reflect on their knowledge of and attitudes toward AI in radiology. In particular, respondents approached by the email invitations were employed at radiology departments in the South-eastern health region, and their responses may therefore not be representative for all Norwegian radiologists. However, respondents could have been employed elsewhere as radiologists were encouraged to forward the invitation to participate in this study.

5.7.4 Data handling and statistical analyses

To minimise errors and protect reliability the data generated was entered twice to check for data entry mistakes. Based on the preliminary analysis of responses it was clear that the small sample would be challenging. The sample was not normally distributed and help from a statistician was sought in order to find the suitable non-parametric tests for analysis of a small sample and the Fisher's Exact test ($p=0.05$) was considered suitable for investigation of associations, if any.

5.8 Recommendations for further research

Due to the methodological challenges and statistical limitations of this study noted above, a replication and/or extension of this research is required in order to draw firmer conclusions regarding the interplay between variables in respect of knowledge of and attitudes toward AI in radiology. Thus, attitudes are a complex phenomenon, they are unlikely to be investigated adequately by single stranded methodologies. Recommendations for future research in respect to this subject could include both qualitative and quantitative approaches in a more cohesive fashion than presented in this study. For example, a qualitative in-depth interview approach might prepare the ground for a cross-sectional questionnaire. It is also believed that radiographers, medical physicists and medical students could be included as they may be using this technology in the future.

Lastly, knowledge of and attitudes toward AI may affect both implementation and use of the technology in the radiological services. More studies are required to inform the hospital management, policy makers and governance to highlight potential local and regional barriers which may prevent radiologists from learning about, adapting to and applying AI in clinical practice. Further work should seek to identify strategies to facilitate more knowledge of AI and training experience in radiology, and to address the link between attitudes to AI and its adoption behaviours. For example, do those radiologists with positive attitudes toward AI fail to seek related training environments as there are limited numbers of them?

6. Conclusion

This study aimed to investigate the characteristics of Norwegian radiologists' knowledge and attitudes toward AI. Self-reported knowledge and course attendance were factors investigated in terms of knowledge and willingness to learn about AI. It was also believed that respondents' attitudes would be affected by their knowledge of AI. This view was supported by the ABC-model of attitudes. Finally, this study examined the association(s) if any between age and the number of examinations and knowledge and attitudes.

The results showed the following:

- Respondents reported lack of knowledge of AI and few had attended courses and/or seminars.
- Respondents were not convinced AI would improve radiology (e.g. improve diagnosis and treatment).
- Respondents were not convinced AI would replace radiologists and take over most of their work tasks.
- Lesion tracking and pathology were favourable areas to apply AI and financial investments should be made in diagnostics and treatments, and possibly in teaching and education of AI.
- Data privacy and security were areas of great concern and the respondents did not believe that patients would refuse radiological examinations because of data concerns.

No association was found between the number of examinations undertaken per day, age and knowledge and attitudes. However, the overall result from this study could be deceptive due to the small sample of only 31 respondents.

The adoption of AI by the Norwegian public and private hospitals appears not to be forthcoming in the short run, as the technology is not ready for adoption, the legislative framework and policies are not sufficient, the public trust and opinion is low, and the end-users are not sufficiently knowledgeable and convinced that AI would improve radiology.
In addition, there is a deepening gap between profit and funding.

References

1. Hosny A, Parmar C, Quackenbush J, Schwartz LH, Aerts HJWL. Artificial intelligence in radiology. Nat Rev Cancer. 2018;18(8):500-10.
2. Greenhalgh T, Robert G, Macfarlane F, Bate P, Kyriakidou O. Diffusion of innovations in service organizations: systematic review and recommendations. Milbank Q. 2004;82(4):581-629.
3. Lo S-C, Chan H-P, Lin J-S, Li H, Freedman M, Mun S. Artificial convolution neural network for medical image pattern recognition. IEEE Trans Med Imaging. 1995;8:1201-14.
4. Cosby JL. Improving Patient Care: The Implementation of Change in Clinical Practice. Qual Saf Health Care [Internet]. 2006; 15(6). Available from: https://www.ncbi.nlm.nih.gov/pmc/articles/PMC2464885/.
5. Jiang F, Jiang Y, Zhi H, Dong Y, Li H, Ma S, et al. Artificial intelligence in healthcare: past, present and future. Stroke Vasc Neurol. 2017;2(4):230.
6. Hofmann BM. Too much technology. BMJ. 2015;350:h705.
7. Thrall JH, Li X, Li Q, Cruz C, Do S, Dreyer K, et al. Artificial Intelligence and Machine Learning in Radiology: Opportunities, Challenges, Pitfalls, and Criteria for Success. J Am Coll Radiol. 2018;15(3, Part B):504-8.
8. Kahn CE. Artificial Intelligence, Real Radiology. Radiol Artif Intell. 2019;1(1):e184001.
9. Manning DJ, Gale A, Krupinski EA. Perception research in medical imaging. Br J Radiol. 2005;78(932):683-5.
10. Suetens P. Fundamentals of Medical Imaging. 2nd ed. Cambridge: Cambridge University Press; 2009. 261 p.
11. Drew T, Evans K, Võ MLH, Jacobson FL, Wolfe JM. Informatics in Radiology: What Can You See in a Single Glance and How Might This Guide Visual Search in Medical Images? Radiographics. 2013;33(1):263-74.
12. van der Gijp A, van der Schaaf MF, van der Schaaf IC, Huige JCBM, Ravesloot CJ, van Schaik JPJ, et al. Interpretation of radiological images: towards a framework of knowledge and skills. Adv Health Sci Educ Theory Pract. 2014;19(4):565-80.
13. Mabotuwana T, Bhandarkar VS, Hall CS, Gunn ML. Detecting Technical Image Quality in Radiology Reports. AMIA Annu Symp Proc. 2018;2018:780-8.
14. The Royal College of Radiologists. Clinical radiology workload: guidance on radiologists' reporting figures. London, GBR: The Royal College of Radiologists; 2012.
15. Eurostat. Healthcare resource statistics - technical resources and medical technology [Internet]. Brussel: European Commission; 2019 [updated 2019 Nov 28; cited 2020 Feb 2]. Available from: https://ec.europa.eu/eurostat/statistics-

