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## Erityispätevyys kliinisen radiografian alalla

Suomen röntgenhoitajaliitto käyttää englanninkielisestä Society of Radiography (UK) lanseeraamasta käsitteestä 'advanced practice' -> 'advanced practitioner' nimitystä erityispätevyys ja mainitsee sen olevan tunnustus, joka tuo esille sen haltijan osaamisen säteilynkäytön ammattilaisena. Lisäksi sen mainitaan luovan mahdollisuuden uusiin tehtäväkuviin ja palkkakehitykseen. Society of Radiographers mainitsee, että nämä advanced practice roolit kuuluvat erityisesti Masters-tasoisien röntgenhoitajien työnkuvaan ja rakentuvat neljälle pilarille, jotka ovat röntgenhoitajan kliininen työ, johtaminen, koulutus ja tutkimus. European Federation of Radiography Societies (EFRS 2012) käyttää näistä erityispätevyyden omaavista röntgenhoitajista myös nimitystä 'advanced practitioner' ja mainitsee esimerkkeinä röntgenhoitajan erityispätevyyksistä mammografian, sonografian ja luustokuvausten saneluosaamisen. Mielenkiintoisesti ja loogisesti nämä röntgenhoitajan erityisosaamisalueet ovat lähes samat, jotka [Törnroosin ym. \(2024\)](#) tutkimuksessa määrittävät radiografiatieteen peruskäsitteiksi nimittäin radiografian kliiniset käytännöt, röntgenhoitajan työ, turvallinen ja laadukas säteilynkäyttö ja teknologia.

Suomen röntgenhoitajaliitto ilmoittaa sivuillaan, että röntgenhoitajan erityispätevyyttä voi hakea liitolta diagnostisen ja terapeutin radiografian aloilta. Asiaa ohjaava dokumentti on päivätty vuodelle 2008 mutta nyt kyseinen taho on perustanut työryhmän päivittämään erityispätevyyden määrittelyä Suomessa ja työryhmään on tällä kertaa kutsuttu myös alan opettajia ja tutkijoita. Vuonna 2025 sosiaali- ja terveystieteiden ministeriön Hoitohenkilöstön koordinaatiojaosto laati esityksen terveysalan ammattilaisten erikoistumiskoulutustarpeista ([Välimäki ym. 2025](#)). Eurooppalaisella tasolla EFRS pohtii advanced practitioner määrittelynsä päivittämistä. Syynä tähän on se, että röntgenhoitajilla on tarvetta yhä erikoistuvampaan osaamiseen, työnkuviin ja tutkimukseen esimerkiksi tekoälyn, molekyyläri- ja hybridikuvantamisen ja lisääntyvän terveysteknologian arviointitarpeen tiimoilta. Myös johtamis-, opetus- ja tutkimustehtävissä toimivien röntgenhoitajien työnkuva laajenee kliinisten alueiden laajenemisen ja röntgenhoitajien koulutustason lisääntymisen myötä. Näistä mainittakoon erilaiset potilasryhmäkohtaisten yksiköiden johtamis- ja kehittämistehtävät, digitaaliseen ja simulaatio-opetukseen erikoistuminen ja radiografian alan tutkimus- ja kehittämissuhteiden vastuutehtävät. Lisäksi monet röntgenhoitajat toimivat muun muassa laajavastuisissa erilaisissa kaupallisissa ja laitteiden hankintaan liittyvissä tehtävissä hankkien ja käyttäen erityisosaamistaan näillä alueilla. On erittäin hienoa, että kliininen erikoisosaaminen tunnustetaan ja tunnustetaan radiografian alalla mutta lisäksi soisi sen tapahtuvan myös muilla osaamisalueilla, joilla röntgenhoitajat toimivat. Sitä odotellessa kiitän Kliinisen Radiografiateiede -lehden lukijoita ja luovutan päätoimittajan tehtävän nuoremmilla alan päteville tutkijoille ja kehittäjille.

Eija Metsälä  
Päätoimittaja vuosina 2012–2026

## Defining advanced practice in the field of radiography

The Finnish society of radiographers translates advanced practitioner that is a concept used by Society of Radiography (UK) as 'erityispätevyys' and defines it as a confession that emphasizes its possessors' competence in the professional use of radiation. In addition, it creates potential to new work description and salary development. According to the Society of Radiographers this is underpinned by a master's level award or equivalent that encompasses the four pillars of clinical practice, leadership and management, education research, with demonstration of core capabilities and area specific clinical competence.' European Federation of Radiography Societies (EFRS 2012) mentions mammography, sonography and reporting musculoskeletal images as examples of radiographers' advanced roles. Interestingly and logically these advanced practice areas are almost the same Törnroos et al. (2024) finds as basic concepts of radiography science namely clinical practices in radiography, radiographers' profession, safe and high-quality radiation use, and technology in radiography.

Finnish society of radiographers informs that they grant advanced practitioner status in the fields of diagnostic and therapeutic radiography. However, guiding document from year 2008 is now being updated in a group comprising diagnostic and therapeutic clinicians and educators and researchers this time. At the same time a coordination group of health care workforce prepares updates of specialization education needs of health care workforce. Also, EFRS considers updating their advanced practitioner document. This is because radiographers need advanced practice e.g. because of the emergence of artificial intelligence, molecular- and hybrid imaging and need of health technology assessment. Also, the work description of radiographers working in leadership and management, education and research is evolving due to advancements in clinical practice areas and rise of the educational level of radiographers. In addition, many radiographers work in commercial and radiography and radiation therapy device procurement processes. It is really important that radiographers' clinical competences are acknowledged with advanced practice status, but it would be excellent to see this happening also in the other competence areas radiographers are working. While waiting for that to happen I thank readers of Clinical Radiography and Radiotherapy journal and give way in this post for younger talents in radiography research.

Eija Metsälä  
Editor in Chief during 2012–2026

# The emerging potential of a mobile low-dose computed tomography unit in lung cancer screening: a scoping review

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## Abstract

### Introduction

The societal impact of lung cancer is significant due to its high mortality rate. Healthcare systems are looking for solutions to prevent lung cancer and to detect cancer earlier to improve treatment prognosis. However, the challenges of screening programs comprise accessibility, reaching individuals with highest risk and commitment to the program. The aim of this review was to investigate the potential of mobile low-dose computed tomography (LDCT) unit as part of national lung cancer screening (LCS) programs.

### Methods

This study was conducted as a scoping review. A systematic literature search was performed in three databases: CINAHL, PubMed and ProQuest. The selection of articles was carried out according to predetermined inclusion criteria. After the article screening, eleven articles were included in the final review and underwent a quality assessment. The data was charted, and the selected articles were analyzed using qualitative content analysis through an inductive approach.