explained/index.php/Healthcare_resource_statistics_-_technical_resources_and_medical_technology.
16. Riksrevisjonen. Riksrevisjonens undersøkelse av bruken av poliklinisk bildediagnostikk [translated: The Office of the Auditor General's investigation of the use of medical imaging examinations]. Oslo: Riksrevisjonen; 2017. In Norwegian.
17. Rosenkrantz AB, Hughes DR, Duszak R. The U.S. Radiologist Workforce: An Analysis of Temporal and Geographic Variation by Using Large National Datasets. Radiology. 2015;279(1):175-84.
18. The Royal College of Radiologists. Clinical radiology UK workforce census 2017 report. London, GBR: The Royal College of Radiologists; 2018.
19. Aguilar T. Bekymret over lang svartid [translated: Worried about turnaround time]. Hold Pusten [Internet]. 2017 Sep 5 [cited 2020 Feb 20]. Available from: https://www.holdpusten.no/artikler/bekymret-over-lang-svartid/404926 . In Norwegian.
20. Bluth EI, Goodman TR, Bender CE. The Late-Career Radiologist: Options and Opportunities. RadioGraphics. 2018;38(6):1617-25.
21. The Royal Australian and New Zealand College of Radiologists. 2016 Clinical Radiology Workforce Census Report: New Zealand, Version 1.0. Sydney, AUS: The Royal Australian and New Zealand College of Radiologists 2016.
22. Silvestrin C. Europe's Looming Radiology Capacity Challenge - A comparative study. Barcelona: Telemedicine Clinic; 2016.
23. Ip IK, Schneider L, Seltzer S, Smith A, Dudley J, Menard A, et al. Impact of Provider-led, Technology-enabled Radiology Management Program on Imaging. Am J Med. 2013;126(8):687-92.
24. Ranschaert E. The Impact of Information Technology on Radiology Services: An Overview. J Belg Soc Radiol. 2016;100(1):93.
25. Hurlen P. Teleradiology-opportunities and challenges. Tidsskr Nor Laegeforen. 2012;132(23-24):2622-4.
26. Telerad Tech. Unlock Productivity, Quality and Communications with Radiology workflow orchestration [Internet]. Minnetonka: Telerad Tech; 2018 Oct 9 [cited 2020 Feb 20]. Available from: https://www.teleradtech.com/unlock-productivity-quality-and-communication-with-radiology-workflow-orchestration/.
27. Neri E, de Souza N, Brady A, Bayarri AA, Becker CD, Coppola F, et al. What the radiologist should know about artificial intelligence – an ESR white paper. Insights Imaging. 2019;10(1):44.
28. W. H. O. Global Observatory for eHealth. Telemedicine: opportunities and developments in Member States: report on the second global survey on eHealth. Geneva: World Health Organization; 2010.
29. Siemens Healthineers. Medicalis Workflow Orchestrator [Internet]. Erlangen: Siemens Healthcare GmbH [date unknown] [cited 2020 May 20]. Available from:

https://www.siemens-healthineers.com/en-in/digital-health-solutions/digital-solutions-overview/service-line-managment-solutions/imaging-service-line/medicalis/workflow-orchestrator.
30. Marr B. What Is The Difference Between Artificial Intelligence And Machine Learning? Forbes [Internet]. 2016 Dec 6 [cited 2020 Mar 19]. Available from: https://www.forbes.com/sites/bernardmarr/2016/12/06/what-is-the-difference-between-artificial-intelligence-and-machine-learning/#52b714802742.
31. Oxford Learner's Dictionaries [Internet]. Oxford: Oxford University Press; 2020. Artificial Intelligence; [cited 2020 Feb 2]; [about 1 screen]. Available from: https://www.oxfordlearnersdictionaries.com/definition/english/artificial-intelligence?q=Artificial+intelligence.
32. Cambridge Dictionary [Internet]. Cambridge: Cambridge University Press; 2020. Machine Learning; [cited 2019 Sep 12]; [about 1 screen]. Available from: https://dictionary.cambridge.org/dictionary/english/machine-learning.
33. Choy G, Khalilzadeh O, Michalski M, Do S, Samir AE, Pianykh OS, et al. Current Applications and Future Impact of Machine Learning in Radiology. Radiology. 2018;288(2):318-28.
34. Bi WL, Hosny A, Schabath MB, Giger ML, Birkbak NJ, Mehrtash A, et al. Artificial intelligence in cancer imaging: Clinical challenges and applications. CA Cancer J Clin. 2019;69(2):127-57.
35. Chartrand G, Cheng PM, Vorontsov E, Drozdzal M, Turcotte S, Pal CJ, et al. Deep Learning: A Primer for Radiologists. Radiographics. 2017;37(7):2113-31.
36. Pesapane F, Codari M, Sardanelli F. Artificial intelligence in medical imaging: threat or opportunity? Radiologists again at the forefront of innovation in medicine. Eur Radiol Exp. 2018;2(1):35.
37. Erickson BJ, Korfiatis P, Kline TL, Akkus Z, Philbrick K, Weston AD. Deep Learning in Radiology: Does One Size Fit All? J Am Coll Radiol. 2018;15(3, Part B):521-6.
38. Kohli M, Prevedello LM, Filice RW, Geis JR. Implementing Machine Learning in Radiology Practice and Research. AJR Am J Roentgenol . 2017;208(4):754-60.
39. Oxford Learner's Dictionaries [Internet]. Oxford: Oxford University Press; 2020. Algorithm; [cited 2020 May 6]; [about 1 screen]. Available from: https://www.oxfordlearnersdictionaries.com/definition/english/algorithm.
40. Deo Rahul C. Machine Learning in Medicine. Circulation. 2015;132(20):1920-30.
41. Salian I. SuperVize Me: What's the Difference Between Supervised, Unsupervised, Semi-Supervised and Reinforcement Learning? : NVIDIA Blog; 2018 [cited 2019 8/29]. Available from: https://blogs.nvidia.com/blog/2018/08/02/supervised-unsupervised-learning/.

42. Lundervold AS, Lundervold A. An overview of deep learning in medical imaging focusing on MRI. Zeitschrift für Medizinische Physik. 2019;29(2):102-27.
43. Mayo RC, Leung J. Artificial intelligence and deep learning – Radiology's next frontier? Clinical Imaging. 2018;49:87-8.
44. Nguyen G, Dlugolinsky S, Bobák M, Tran V, López García Á, Heredia I, et al. Machine Learning and Deep Learning frameworks and libraries for large-scale data mining: a survey. Artificial Intelligence Review. 2019;52(1):77-124.
45. Soffer S, Ben-Cohen A, Shimon O, Amitai MM, Greenspan H, Klang E. Convolutional Neural Networks for Radiologic Images: A Radiologist's Guide. Radiology. 2019;290(3):590-606.
46. Erickson BJ, Korfiatis P, Akkus Z, Kline TL. Machine Learning for Medical Imaging. Radiographics. 2017;37(2):505-15.
47. Berlin A, Sorani M, Sim I. A taxonomic description of computer-based clinical decision support systems. J Biomed Inform
. 2006;39(6):656-67.
48. Lehoux P, Gauthier P, Williams-Jones B, Miller FA, Fishman JR, Hivon M, et al. Examining the ethical and social issues of health technology design through the public appraisal of prospective scenarios: a study protocol describing a multimedia-based deliberative method. Implement Sci. 2014;9:81-.
49. Schork NJ. Artificial Intelligence and Personalized Medicine. In: Von Hoff DD, Han H, editors. Precision Medicine in Cancer Therapy. Cham: Springer International Publishing; 2019. p. 265-83.
50. Hamet P, Tremblay J. Artificial intelligence in medicine. Metabolism. 2017;69:S36-S40.
51. Jalal S, Nicolaou S, Parker W. Artificial Intelligence, Radiology, and the Way Forward. Can Assoc Radiol J. 2019;70(1):10-2.
52. Oakden-Rayner L. The Rebirth of CAD: How Is Modern AI Different from the CAD We Know? Radiol Artif Intell. 2019;1(3):e180089.
53. Fenton JJ, Taplin SH, Carney PA, Abraham L, Sickles EA, D'Orsi C, et al. Influence of Computer-Aided Detection on Performance of Screening Mammography. N Engl J Med. 2007;356(14):1399-409.
54. Doi K. Computer-aided diagnosis in medical imaging: historical review, current status and future potential. Comput Med Imaging Graph. 2007;31(4-5):198-211.
55. Castellino RA. Computer aided detection (CAD): an overview. Cancer Imaging. 2005;5(1):17-9.
56. Lee YJ, Park JM, Park HW. Mammographic mass detection by adaptive thresholding and region growing. Int J Imaging Syst Technol. 2000;11(5):340-6.
57. Medical Imaging and Technology Alliance. Glossary of AI terms [Internet]. Medical Imaging and Technology Alliance National Electrical Manufacturers

Association [date unknown] [cited 2020 May 8]. Available from: https://www.medicalimaging.org/standards/ai-glossary/.
58. Shiraishi J, Li Q, Appelbaum D, Doi K. Computer-Aided Diagnosis and Artificial Intelligence in Clinical Imaging. Semin Nucl Med. 2011;41(6):449-62.
59. Philpotts LE. Can Computer-aided Detection Be Detrimental to Mammographic Interpretation? Radiology. 2009;253(1):17-22.
60. Hassani C, Varghese BA, Nieva J, Duddalwar V. Radiomics in Pulmonary Lesion Imaging. AJR Am J Roentgenol. 2019;212(3):497-504.
61. National Cancer Insitute. NCI Dictionary of Cancer Terms, [Internet]. NCI Dictionary of Cancer Terms: National Cancer Insitute at the National Insitutes of Health; [date unknown] [cited 2020 May 7]. Available from: https://www.cancer.gov/publications/dictionaries/cancer-terms/def/lesion.
62. Oxford Learner's Dictionaries [internet]. Oxford: Oxford University Press; 2020. Phoenotype; [cited 2020 May 7]; [about 1 screen]. Available from: https://www.oxfordlearnersdictionaries.com/definition/english/phenotype?q=phenotype.
63. The Sol Goldman Pancreatic Cancer Research Center. What is cancer? [Internet]. Baltimore: Johns Hopkins University; 2018 [date unknown] [cited 2020 May 7]. Available from: http://pathology.jhu.edu/pc/BasicTypes1.php.
64. Kumar V, Gu Y, Basu S, Berglund A, Eschrich SA, Schabath MB, et al. Radiomics: the process and the challenges. Magn Reson Imaging. 2012;30(9):1234-48.
65. Lambin P, Rios-Velazquez E, Leijenaar R, Carvalho S, van Stiphout RGPM, Granton P, et al. Radiomics: Extracting more information from medical images using advanced feature analysis. Eur J Cancer. 2012;48(4):441-6.
66. Afshar P, Mohammadi A, Plataniotis KN, Oikonomou A, Benali H. From Handcrafted to Deep-Learning-Based Cancer Radiomics: Challenges and Opportunities. IEEE Signal Process Mag. 2019;36(4):132-60.
67. Gatta R, Depeursinge A, Ratib O, Michielin O, Leimgruber A. Integrating radiomics into holomics for personalised oncology: from algorithms to bedside. Eur Radiol Exp. 2020;4(1):11.
68. Wong AJ, Kanwar A, Mohamed AS, Fuller CD. Radiomics in head and neck cancer: from exploration to application. Transl Cancer Res. 2016;5(4):371-82.
69. Gillies RJ, Kinahan PE, Hricak H. Radiomics: Images Are More than Pictures, They Are Data. Radiology. 2015;278(2):563-77.
70. Larue RTHM, Defraene G, De Ruysscher D, Lambin P, van Elmpt W. Quantitative radiomics studies for tissue characterization: a review of technology and methodological procedures. Br J Radiol. 2016;90(1070):20160665.
71. Nature. Editor's choice: Radiomics. Nature [Internet]. 2019 Sep 11 [cited 2019 Apr 12]. Available from: https://www.nature.com/collections/ksgfknntbs/.