### Results

In total, 143 studies were screened, of which 11 articles were included. The articles have been published between 2019 and 2023 and originate from five countries. Four main themes emerged: barriers to participation in and commitment to LCS, barriers to the introduction and use of mobile LDCT units in LCS, opportunities for using a mobile LDCT unit in LCS, and future prospects for mobile LDCT units in LCS.

## Conclusions

The findings suggest that mobile LDCT units have the potential to improve accessibility and thus increase the commitment of high-risk individuals to screening programs while contributing to the realization of health equity.

## Implications for practice

Understanding the benefits, barriers, and facilitators of mobile LDCT units as part of LCS programs can support radiography researchers, policymakers, and clinicians in planning further studies and potential pilot projects from both the perspectives of screening participants and service providers.

## Keywords

lung cancer, screening program, mobile LDCT, scoping review

## Introduction

Lung cancer is still one of the most common cancers causing mortality in the world. In 2022, approximately 1.8 million people died of lung cancer worldwide (WHO 2024). Lung cancer is the third most common cancer in Finland (Salomaa 2022), and according to the Finnish Cancer Registry, 1495 men and 915 women died of lung cancer in 2022 (Finnish Cancer Registry n.d.). In the past decades, efforts have been made in the healthcare systems around the world to organize lung cancer prevention measures at both the primary and secondary prevention levels in order to reduce mortality. Smoking is the most pronounced risk factor for lung cancer. About 80–90% of lung cancer patients smoke or have smoked at some point of their lives. Although smoking is one of the most significant risk factors, lung cancer can also be caused by long-term exposure to second-hand smoke, air pollution or occupational exposure to various toxic compounds. (Salomaa 2022).

The effects of lung cancer are visible from an individual level to society, as it places a significant burden on healthcare systems and the economy (Zhang et al. 2023). Diagnosing lung cancer is complicated by the fact that cancer symptoms often only appear when the cancer has already spread. The prognosis of cancer that has spread is poor, which is why detecting its precursors is critical. (Salomaa 2022) Plain X-ray and computed tomography (CT) are primarily used in the initial diagnosis of the cancer (Lappi-Blanco et al. 2016) and radiographers are in major role in delivering these examinations.

In order to support the secondary prevention of lung cancer, various lung cancer screening programs (LCS) have been introduced in recent years to detect cancer earlier and thus improve the prognosis of recovery. For example, the goal of The Strengthening the screening of Lung Cancer in Europe (SOLACE) project launched in Europe is to promote the implementation of sustainable lung cancer screening programs and to provide tools for planning screening programs taking into account the special needs of different European countries (SOLACE n.d.). In Finland, the Finnish Cancer Centre FICAN is a key player in the national harmonization of cancer prevention, diagnosis and treatment practices (FICAN n.d.a). As part of FICAN's activities, there is a national cancer screening steering group

that guides and monitors the launch, implementation and development of national cancer screening programs, including lung cancer (FICAN n.d.b).

Screening is primarily performed with low-dose computed tomography (LDCT), which has been found to be sufficient to detect early-stage lung cancers (Horeweg et al. 2014; Tanoue et al. 2015; Hoffman et al. 2020). Screening programs are mainly aimed at persons belonging to the risk group, such as current and former long-term smokers, who have an increased risk of developing lung cancer (Tanoue et al. 2015). According to previous studies, screening programs have been found to be cost-effective when the program in question is aimed at high-risk individuals (Jaine et al. 2018; Gómez-Carballo et al. 2022; Kowada et al. 2022; Zhang et al. 2023). However, the planning of screening programs must take into account not only the cost-effectiveness of the program, but also possible risks and harms for the screening participants, such as radiation dose, overdiagnosis, false positive results and thus possible mental suffering (Lappi-Blanco et al. 2016; Salomaa 2022).

The importance of enhancing lung cancer screening has also been taken into account by the European Commission. In September 2022, the European Commission issued a new recommendation on the earlier detection of cancers to increase preventive measures. The aim of the actions is to expand screening programs to cover lung cancer along with other commonly occurring cancers. The recommendation urges the member states of the European Union to find out the feasibility and effectiveness of LDCT in persons belonging to the risk group and to simultaneously reinforce preventive measures supporting primary prevention (European Council 2022a).

However, the success of screening programs is determined by how well the screenings reach people belonging to the risk group (Camilloni et al. 2013). Therefore, improving the availability of screening by reducing various individual and social participation restrictions has become an essential part of the planning of screening programs as the participation in cancer screening should be as effortless as possible. Reaching out to those who belong to risk groups would be both beneficial for the individual and socially cost-effective (European Council 2022b).

Previous studies have explored reasons (Schütte et al. 2018; Chien et al. 2020) and barriers (Haas et al. 2018; Holden et al. 2021) for not participating in cancer care and screenings and also examined solutions for reaching high-risk population groups (Camilloni et al. 2013; Van Hal et al. 2021). To increase the accessibility, interest in the use of mobile LDCT units for lung cancer screening has increased, especially in areas with limited access to hospital-based screening programs due to geographic and socioeconomic factors (Raghavan et al. 2020; Chiarantano et al. 2022). In order to develop appropriate and cost-effective LCS programs, it is therefore important to find out which factors affect the use of mobile LDCT units, what are their possibilities of use and possible threats as part of future screening programs. It is also vital for the sustainability of the screening programs that the radiographers performing these screening examinations are aware of the prerequisites for these programs and are involved in their design. The aim of this review was to determine the quantity and quality of available information on the extent to which mobile LDCT units are already in use and what kind of user experiences have been obtained among both screening participants and professionals providing them. The scoping review was therefore guided by the following research question: "What are the possibilities for using a mobile LDCT unit in lung cancer screening?".

## **Materials and methods**

This study was conducted as a scoping review and was carried out in seven steps according to the Joanna Briggs Institute (JBI) Manual for Evidence Synthesis (Aromataris & Munn 2022) which presents a revised version of Arksey and O'Malley's (2005) original framework for conducting scoping reviews. The study followed the Preferred Reporting Items for Systematic Reviews and Meta-Analysis Extended for Scoping Reviews (PRISMA-ScR) guidelines (Tricco et al. 2018) and was reported accordingly.

### **Search strategy**

In order to find keywords suitable for the review, several preliminary literature searches were conducted. These preliminary searches were carried out in several stages between 20 May 2023 and 6 October 2023 to familiarize with the topic and find the most relevant search terms.

The PCC (Population/Concept/Context) framework was used to identify the main concepts of the research question. The categories selected for the PCC framework were based on concepts generated through preliminary searches. The key population in this study was people belonging to risk groups for developing lung cancer. The concept was possible medical diagnostic techniques to be used, i.e., in this case mobile LDCT imaging devices. The context of the study was the national screening programs organized for risk groups. Thus, "mobile CT", "mobile computed tomography", "mobile low-dose computed tomography", "lung cancer" and "screening" were formulated as the most relevant search terms. The term "mobile" was included as an integral part of the term "CT" or "computed tomography" or "low-dose computed tomography" because the study was specifically focused on the usability of mobile imaging devices.