72. Boedeker K. AiCE Deep Learning Reconstruction: Bringing the power of Ultra-High Resolution CT to routine imaging. Canon Medical Systems [Internet]. 2019 Jan [unknown date] [cited 2020 May 27]. Available from: https://global.medical.canon/publication/ct/2019WP_AiCE_Deep_Learning.
73. Hsieh J, Liu E, Nett B, Tang J, Thibault J-B, Sahney S. A new era of image reconstruction: TrueFidelity [Internet]. [place unknown]: General Electric Company; [cited 2020 May 27]. Available from: https://www.gehealthcare.com/-/jssmedia/040dd213fa89463287155151fdb01922.pdf.
74. Aerts HJWL. Data Science in Radiology: A Path Forward. Clin Cance Res. 2018;24(3):532.
75. Morey JM, Haney NM, Kim W. Applications of AI Beyond Image Interpretation. In: Ranschaert ER, Morozov S, Algra PR, editors. Artificial Intelligence in Medical Imaging: Opportunities, Applications and Risks. Cham: Springer International Publishing; 2019. p. 129-43.
76. Lakhani P, Prater AB, Hutson RK, Andriole KP, Dreyer KJ, Morey J, et al. Machine Learning in Radiology: Applications Beyond Image Interpretation. J Am Coll Radiol. 2018;15(2):350-9.
77. Huang HK. Short history of PACS. Part I: USA. Eur J Radiol. 2011;78(2):163-76.
78. Lemke HU. Short history of PACS (Part II: Europe). Eur J Radiol. 2011;78(2):177-83.
79. Litjens G, Kooi T, Bejnordi BE, Setio AAA, Ciompi F, Ghafoorian M, et al. A survey on deep learning in medical image analysis. Med Image Anal. 2017;42:60-88.
80. Montagnon E, Cerny M, Cadrin-Chênevert A, Hamilton V, Derennes T, Ilinca A, et al. Deep learning workflow in radiology: a primer. Insights Imaging. 2020;11(1):22.
81. Farhat N, Kapur T, Kikinis R. Role of Computers and Image Processing in Image-Guided Brain Tumor Surgery. In: Golby AJ, editor. Image-Guided Neurosurgery. Boston: Academic Press; 2015. p. 143-61.
82. Lu H, Loh E, Huang S, editors. The Classification of Mammogram Using Convolutional Neural Network with Specific Image Preprocessing for Breast Cancer Detection. Proceedings of the 2019 2nd International Conference on Artificial Intelligence and Big Data (ICAIBD); 2019 25-28 May; Chengdu, CHN: IEEE.
83. Singh R, Digumarthy SR, Muse VV, Kambadakone AR, Blake MA, Tabari A, et al. Image Quality and Lesion Detection on Deep Learning Reconstruction and Iterative Reconstruction of Submillisievert Chest and Abdominal CT. AJR Am J Roentgenol. 2020;214(3):566-73.
84. Thein N, Nugroho HA, Adji TB, Hamamoto K, editors. An image preprocessing method for kidney stone segmentation in CT scan images. Proceedings of the 2018 International Conference on Computer Engineering, Network and

Intelligent Multimedia (CENIM); 2018 26-27 Nov; Surabaya, IDN: 2018 International Conference on Computer Engineering, Network and Intelligent Multimedia (CENIM); 2018.
85. Rodríguez-Cristerna A, Guerrero-Cedillo CP, Donati-Olvera GA, Gómez-Flores W, Pereira WCA, editors. Study of the impact of image preprocessing approaches on the segmentation and classification of breast lesions on ultrasound. Proceedings of the 14th International Conference on Electrical Engineering, Computing Science and Automatic Control (CCE); 2017 20-22 Sept; Mexico City, MEX. 14th International Conference on Electrical Engineering, Computing Science and Automatic Control (CCE) 2017.
86. Odaibo D, Zhang Z, Skidmore F, Tanik M, editors. Detection of Visual Signals for Pneumonia in Chest Radiographs using Weak Supervision. Proceedings of the 2019 SoutheastCon; 2019 11-14 Apr; Huntsville, AL, USA: IEEE Service Center; 2020.
87. Thian YL, Li Y, Jagmohan P, Sia D, Chan VEY, Tan RT. Convolutional Neural Networks for Automated Fracture Detection and Localization on Wrist Radiographs. Radiol Artif Intell. 2019;1(1):e180001.
88. Zhou Z, Sanders JW, Johnson JM, Gule-Monroe MK, Chen MM, Briere TM, et al. Computer-aided Detection of Brain Metastases in T1-weighted MRI for Stereotactic Radiosurgery Using Deep Learning Single-Shot Detectors. Radiology. 2020:191479.
89. Christ PF, Elshaer MEA, Ettlinger F, Tatavarty S, Bickel M, Bilic P, et al., editors. Automatic Liver and Lesion Segmentation in CT Using Cascaded Fully Convolutional Neural Networks and 3D Conditional Random Fields. Proceedings of the Medical Image Computing and Computer-Assisted Intervention – MICCAI 2016; 2016 17-21 Oct; Athens, GRC: Springer International Publishing.
90. Cha KH, Hadjiiski L, Samala RK, Chan H-P, Caoili EM, Cohan RH. Urinary bladder segmentation in CT urography using deep-learning convolutional neural network and level sets. Med Phys. 2016;43(4):1882-96.
91. Grøvik E, Yi D, Iv M, Tong E, Rubin D, Zaharchuk G. Deep learning enables automatic detection and segmentation of brain metastases on multisequence MRI. J Magn Reson Imaging. 2020;51(1):175-82.
92. Humphries SM, Notary AM, Centeno JP, Strand MJ, Crapo JD, Silverman EK, et al. Deep Learning Enables Automatic Classification of Emphysema Pattern at CT. Radiology. 2019;294(2):434-44.
93. Lakhani P, Sundaram B. Deep Learning at Chest Radiography: Automated Classification of Pulmonary Tuberculosis by Using Convolutional Neural Networks. Radiology. 2017;284(2):574-82.
94. Topol EJ. High-performance medicine: the convergence of human and artificial intelligence. Nat Med. 2019;25(1):44-56.

95. European Medicines Agency. Medical devices [Internet]. European Medicines Agency; [date unknown] [cited 2020 May 21]. Available from: https://www.ema.europa.eu/en/human-regulatory/overview/medical-devices.
96. Baraniuk C. Google's DeepMind to peek at NHS eye scans for disease analysis. BBC [Internet]. 2016 Jul 5 [cited 2020 Feb 29]. Available from: https://www.bbc.com/news/technology-36713308.
97. DeepMind. Predicting eye disease with Moorfields Eye Hospital [cited 2020 Feb 21]. 2018-. In: DeepMind Blog [Internet]. London: DeepMind. 2018-. [about 4 screens]. Available from: https://deepmind.com/blog/article/predicting-eye-disease-moorfields.
98. Baraniuk C. Google DeepMind targets NHS head and neck cancer treatment. BBC [Internet]. 2016 Aug 31 [cited 2020 Jan 21]. Available from: https://www.bbc.com/news/technology-37230806.
99. Knight W. IBM's Watson Is Everywhere - But What Is it? . MIT Technology Review [Internet]. 2016 Oct 27 [cited 2020 Feb 20]. Available from: https://www.technologyreview.com/2016/10/27/156388/ibms-watson-is-everywhere-but-what-is-it/.
100. Kuan R. Adopting AI in Health Care Will Be Slow and Difficult. Harvard Business Review [Internet]. 2019 Oct 9 [cited 2020 Apr 9]. Available from: https://hbr.org/2019/10/adopting-ai-in-health-care-will-be-slow-and-difficult.
101. Colling R, Pitman H, Oien K, Rajpoot N, Macklin P, Group CM-PAiHW, et al. Artificial intelligence in digital pathology: a roadmap to routine use in clinical practice. J Pathol. 2019;249(2):143-50.
102. Harrington SG, Johnson MK. The FDA and Artificial Intelligence in Radiology: Defining New Boundaries. J Am Coll Radiol. 2019;16(5):743-4.
103. Kelly CJ, Karthikesalingam A, Suleyman M, Corrado G, King D. Key challenges for delivering clinical impact with artificial intelligence. BMC Medicine. 2019;17(1):195.
104. Racine E, Boehlen W, Sample M. Healthcare uses of artificial intelligence: Challenges and opportunities for growth. Healthc Manage Forum. 2019;32(5):272-5.
105. Carter SM, Rogers W, Win KT, Frazer H, Richards B, Houssami N. The ethical, legal and social implications of using artificial intelligence systems in breast cancer care. Breast. 2020;49:25-32.
106. Klosowski T. What to Consider Before Trading Your Health Data for Cash. The New York Times [Internet]. 2019 Nov 27 [cited 2020 Mar 7]. Available from: https://www.nytimes.com/2019/11/27/smarter-living/wirecutter/what-to-consider-before-trading-your-health-data-for-cash.html.
107. European Commission, Publications. White Paper on Artificial Intelligence: a European approach to excellence and trust [Internet]. Brussels: European Commision; 2020 feb 19 [cited 2020 Feb 23]. Available from:

https://ec.europa.eu/info/sites/info/files/commission-white-paper-artificial-intelligence-feb2020_en.pdf.
108. Regjeringen. National Strategy for Artificial Intelligence: Norwegian Ministry of Local Government and Modernisation; 2020 [cited 2020 2/22]. Available from: https://www.regjeringen.no/contentassets/1febbbb2c4fd4b7d92c67ddd353b6ae8/en-gb/pdfs/ki-strategi_en.pdf.
109. Geis JR, Brady AP, Wu CC, Spencer J, Ranschaert E, Jaremko JL, et al. Ethics of Artificial Intelligence in Radiology: Summary of the Joint European and North American Multisociety Statement. Radiology. 2019;293(2):436-40.
110. Hardiker NR, Grant MJ. Factors that influence public engagement with eHealth: A literature review. Int J Med Inform. 2011;80(1):1-12.
111. Phaneuf A. Use of AI in healthcare & medicine is booming – here's how the market is benefiting from AI in 2020 and beyond. Business Insider [Internet]. 2019 Jul 31 [cited 2020 2/1]. Available from: https://www.businessinsider.com/artificial-intelligence-healthcare?r=US&IR=T.
112. Deller R. Book Review: Imagined Futures: Fictional Expectations and Capitalist Dynamics by Jens Beckert. 2016 Sept 7 [cited 2020 Mar 3]. 2020-. In: LSE Review of Books [Internet]. The London School of Economics and Political Science. 2020-. [about 6 screens]. Available from: https://blogs.lse.ac.uk/lsereviewofbooks/2016/09/07/book-review-imagined-futures-fictional-expectations-and-capitalist-dynamics-by-jens-beckert/.
113. Walter M. RSNA 2018: What to make of the increased hype surrounding AI in radiology. Radiology Business [Internet]. 2018 Nov 28 [cited 2020 Mar 3]. Available from: https://www.radiologybusiness.com/sponsored/9667/topics/imaging-informatics/rsna-2018-hype-ai-radiology-paul-chang.
114. Cambridge Dictionary [Internet]. Cambridge: Cambridge University Press; 2020. Hype; [cited 2020 June 26]; [about 1 screen].
115. Understanding Patient Data. Public attitudes to new technologies [Internet]. London: Wellcome Trust Ltd.; [date unknown] [cited 2020 Feb 29]. Available from: https://understandingpatientdata.org.uk/public-attitudes-new-technologies.
116. High-Level Expert Group on AI (AI HLEG). Policy and investment recommendations for trustworthy Artificial Intelligence. Brussels, BEL: European Commission; 2019.
117. Cambridge Dictionary [Internet]. Cambridge: Cambridge University Press; 2020. Knowledge; [cited 2020 May 11]; [about 1 screen]. Available from: https://dictionary.cambridge.org/dictionary/english/knowledge.
118. Collado-Mesa F, Alvarez E, Arheart K. The Role of Artificial Intelligence in Diagnostic Radiology: A Survey at a Single Radiology Residency Training Program. J Am Coll Radiol. 2018;15(12):1753-7.