### **Inclusion criteria**

We included articles which were published in English and where the full text was available, covered key concepts in a way that was relevant to the research question, and were peer-reviewed empirical studies, or reviews or relevant policy documents. Solutions related to mobile LDCT imaging and their use, especially in lung cancer screening and/or diagnostics, were defined as the key concepts of the study. There were no restrictions regarding the context, and there was material from different healthcare environments around the world. It was decided to include only material published in English due to the language skills of the authors and those involved in the screening of research articles. In addition, only peer-reviewed and evidence-based materials were included to ensure the reliability of the data for the review.

### **Study selection and critical appraisal**

The literature search for the scoping review was conducted using PubMed, ProQuest, and CINAHL, with all searches completed on 7 October 2023. The search strings were compiled based on the search terms identified in the preliminary searches using the PCC framework. All three final searches were performed using English search terms due to the selection of databases.

A total of 143 articles were obtained through database searches (Fig. 1). The search in PubMed produced 16 results and ProQuest 55 results. The initial search in CINAHL produced 863 hits, but by limiting the search to only peer-reviewed articles, it was reduced to 72 results. All citations were imported into Rayyan software, a web-tool for researchers conducting systematic reviews, which was used to sort and select the articles (Ouzzani et al. 2016). After duplicate detection and removal (n=26), 117 (n=117) articles remained for the first stage of title and abstract screening, which was performed independently by a total of four reviewers. The choices were discussed in an online meeting and disagreements were resolved between the reviewers. After screening the titles and abstracts, 12 (n=12) articles remained for full-text screening. Three people participated in reviewing the full-text articles. The articles were reviewed independently, after which the choices were discussed and any disagreements that arose were negotiated and resolved in joint discussion. Eight (n=8) articles were included in the review from the original database search. In addition, a manual citation search yielded three (n=3) additional articles for eligibility assessment. Thus, a total of 11 (n=11) articles remained for quality assessment.

Two authors of this article (blinded for review) independently performed a quality assessment of the articles selected for review to compensate for bias. Studies were critically appraised using the Mixed Method Appraisal Tool (MMAT) version 2018 (Hong et al. 2016) and JBI's critical appraisal tools for systematic reviews and research syntheses (Aromataris et al. 2015) and economic evaluations (Gomersall et al. 2015). In the quality assessment of the studies, conflicts that arose were discussed and disagreements were resolved through discussion and re-examination of the articles to reach a consensus. In general, the quality of some of the studies was weakened by the shortcomings observed in the reporting, e.g., regarding the clarity of the research questions, the representativeness of the research sample of the target population, and incomplete outcome data. However, it was decided to include all articles in the review due to the paucity of available information.

### **Data extraction and analysis**

Data from the articles included in the study were extracted and synthesized using conventional content analysis. The study characteristics extracted and tabulated from the studies included author(s), year of publication, country, title, aim, methods and main results related to the review question (Table 1). The included articles were analyzed by qualitative content analysis through an inductive approach. In the content analysis, meaning units were highlighted from the data and the collected material was coded and the codes were further classified into sub-themes, after which the main themes were formed from the sub-themes. The research question guided data collection and analysis throughout the process. Meaning units and the codes formed from them were presenting the potential areas to be considered in the planning and organization of LCS programs using mobile LDCT units.

### **Results**

#### **Overview of the selected studies**

A total of 143 articles were screened for relevance and eligibility. Of these screened articles, 11 (n=11) were assessed for quality and selected for the final review. Among the articles, one was a randomized controlled trial (n=1), one was a systematic review (n=1), one was an economic evaluation (n=1), one was a qualitative study (n=1), three were descriptive quantitative studies (n=3), and four were non-randomized quantitative studies (n=4). All articles were published between 2019 and 2023. The articles originated from the United Kingdom (n=5), Canada (n=1), the United States (n=2), Japan (n=2) and Brazil (n=1).

A large part of the studies examined implemented pilot programs with mobile LDCT units (Sone et al. 2001; Balata et al. 2019; Crosbie et al. 2019; Barlett et al. 2020; Raghavan et al. 2020; Crosbie et al. 2022), which explored, for example, the detection rate of lung cancer, participation and compliance to the screening program, and the participants' views on the implementation of the program. One study examined the results of a lung cancer screening program implemented with a mobile LDCT unit, but also the effects of a smoking cessation group conducted simultaneously with the screening on the decision to quit smoking (Chiarantano et al. 2022).

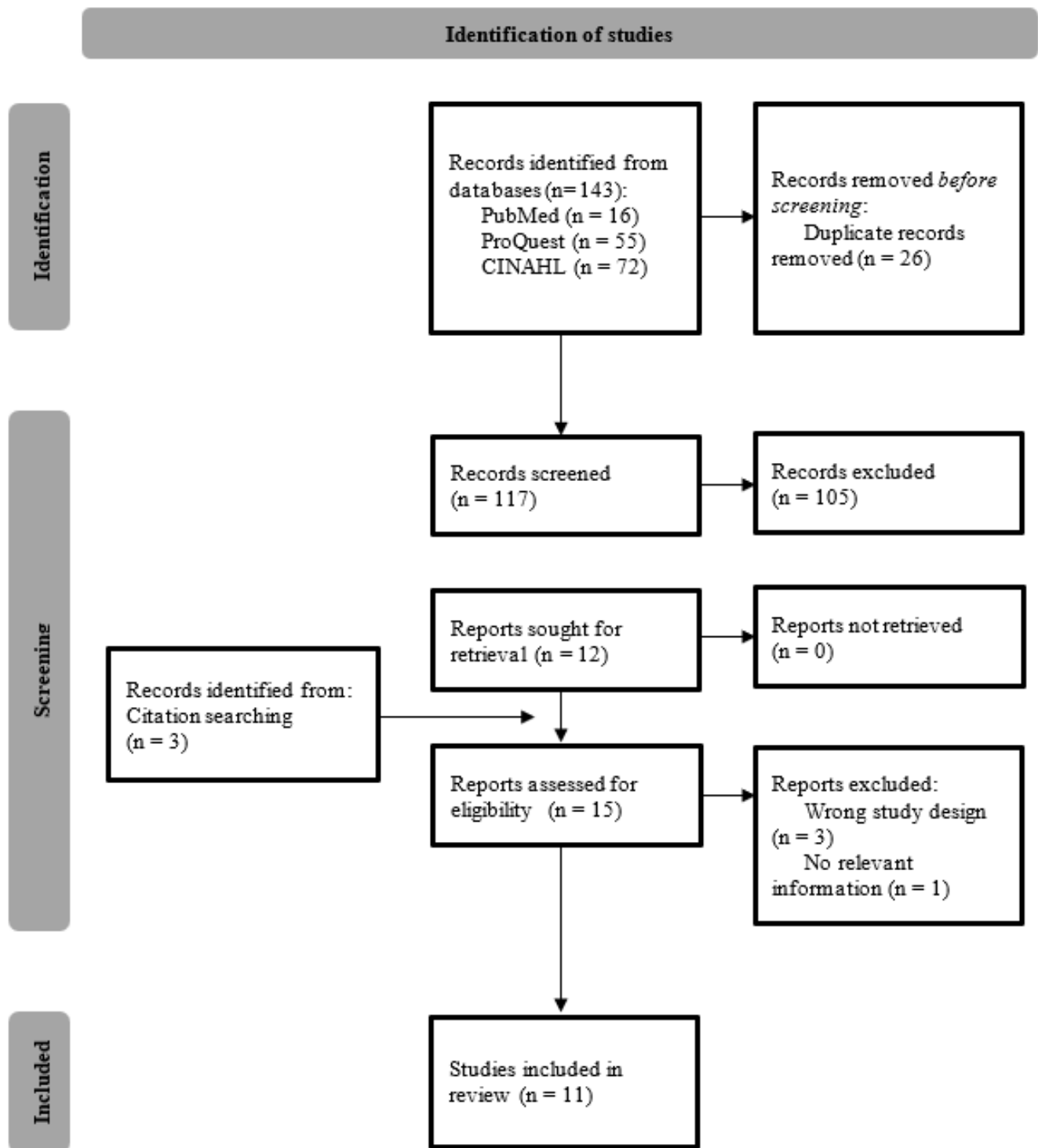


Figure 1. PRISMA flowchart showing the article selection process.

Table 1. Articles included in the review.

Author(s), year, country	Article	Study aim	Study methods	Main results
Balata H, Tonge J, Barber PV, Colligan D, Elton P, Evison M et al. 2019 UK	Attendees of Manchester's Lung Health Check pilot express a preference for community-based lung cancer screening	To explore participants' views on mobile CT screening and determine whether the use of a mobile unit was an important factor when they considered participating in the second round of the National Health Service (NHS) screening program.	A quantitative study in which participants who were eligible for the study were asked to complete a standard 7-point Likert scale, as well as answer open-ended questions, with practical questions related to the organization of the LCS program. Participants were divided into two groups based on whether they were willing to participate in a hospital-based screening program. The results of two groups were compared.	The answers of 938 participants were considered in the analysis. For 74.7% (n=701) of those who participated in the survey, the location influenced the decision to participate. In addition, 23% (n=216) of the respondents would have less often participated in a corresponding hospital-based screening program, most visible in those belonging to the lowest socioeconomic group and heavy smokers. The main reasons for not participating in a hospital-based screening program were various logistical problems, additional costs incurred by the participant, and inconvenience.
Bartlett EC, Kemp SV, Ridge CA, Desai SR, Mirsadraee S, Morjaria JB et al. 2020 UK	Baseline Results of the West London lung cancer screening pilot study—Impact of mobile scanners and dual risk model utilisation	To compare participant uptake of lung cancer screening between mobile and hospital-based CT units and assess the effect of cancer detection using two lung cancer risk models which have been previously used in the UK to determine suitability for LDCT screening.	Persons belonging to the risk group were invited to the LCS either at the hospital or at the location of the mobile CT unit. The study considered the detection rate of lung cancer, the stage of the cancer and the recall rate. Participant uptake was compared at both imaging sites, and LDCT eligibility and cancer detection rate were compared between participants according to each risk model. Participants were sent a customer satisfaction feedback survey.	A total of 20.9% (1749/8366) participated in the study, of which 1047/5135 (20.4%) responded to the hospital invitation and 702/3231 (21.7%) responded to the mobile site invitation. The median distance for the study participants to the hospital was 3.3 km (2.6–4.1 km), which was significantly lower than the median distance to a mobile location of 6.4 km (4.2–8.6 km). The feedback survey was answered by 274 participants at the hospital site and 90 at the mobile site. The two participating groups did not differ much in their answers regarding the suitability and functionality of the screening site. Of the 1145 CT examinations performed, 19 (1.7%) were positive and 163 (14.2%) were indeterminate and 963 (84.1%) were negative. After additional scans, a total of 34 participants (34/1145, 3.0%) had a positive scan result and were referred for further investigations. 29/34 (85.3%) participants were later diagnosed with cancer.