119. Waymel Q, Badr S, Demondion X, Cotten A, Jacques T. Impact of the rise of artificial intelligence in radiology: What do radiologists think? Diagn Interv Imaging. 2019;100(6):327-36.
120. Gong B, Nugent JP, Guest W, Parker W, Chang PJ, Khosa F, et al. Influence of Artificial Intelligence on Canadian Medical Students' Preference for Radiology Specialty: ANational Survey Study. Acad Radiol. 2019;26(4):566-77.
121. Pinto dos Santos D, Giese D, Brodehl S, Chon SH, Staab W, Kleinert R, et al. Medical students' attitude towards artificial intelligence: a multicentre survey. Eur Radiol Exp. 2019;29(4):1640-6.
122. Coppola F, Faggioni L, Regge D, Giovagnoni A, Golfieri R, Bibbolino C, et al. Artificial intelligence: radiologists' expectations and opinions gleaned from a nationwide online survey. Radiol Med. 2020.
123. Sit C, Srinivasan R, Amlani A, Muthuswamy K, Azam A, Monzon L, et al. Attitudes and perceptions of UK medical students towards artificial intelligence and radiology: a multicentre survey. Insights Imaging. 2020;11(1):14.
124. van Hoek J, Huber A, Leichtle A, Härmä K, Hilt D, von Tengg-Kobligk H, et al. A survey on the future of radiology among radiologists, medical students and surgeons: Students and surgeons tend to be more skeptical about artificial intelligence and radiologists may fear that other disciplines take over. Eur J Radiol. 2019;121:108742.
125. Codari M, Melazzini L, Morozov SP, van Kuijk CC, Sconfienza LM, Sardanelli F, et al. Impact of artificial intelligence on radiology: a EuroAIM survey among members of the European Society of Radiology. Insights Imaging. 2019;10(1):105.
126. Cambridge Dictionary [Internet]. Cambridge: Cambridge University Press; 2020. Attitude; [cited 2020 May 11]; [about 1 screen]. Available from: https://dictionary.cambridge.org/dictionary/english/attitude.
127. Kapoor R, Madichie NO. Consumer Behaviour: Text and Cases: Text and Cases: Mc Graw Hill India; 2012. 444 p.
128. Statistisk Sentralbyrå. 07935: Spesialistutdanning. 4.kvartal, etter spesialitet, alder, kjønn, statistikkvariabel og år [translated: 07935: Specialist education for physicians, dentists and optometry, by sex and age] [Internet]. Oslo: Statistisk Sentralbyrå; 2018 [date unknown] [cited 2020 Sep 18]. Available from: https://www.ssb.no/statbank/table/07935/tableViewLayout1/ . In Norwegian.
129. University of Porto. Artificial Intelligence in Medicine. [Internet]. Porto: University of Porto Faculdade de Medicina 2018 [date unknown] [cited 2018 Sep 11]. Available from: http://medicina.med.up.pt/im/trabalhos_09_10/Sites/Turma7/Survey%20-%20Artificial%20Intelligence%20in%20Medicine%20the%20medical%20education%20point%20of%20view.pdf.

130. Boynton PM, Greenhalgh T. Selecting, designing, and developing your questionnaire. BMJ. 2004;328(7451):1312.
131. University Of Oslo. Short introduction to Nettskjema [Internet]. Oslo: University of Oslo; 2018 Feb 12 [updated 2020 Feb 7; cited 2020 Apr 12]. Available from: https://www.uio.no/english/services/it/adm-services/nettskjema/about-nettskjema.html.
132. The Norwegian National Committees for Research Ethics. Guidelines for Research Ethics in the Social Sciences, Humanities, Law and Theology. Oslo, NOR: Ministry of Education and Research; 2016.
133. Levy JM, Hessel SJ. Training in computer sciences for radiologists. Radiology. 1982;145(3):853-.
134. Pakdemirli E. Artificial intelligence in radiology: friend or foe? Where are we now and where are we heading? Acta Radiol Open. 2019;8(2):2058460119830222-.
135. Davenport TH, Dreyer KJ. AI Will Change Radiology, but It Won't Replace Radiologists. Harvard Business Review [Internet]. 2018 Mar 27 [cited 2020 Mar 18]. Available from: https://hbr.org/2018/03/ai-will-change-radiology-but-it-wont-replace-radiologists.
136. Bluemke DA. Radiology in 2018: Are You Working with AI or Being Replaced by AI? Radiology. 2018;287(2):365-6.
137. Fornell D. How Artificial Intelligence Will Change Medical Imaging. Imaging Technology News [Internet]. 2017 Feb 24 [cited 2020 May 6]. Available from: https://www.itnonline.com/article/how-artificial-intelligence-will-change-medical-imaging.
138. Sparrow B. Exploring how artificial intelligence may support human interpretation of medical images [Internet]. London: The Royal College of Radiologists; 2016 Feb 9 [cited 2020 6/8]. Available from: https://www.rcr.ac.uk/posts/exploring-how-artificial-intelligence-may-support-human-interpretation-medical-images.
139. Mohan C. Artificial intelligence in radiology – Are we treating the image or the patient? Indian J Radiol Imaging. 2018;28:137.
140. Insights Team. AI and Healthcare: A giant Opportunity. Forbes [Internet]. 2019 Feb 11 [cited 2020 Mar 15]. Available from: https://www.forbes.com/sites/insights-intelai/2019/02/11/ai-and-healthcare-a-giant-opportunity/#121d255f4c68.
141. Handelman GS, Kok HK, Chandra RV, Razavi AH, Huang S, Brooks M, et al. Peering Into the Black Box of Artificial Intelligence: Evaluation Metrics of Machine Learning Methods. AJR Am J Roentgenol. 2018;212(1):38-43.
142. Mayes K. Putting patients at the heart of Artificial Intelligence [Internet]. London: tech UK; 2019 May 10 [cited 2020 Mar 1]. Available from: https://www.techuk.org/insights/reports/item/15353-putting-patients-at-the-heart-of-artificial-intelligence.