<p><b>Chiarantano RS, Vazquez FL, Franco A, Ferreira LC, Cristina da Costa M, Talarico T et al.</b></p> <p>2022</p> <p>Brazil</p>	<p>Implementation of an Integrated Lung Cancer Prevention and Screening Program Using a Mobile Computed Tomography (CT) Unit in Brazil</p>	<p>To describe the implementation and results of an innovative lung cancer prevention program that combines smoking cessation counseling and LCS with using a mobile CT unit. The study examines the effectiveness of mobile LDCT screening and participation in a smoking cessation program, as well as the impact of the program on smoking cessation.</p>	<p>In the experimental study, Brazilian health professionals from 18 public primary health care units were trained to provide smoking cessation counseling. A mobile LDCT unit was designed for the study, which was used in LCS. Eligible high-risk participants of the program were invited to participate in the study, either through health professionals or through opportunistic screening. The participants were surveyed by phone one year after the intervention.</p>	<p>Among the 233 screened participants, 54.9% were women, the average age was 62 years old, and 52.8% of participants showed high or very high nicotine dependence. After the 1-year follow-up, 27.8% of participants who were involved in smoking cessation groups had stopped smoking. The first LDCT round revealed that the majority of participants (83.7%) exhibited lung-Rads 1 or 2; 7.3% exhibited lung-Rads 3; 7.7% exhibited lung-Rads 4a; and 3% exhibited lung-Rads 4b or 4x. Among the 233 screened participants, three lung cancers were diagnosed, thus leading to a diagnosis rate of 12.8/1000.</p>
<p><b>Crosbie PA, Balata H, Evison M, Attack M, Bayliss-Brideaux V, Colligan D et al.</b></p> <p>2019</p> <p>UK</p>	<p>Implementing lung cancer screening: baseline results from a community-based 'Lung Health Check' pilot in deprived areas of Manchester</p>	<p>To report baseline results from a community based LDCT LCS pilot which was implemented in deprived areas of Manchester.</p>	<p>2541 participants (n=2541), were invited to a community-based lung cancer screening in 14 locations, where they were assessed for risk of getting lung cancer. Participants were offered annual screening, over two screening rounds, including an immediate LDCT scan.</p>	<p>Of the final 1429 eligible participants, 1384 were screened. 82.6% of the studies conducted were classified as negative (n = 1143), 12.7% indeterminate (n = 176) and 4.7% positive (n = 65). Of 81 (5.9%) participants further assessed in the cancer clinic, 42 had lung cancer. The prevalence of lung cancer was 3%, 42/1384. The proportion of false positives in those sent for follow-up examinations was 48.1% (n=39/81), i.e., 2.8% of all those screened.</p>
<p><b>Crosbie PA, Gabe R, Simmonds I, Hancock N, Alexandris P, Kennedy M et al.</b></p> <p>2022</p> <p>UK</p>	<p>Participation in community-based lung cancer screening: the Yorkshire Lung Screening Trial</p>	<p>To assess participation and adherence to a community based LCS program with mobile LDCT compared to usual care in a population at risk.</p>	<p>Randomized controlled trial in which the subjects of the study were 55–80-year-olds with a history of smoking, who were randomized to either a phone call for lung cancer risk assessment or conventional care (meaning no invitation). The invitation strategy included GP approval, advance invitation and two reminder invitations if necessary. Following the classification after the phone invitations, the participants with high risk were invited to a lung health check (LHC) using a mobile LDCT unit.</p>	<p>Of the total of 44,943 invited, 50.8% responded. Of the respondents, 34.4% were potentially eligible, 29.9% participated in LHC, and 29.1% (n = 6650) participated in LDCT screening. The probability of answering decreased by 56% in people who smoke. People who self-reported smoking had 27% less screening participation. People in the lowest socioeconomic status had a 42% lower probability of responding than those in a higher socioeconomic status, as well as a 22% lower likelihood of participating in LHC. Lower LHC participation probabilities were also found based on age; older people would be less likely to participate. The response rate of people belonging to ethnic minorities was also lower than that of Caucasians.</p>
<p><b>Dodd RH, Sharman AR, Marshall HM, Yap ML, Stone E, Rhee J et al.</b></p> <p>2023</p> <p>UK, Australia</p>	<p>“What do I think about implementing lung cancer screening? It all depends on how.” Acceptability and feasibility of lung cancer screening in Australia: The view of key stakeholders about health system factors</p>	<p>To explore the views of healthcare providers and policy makers on the acceptability and feasibility of LCS programs, as well as barriers and enablers to implementation in Australia.</p>	<p>A qualitative study in which 24 focus groups and three interviews were conducted in 2021. Participants included 84 health professionals, researchers and current cancer screening program managers and decision makers from across Australia. Most of the focus groups (22/24) and all interviews were completed online.</p>	<p>Most of the participants had a positive attitude towards LCS and considered it feasible. However, several implementation-related challenges emerged in the interviews, which must be weighed when planning the screening program. The challenges included e.g., LCS program delivery, costs, workforce considerations, quality assurance, health systems complexity, the simplicity of referral practices and the use of mobile screening units to improve accessibility as well as equity.</p>

<p><b>Hamaguchi M, Tsubata Y, Tanino A, Mitarai Y, Hata K, Kobayashi M et al.</b></p> <p>2022</p> <p>Japan</p>	<p>Results of 10-year mobile low-dose computed tomography screenings for lung cancer in Shimane, Japan</p>	<p>Reviewing the accuracy of a previously completed lung cancer CT screening program and determining the current status of the CT screening program.</p>	<p>A retrospective study in which the occurrence of lung cancer was investigated over a period of ten years, from April 2009 to March 2019. During the study, 25,189 participants underwent chest CT screening with a mobile LDCT unit. The group of participants was not strictly limited by age or smoking background.</p>	<p>Lung cancer was found in 82 of the 25,189 participants, thus over 10 years the lung cancer detection rate was 0.33%. Lung cancer was detected in 46 men and 36 women, whose median age was 69 (range 45–89) years. Of the diagnosed lung cancers, the proportion of non-smokers was 54.9%, therefore the occurrence of lung cancer in smokers was similar to that in never-smokers. Lung cancer occurred more in men who were current or former smokers, while non-smokers who tested positive were more often women.</p>
<p><b>Headrick Jr JR, Morin O, Miller AD, Hill L &amp; Smith J.</b></p> <p>2020</p> <p>USA</p>	<p>Mobile Lung Screening: Should We All Get on the Bus?</p>	<p>The mobile LCS program was developed to bring solutions for better accessibility, to improve lung screening participation rate and to serve patients belonging to the risk group living in rural areas. The study analyzes the program development process, program results and costs.</p>	<p>An economic evaluation study in which the research team and partners developed a prototype of a mobile LDCT unit. For ten months, the bus traveled to 104 destinations and screened a total of 548 participants. LCS results were reported according to lung RADS 0-4. Generally accepted calculation principles were used in the evaluation of the economic effects.</p>	<p>The mean age of the participants was 62 years, and the mean pack-year of smoking was 41. Significant pulmonary findings were observed in 51 patients (9%), five of whom were diagnosed with lung cancer, of which 80% were at an early stage. Non-pulmonary diseases were also observed in 152 (28%) screened persons, such as moderate or severe coronary artery disease in 101 (66%) participants. The profitability analysis was exceeded by 28%. During 5 years of use, the calculations yielded a net present value of 1 million euros, an internal rate of return of 34.6% and a profitability index of 2.2. The mechanical problems identified were related to the air conditioners and electrical interruptions with the need to replace some power equipment.</p>
<p><b>Lam AC, Aggarwal R, Cheung S, Stewart EL, Darling G, Lam S et al.</b></p> <p>2020</p> <p>Canada</p>	<p>Predictors of participant nonadherence in lung cancer screening programs: a systematic review and meta-analysis</p>	<p>To identify predictors of participant nonadherence to annual LCS follow-up.</p>	<p>A systematic review and meta-analysis in which four databases (Ovid MEDLINE, Ovid EMBASE, EBSCO CINAHL and EBSCO AgeLine) were searched using predefined search terms. An additional hand-search was performed from reference lists and gray literature.</p>	<p>Of 3668 studies screened for title/abstract and 155 for full text, 13 studies were included for the review. According to the 13 studies selected, the rate of non-adherence was 28%. Reasons for non-adherence were e.g., age under 60 or over 74, long distances to screening locations, low risk of lung cancer, current smoking status and ethnicity. No differences were found between male and female participants. In addition, non-commitment was influenced by e.g., coordination of the screening program, the availability of reminder calls/letters and the use of mobile LDCT scanners.</p>
<p><b>Raghavan D, Wheeler M, Doege D, Doty JD, Levy H, Dungan KA et al.</b></p> <p>2020</p> <p>USA</p>	<p>Initial Results from Mobile Low-Dose Computerized Tomographic Lung Cancer Screening Unit: Improved Outcomes for Underserved Populations</p>	<p>To investigate how a mobile CT unit would improve access to the LCS for a population belonging to an underserved group (no insurance or poorly insured, i.e., not covered by Medicare) and who have the highest risk of dying from lung cancer.</p>	<p>The study is an experimental study in which researchers and their collaborators developed BodyTom CT, a portable 32-slice low-dose CT scanner built inside a bus. The participants were from underserved groups who do not have access to an insurance-reimbursed screening program. To make the results comparable with the NLST (National Lung Screening Trial) and Dutch-Belgian NELSON trial data, participants older than 64 years were excluded from the study.</p>	<p>550 participants were scanned with a mobile LDCT unit. Lung CT Screening Reporting and Data System (Lung-RADS) approach was used for lesion classification. A total of 601 lung nodules were found, of which Lung-RADS 1 was found in 267 participants, Lung-RADS 2 was found in 183 participants, Lung-RADS 3 found 62 participants and Lung-RADS 4 found in 38 participants. Lung cancer was identified in 12 participants. Participants were found to be committed to completing the program.</p>

<p>Sone S, Li F, Yang ZG, Honda T, Maruyama Y, Takashima S et al.</p> <p>2001</p> <p>Japan</p>	<p>Results of three-year mass screening programme for lung cancer using mobile low-dose spiral computed tomography scanner</p>	<p>To assess the utility of annual LCS with a mobile LDCT and to examine the characteristics of identified lung cancers.</p>	<p>In the study, using a mobile LDCT scan, a population-based screening was performed in 29 local municipalities in the Nagano Prefecture, Japan. Participants consisted of 5,483 subjects who were 40-74 years old. Participants had their first CT scan in 1996, followed by annual repeat scans in 1997 and 1998 for most participants. A total of 13,786 scans were performed between 1996 and 1998. Participants with suspicious lesions underwent further investigations with diagnostic CT scans.</p>	<p>At initial screening in 1996, suspicious nodules were found in 279 (5.1%) of 5,483 subjects, and 22 (8%) were confirmed to have lung cancer in further examinations. In 1997, 173 (3.9%) suspicious nodules were found in 4425 participants and 25 (14%) of 173 had lung cancer, and in 1998 the results were 136 (3.5%) of 3878 and 9 (7%) of 136. The sensitivity and specificity for the detection of surgically confirmed lung cancer was 55% (22/40) and 95% (4960/5199) in 1996 and 83% (25/30) and 97% (4113/4252) in the 1997 screening.</p>
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In a retrospective study, instead, an attempt was made to validate the results obtained in an earlier 10-year follow-up of the lung cancer screening program using a mobile LDCT unit (Hamaguchi et al. 2022). One study also looked at the economic value and costs of a community-based lung cancer screening program (Headrick et al. 2020). In addition, one of the studies investigated the views of key stakeholders on lung cancer screening programs (Dodd et al. 2023). Also, Lam et al. (2020) explored the reasons for not participating in screenings through a systematic literature review.

### Overview of the emerged themes

Four main themes related to the use of mobile LDCT units in lung cancer screening emerged from the data; 1) barriers to participation and adherence to LCS, 2) barriers to the implementation and use of mobile LDCT units in LCS, 3) opportunities for using a mobile LDCT unit in LCS and 4) future prospects for mobile LDCT unit in LCS (Fig. 2).

#### 1. Barriers to participation and adherence to LCS

Some of the studies highlighted how participation in lung cancer screening is affected by the nature of the screening program and various practical obstacles, but also different emotional factors affect the willingness to participate. From a practical point of view, various challenges that came up were e.g., logistical reasons, such as distances, availability of parking spaces and public transport connections (Balata et al. 2019; Bartlett et al. 2020). Thus, for example, Balata et al. (2019) found that a quarter of the participants would have been less likely to have participated in the screening if it had been organized

in a hospital. In addition, in the same study, one third of the respondents considered the location of the mobile LDCT unit to be important in terms of participation in further screening (Balata et al. 2019). Long distances were thus considered one of the biggest obstacles to continuing the screening program and participating in follow-up studies (Sone et al. 2001; Hamaguchi et al. 2022; Dodd et al. 2023). Financial barriers were considered to limit possibilities to participate, for example due to travel costs and loss of working time (Balata et al. 2019; Bartlett et al. 2020; Lam et al. 2020; Raghavan 2020).

In addition to practical barriers, studies highlighted various emotional reasons for not participating in screening. Fear and worries (Raghavan 2020), stigmatization (Dodd et al. 2023), a feeling of being asymptomatic and misunderstandings about the purpose of screening (Lam et al. 2020) came to the fore. Several studies pointed out how the biggest predictors for not participating in screenings are old age, heavy smoking and low socioeconomic status (Balata et al. 2019; Lam et al. 2020; Crosbie et al. 2022). Crosbie et al. (2022) found that often people who are at the highest risk of getting lung cancer do not participate in screenings.

#### 2. Barriers to implementation and use of mobile LDCT units in LCS

Common problems observed in the design and implementation of screening programs were overall costs and the functionality of the funding model (Dodd et al. 2023), reaching screening participants (Headrick et al. 2020; Crosbie et al. 2022; Dodd et al. 2023) and prevailing attitudes towards new screening tools (Headrick et al. 2020).