143. Slagstad K. Mye hype, men lite kunnskap om kunstig intelligens [translated: A lot of hype, but limited knowledge of artificial intelligence]. Tidsskr Nor Legeforen [Internet]. 2020 Jun 4 [cited 2020 Jun 6]. Available from: https://tidsskriftet.no/2020/05/fra-andre-tidsskrifter/mye-hype-men-lite-kunnskap-om-kunstig-intelligens .In Norwegian.
144. Kent J. How Artificial Intelligence is Changing Radiology, Pathology. Health IT analytics [Internet]. 2018 Aug 3 [cited 2020 Jun 26]. Available from: https://healthitanalytics.com/news/how-artificial-intelligence-is-changing-radiology-pathology.
145. Couzin-Frankel J. Artificial intelligence could revolutionize medical care. But don't trust it to read your x-ray just yet. Science [Internet]. 2019 Jun 17 [cited 2020 Jun 26]. Available from: https://www.sciencemag.org/news/2019/06/artificial-intelligence-could-revolutionize-medical-care-don-t-trust-it-read-your-x-ray.
146. GE Healthcare. How AI and Deep Learning Are Revolutionizing Medical Imaging [place unknown]: GE Healthcare; 2019 May 19 [cited 2020 Jun 25]. Available from: https://www.gehealthcare.co.uk/long-article/how-ai-and-deep-learning-are-revolutionizing-medical-imaging.
147. O'Regan D. How will AI revolutionize medical imaging? [Internet]. [place unknown]: Philips; 2017 Sep 19 [cited 2020 Jun 26]. Available from: https://www.philips.com/a-w/about/news/archive/future-health-index/articles/20170919-how-will-AI-revolutionize-medical-imaging.html.
148. Ranschaert E. A.I. in Radiology: Hype or Hope? [date unknown] [cited 2020 Jun 27]. 2020-. In: LinkedIn SlideShare [Internet]. LinkedIn [about 60 slides]. Available from: https://www.slideshare.net/eransch/ai-in-radiology-hype-or-hope.
149. Kubota T. Algorithm better at diagnosing pneumonia than radiologists. Stanford Medicine [Internet]. 2017 Nov 15 [cited 2020 Jun 29]. Available from: https://med.stanford.edu/news/all-news/2017/11/algorithm-can-diagnose-pneumonia-better-than-radiologists.html.
150. Morrison K. Dissecting the literature: the importance of critical appraisal. Royal College of Surgeons England [Internet]. 2017 Dec 08 [cited 2020 Jun 29]. Available from: https://www.rcseng.ac.uk/library-and-publications/library/blog/dissecting-the-literature-the-importance-of-critical-appraisal/.
151. Rouger M. Medical imaging AI: the bubble will break in 2-3 years. [date unknown] [cited 2020 Jun 27]. 2020-. In: AI blog [Internet]. European Society of Radiology. 2020-. [about 4 screens]. Available from: https://ai.myesr.org/healthcare/medical-imaging-ai-the-bubble-will-break-in-2-3-years/.
152. Signify Research. Machine Learning in Medical Imaging-World-2018 [place unknown]: Singify Research; 2018.

153. Harvey H. Where to invest in Radiology AI. Towards data science [Internet]. 2017 Jul 11 [cited 2020 Jun 27]. Available from: https://towardsdatascience.com/where-to-invest-in-radiology-ai-31213f4ba7a8.

Appendices

Appendix 1: Information Letter

Invitasjon til forskningsstudie

Du inviteres nå til å delta i en spørreundersøkelse om kunnskap og holdninger til kunstig intelligens i radiologi. Svarene dine vil bli brukt i forbindelse med en masteroppgave ved Det medisinske fakultet, Institutt for helse og samfunn ved Universitetet i Oslo.

Det er frivillig å delta og svarene dine behandles konfidensielt. Ved å svare på denne spørreundersøkelsen samtykker du til at opplysninger vil bli brukt i masteroppgaven.
Det vil dessverre ikke være mulig å trekke seg etter at svarene har blitt sendt inn. Det er fordi Nettskjema anonymiserer svarene dine og det vil derfor ikke være mulig å spore opp ditt svar.

Tusen takk.

Student:
Karoline A. Nyberg Lippert
Masterstudent
k.a.n.lippert@studmed.uio.no
karolali@matnat.uio.no

Ansvarlige veileder:
Anne Catrine T. Martinsen
Avdelingsleder, Avdeling for Radiologi og nukleærmedisin
uxneti@ous-hf.no

Bi-veileder:
Morten Magelssen
Forsker, Senter for Medisinsk Etikk
Morten.magelssen@medisin.uio.no

Appendix 2: Original questionnaire, in Norwegian

Kunstig intelligens (KI) i Radiologi

Alder

- 20 - 29
- 30 - 39
- 40 - 49
- 50 - 59
- 60 - 69
- 70 +

Kjønn

- Mann
- Kvinne

1) Hva er artificial intelligence (AI) i radiologi? Gi eksempler.