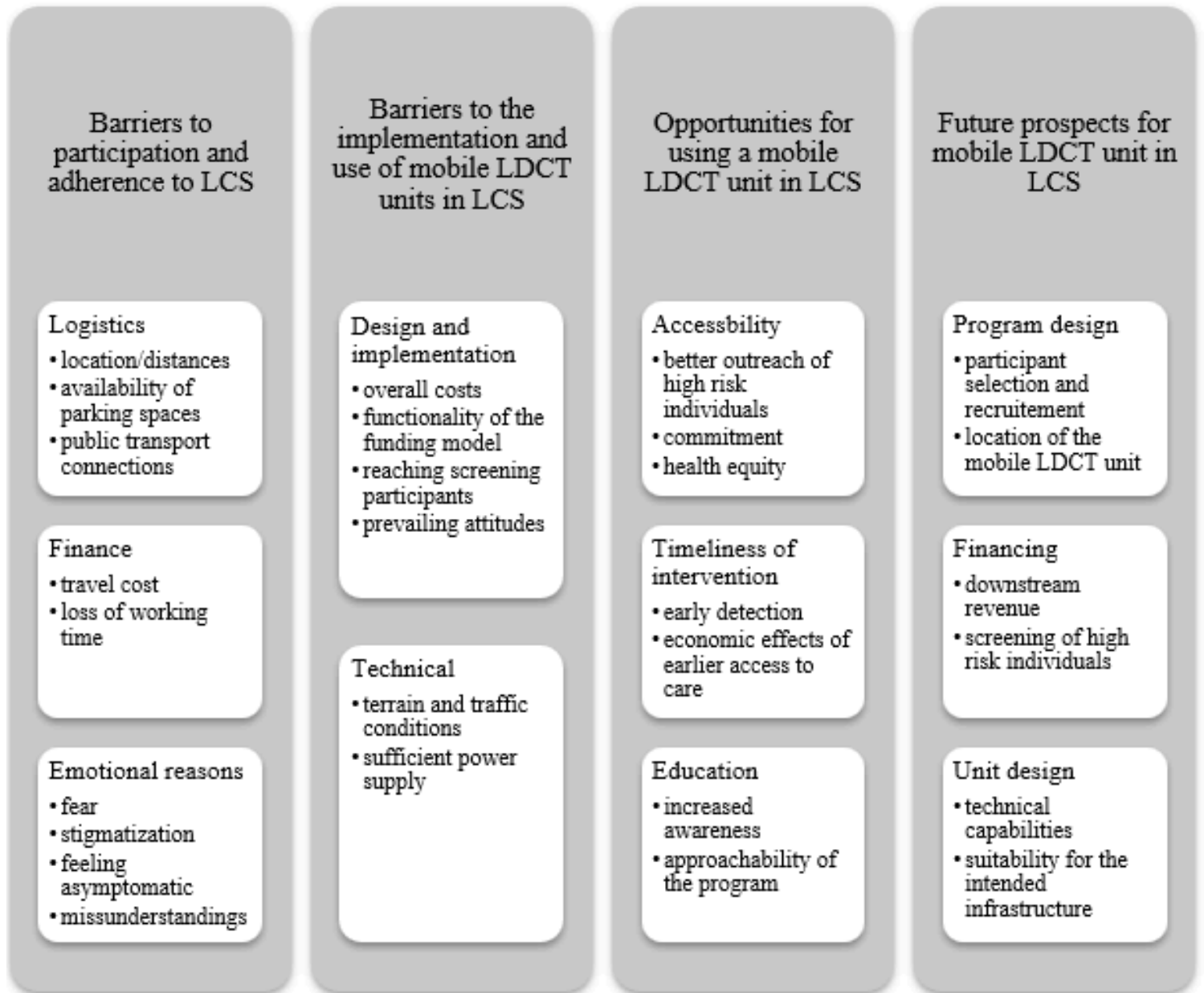


Figure 2. Main and subcategories of the emerging themes.

Since the areas of use of mobile devices would be more remote areas, various technical problems in the design and use of the mobile unit was considered to potentially hinder its wider use (Headrick et al. 2020; Chiarantano et al. 2022). According to the literature, problems can be caused, for example, by poor traffic conditions in rural areas, which can affect the operation of sensitive imaging equipment (Chiarantano et al. 2022). In addition, the devices require a sufficient power supply at their place of use (Headrick et al. 2020). However, Headrick et al. (2020) found that the use of mobile LDCT unit did not require major technical repairs, only basic maintenance procedures during their implemented pilot program.

### *3. Opportunities for using a mobile LDCT unit in LCS*

The use of mobile LDCT units was seen e.g., to increase the access of those belonging to the risk group to screenings, to help their commitment and to promote the realization of equity. Several studies found that the use of mobile LDCT units would promote health equity and enable everyone to access the screening program, regardless of where they live (Crosbie et al. 2019; Raghavan et al. 2020; Chiarantano et al. 2022; Dodd et al. 2023).

With better availability of screening, it was also seen that it would enable better outreach to those belonging to highest risk groups and would lower their threshold to participate in screening (Balata et al. 2019; Raghavan et al. 2020; Chiarantano et al. 2022; Crosbie et al. 2022) Also, Lam et al. (2020) found that the screenings programs using mobile LDCT units have lower nonadherence rate.

Better accessibility of screenings among risk groups was also seen to improve the survival rate when access to treatment is timelier (Raghavan et al. 2020; Dodd et al. 2023). Early detection, on the other hand, was found to potentially have significant economic implications when looking at the national economic ramifications caused by lung cancer morbidity and mortality (Raghavan et al. 2020)

In addition, a couple of studies that investigated the functionality of pilot programs, showed that the mobile LDCT unit also has the opportunity to act as an educational tool and a way to increase awareness of lung cancer and screening programs in an easily approachable way among various population groups (Headrick et al. 2020; Chiarantano et al. 2022).

### *4. Future prospects for mobile LDCT unit in LCS*

In terms of the future, the feasibility of mobile LDCT units as part of lung cancer screening programs depended on the program's design, incurred costs and financial sustainability (Headrick et al. 2020; Chiarantano et al. 2022), stakeholders commitment (Dodd et al. 2023), the LDCT unit's technical capabilities (Headrick et al. 2020; Chiarantano et al. 2022), and also reaching the right target group for the screening (Crosbie et al. 2019; Headrick et al. 2020; Crosbie et al. 2022). Special attention should be paid to reaching risk groups, where accessibility and screening in communal places are an important part (Balata et al. 2019). However, Bartlett et al. (2020) concluded that the use of mobile LDCT units in cities probably does not add value, as hospital-based screenings are generally easily accessible.

The organization and sustainability of the financing of the screening program was highlighted in a few studies (Headrick et al. 2020; Chiarantano et al. 2022; Dodd et al. 2023). For example, according to Headrick et al. (2020), an essential part of the screening program performed with a mobile LDCT unit is the generated downstream revenue for the program to be viable. When organizing the screening program, the selection and recruitment of participants was considered crucial (Crosbie et al. 2019; Headrick et al. 2020; Crosbie et al. 2022). The pilot projects showed that phone recruitment could be an effective way to get participants to commit (Crosbie et al. 2022). It was also seen that the mobile LDCT units offer a way to do opportunistic recruitment directly at the mobile screening location (Chiarantano et al. 2022). Regardless of the recruitment method, however, recruitment should be aimed at people belonging to risk groups in order to reduce potential unnecessary harm to the participants and keep the program cost-effective (Crosbie et al. 2022).

## Discussion

This scoping review explored the possibilities of using a mobile LDCT unit in lung cancer screening. The identified articles used a variety of research approaches and designs. Most of the studies examined the results of LCS pilot programs using mobile LDCT units and the observations made for a specific population group in a specific research setting. The scoping review showed that the use of mobile LDCT units is primarily aimed at increasing the population's equal opportunities to participate in screenings. Mobile LDCT units were shown to be practical, easily accessible, and thus create a low-threshold service for the early detection of lung cancer. However, mobile LDCT units also proved to be a means of raising awareness and educating the population about lung cancer. By bringing lung cancer screening more concretely visible to the population, it was seen to increase the health literacy by providing reliable information from the healthcare professionals performing the screening examinations. Radiographers are therefore one of the key actors in the multidisciplinary teams carrying out these interventions to convey objective information about LDCT examinations and the risks and effects of radiation. Overall, the implementation of mobile LDCT as part of LCS programs requires sufficient financial resources, thorough training of personnel to adapt to the changing conditions of the mobile unit, appropriate use and handling of sensitive imaging equipment taking into account different terrains and environmental conditions, reaching the right risk group and appropriate management and organization of possible follow-up measures.