Fritekst

2) På hvilke måter tror du artificial intelligence kan påvirke radiologien?

Fritekst

3) Hvordan vurderer du din egen kunnskap om kunstig intelligens innen radiologi?

- Svært god
- God
- Middels
- Lav
- Svært lav

4) I hvilke områder kunne du tenkt deg å bruke AI?

	Ja	Nei
I prediksjon av utfall for en bestemt indikasjon		
I lesion tracking		
I kvantifisering og karakterisering av patologi		
I undervisningssammenheng		
Annet		

5) Har du deltatt på kurs/seminar om AI innen radiologi?

- Ja
- Nei

6) Tror du AI kommer til å forbedre kvalitet og nytte av de radiologiske undersøkelsene?

○ I svært stor grad ○ I stor grad ○ I noen grad ○ I liten grad ○ I svært liten grad

7) Tror du AI vil overta radiologers arbeidsoppgaver i fremtiden?

○ I svært stor grad ○ I stor grad ○ I noen grad ○ I liten grad ○ I svært liten grad

Dette elementet vises dersom et av følgende alternativer er valgt på spørsmål «7) Tror du AI vil overta radiologers arbeidsoppgaver i fremtiden?»: I svært stor grad

Beskriv kort hvorfor?

Fritekst

Dette elementet vises dersom et av følgende alternativer er valgt på spørsmål «7) Tror du AI vil overta radiologers arbeidsoppgaver i fremtiden?»: I svært liten grad

Beskriv kort hvorfor?

Fritekst

8) Tror du AI kan bidra til større presisjon for radiologisvar og dermed bidra til bedre og mer målrettet behandling i fremtiden?

○ I svært stor grad ○ I stor grad ○ I noen grad ○ I liten grad ○ I svært liten grad

Dette elementet vises dersom et av følgende alternativer er valgt på spørsmål «8) Tror du AI kan bidra til større presisjon for radiologisvar og dermed bidra til bedre og mer målrettet behandling i fremtiden?»: I svært stor grad

Beskriv kort hvorfor

Dette elementet vises dersom et av følgende alternativer er valgt på spørsmål «8) Tror du AI kan bidra til større presisjon for radiologisvar og dermed bidra til bedre og mer målrettet behandling i fremtiden?»: I svært liten grad

Beskriv kort hvorfor

9) I hvilket område mener du at det bør investeres (økonomisk) i AI?

	Ja	Nei
I diagnostikk	○	○
I behandling	○	○
I undervisningssammenheng	○	○

10) Velg det alternativet som du mener er mest treffende.

Bruk av AI vil føre til utfordringer for personvern og datasikkerhet

○ Svært enig ○ Enig ○ Vet ikke ○ Uenig ○ Svært uenig

Dette elementet vises dersom et av følgende alternativer er valgt på spørsmål «Bruk av AI vil føre til utfordringer for personvern og datasikkerhet»: Svært enig

Utdyp hvorfor det oppstår utfordringer relatert til personvern og sikkerhet

Fritekst

Dette elementet vises dersom et av følgende alternativer er valgt på spørsmål «Bruk av AI vil føre til utfordringer for personvern og datasikkerhet»: Svært uenig

Utdyp hvorfor det ikke oppstår utfordringer relatert til personvern og sikkerhet

Fritekst

Bruk av AI kan føre til at pasienter blir redde for å gjennomgå radiologiske undersøkelser på grunn av frykt for at pasientdata kan komme på avveie

○ Svært enig ○ Enig ○ Vet ikke ○ Uenig ○ Svært uenig

11) Har du brukt AI på arbeidsplassen?

○ Ja ○ Nei

Dette elementet vises dersom et av følgende alternativer er valgt på spørsmål «11) Har du brukt AI på arbeidsplassen?»: Ja

Hvor har du brukt AI?

Dette elementet vises dersom et av følgende alternativer er valgt på spørsmål «11) Har du brukt AI på arbeidsplassen?»: Ja

	Ja	Nei
I diagnose	○	○
I behandling	○	○
I databehandling	○	○
I undervisningssammenheng	○	○

Dette elementet vises dersom et av følgende alternativer er valgt på spørsmål «11) Har du brukt AI på arbeidsplassen?»: Ja

Hvordan har AI påvirket denne tjenesten?

○ Lite ○ Mindre ○ Middels ○ Mer ○ Mye

12) Hvor mange undersøkelser gransker du gjennomsnittelig pr dag?

13) Hvilken type undersøkelser utgjør hovedtyngden av arbeidet ditt

○ MR
○ CT
○ Konvensjonell røntgen

- ◯ Gjennomlysning/ intervensjon
- ◯ Ultralyd

Appendix 3: Content analysis: Q1 - What is artificial intelligence (AI) in radiology?

Content analysis: Q1 – What is artificial intelligence (AI) in radiology?		
Condensed meaning unit	Code	Total
N/A	N/A	6
Identified application/ labelled description	A labelled application	1
Identification of technology/ what it can do	A computer programme/ aiding system	17
Specified technology/ what it is and can do	Machine learning/ algorithms	7
Total		31

Appendix 4: Content analysis: Q2 - In what way do you think AI could impact radiology?

Content analysis: Q2 – In what way do you think AI could impact radiology?		
Condensed meaning unit	Code	Total
N/A	N/A	7
Aid/ change daily work tasks	Decision support system/ Second opinion	17
Increase quality of detection/ classification/ diagnosis	Improve detection/ classification/ diagnosis	5
Take over most/ all work tasks	Reduce workforce	2
Total		31