The usability of mobile imaging devices and the degree of participation in the program as well as the reasons for non-participation have also been studied as part of other cancer screening programs. With regard to other screening programs, it has been observed that the use of mobile units primarily increases the chances of those in a weaker position to participate in screening, which often also increases the accessibility of those who belong to the highest risk group (De Mil et al. 2019; McElfish et al. 2019; Kalyanpur et al. 2022; Dumky et al. 2023). For example, Dumky et al. (2023) observed how the screening program should take into account how immigrant women's country of birth and religious orientation affect their participation in breast cancer screenings and can therefore increase health

inequity. Thus, mobile LDCT units can act as a participation enhancer by increasing the accessibility of LCS programs by bringing the screening service closer to the most vulnerable. To ensure a program that covers all residential areas and thereby wide coverage of the screening program, cooperation with local healthcare providers is essential for the continuation of the program and ensuring access to follow-up examinations and treatments for people at risk of disease. In Finland, this would mean close cooperation between wellbeing service counties so that proper follow-up measures could be implemented as needed.

However, the implementation of mobile LDCT units requires e.g., acquisition of appropriate equipment, radiography and screening organization staff training, suitable information pathways and recruitment of people belonging to the highest risk group, sufficient financial resources and proper planning of the region of use taking into account local distances and infrastructure. In the planning, the experiences gained from the use of the mobile imaging units of previous programs should be used and thus the practices considered to be the best should be implemented. Through the piloting of screening programs, valuable information can be obtained for the further development of the program.

The results of LCS programs using mobile imaging units have been promising, e.g., in terms of accessibility for persons belonging to the risk group, more timely detection of lung cancer, raising general awareness and the realization of health equity. Therefore, the results of this review can be taken into account when considering which aspects regarding mobile LDCT units should be kept in mind when planning future lung cancer screening programs and how the EU guidelines could be widely implemented into national legislation regarding LCS programs. In this way, the data collected in this review can be used to better understand the requirements set for mobile LCS programs, but also its wide possibilities to promote the implementation of equal and properly targeted screening programs.

However, this review also showed that there is still limited evidence for the use of mobile LDCT units in lung cancer screening. Existing evidence focused primarily on lung cancer detection rates with mobile LDCT units, screening participation and adherence, and economic considerations. Studies have not further evaluated the potential negative effects of

using mobile LDCT units, their cost-effectiveness, and their applicability to different healthcare systems, the impact of providing follow-up interventions on the final assessment of screening program effectiveness, or the additional training required for staff to use mobile units. In light of these results, further research is needed to better assess the requirements, overall benefits and overall costs of large-scale deployment of mobile LDCT units in LCS programs.

### Limitations

This scoping review has limitations that may increase the possibility of bias. The search was limited to English-language and peer-reviewed articles only, which may affect the amount of data collected. The review did not include gray literature and unpublished material, although their importance as a valuable source of research information was recognized.

Furthermore, the validity of the results obtained in the review is limited by the variability of the research designs of the selected studies and the quality of the studies. The data has been collected from studies that were conducted in varying research environments and using varying research populations and methods, making mutual comparison of studies difficult, but on the other hand increasing the generalizability of research results to different settings. The quality assessment of the studies was performed blindly by two reviewers to reduce the risk of bias. The quality deficiencies of the studies were mainly manifested in the clarity of the research reporting and the selection of a suitable study population. Despite certain shortcomings, all articles that went through the quality assessment were included in the final review.

### Conclusions

The new recommendations for the implementation of lung cancer screening programs encourage health systems to find solutions for implementing programs that are timely, properly targeted, equitable and cost-effective. However, the overview of the research on the use of mobile LDCT units in lung cancer screening shows the limited availability of existing evidence. The current research points to the possibilities of using mobile LDCT units, especially in terms of easier accessibility of the population belonging to risk groups and thus increasing the realization of health equity. Nevertheless, the

infrastructure of the area and its suitability for a mobile unit, the preparedness of the staff, the possibilities for arranging follow-up care, and financial considerations must be taken into account to make the program cost-effective. With the increase in the use of various mobile solutions in cancer screening programs, research into the introduction of mobile LDCT units as part of national lung cancer screening can therefore be considered a necessary and promising part of the future research. It is important that in addition to policy makers and screening organizations, also the ones performing the examinations have their role to play in planning screening programs to ensure the successful implementation of the programs.

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# MRI Image Enhancement: A Scoping Review of Traditional Techniques and Deep Learning Approaches

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## Abstract

### Background

Magnetic Resonance Imaging (MRI) enhancement techniques, including traditional methods and deep learning approaches, improve image quality by reducing artefacts, noise, and enhancing resolution, yet no single method universally excels across scenarios.

### Methods

This PRISMA-guided scoping review screened 1337 articles and 67 patents from ScienceDirect, CINAHL, PubMed, and Lens.org, including 36 articles, 7 patents, and 2 grey literature sources on MRI-specific enhancement (artefact reduction, noise minimization, resolution improvement). Studies without empirical validation or deep learning details were excluded following title/abstract and full-text screening.

### Key Results

Traditional techniques like NLM filtering and motion correction effectively reduce noise and artefacts but falter in dynamic imaging. Deep learning accelerates acquisition, boosts signal-to-noise ratios, and enhances diffusion-weighted imaging, though challenges persist in generalizability and transparency. Hybrid approaches combining both, show promise for overcoming limitations.

### Conclusions

The review maps strengths and gaps in MRI enhancement, recommending hybrid traditional-deep learning methods and deeper model interpretability to advance clinical diagnostics.

### Keywords

Artefact Reduction; Denoising; MRI; Image Quality; Super Resolution.

## Introduction

As a non-invasive and high-resolution soft tissue imaging modality, Magnetic Resonance Imaging has emerged as an essential workhorse within the realm of contemporary medicine, allowing healthcare professionals to acquire elaborate and nuanced insights into the complex anatomical structures and physiological functions of the human body (Bammer et al. 2005). Nevertheless, the efficacy of MRI can be significantly undermined by a multitude of challenges, including, but not limited to, the presence of noise, various artefacts, and insufficient contrast, all of which can interfere with diagnosis and the formulation of effective treatment strategies (Tamada 2020).

It is important to note that commercial deep learning algorithms are gaining traction in adoption worldwide, which could potentially facilitate the implementation of advanced MRI enhancement methods in clinical settings. Federated machine learning (FL) directly addresses the issues of data confidentiality and limited dataset availability, enabling global clinical research centres to engage in decentralized data sharing. This decentralized approach to training machine learning models helps address data confidentiality and dataset limitations, facilitating the use of advanced MRI enhancement techniques in clinical practice. (Chen et al., 2022.)

### **Purpose and aim**

The purpose of this scoping review is to map and evaluate the advancements in MRI Image Processing, particularly focusing on efforts to overcome constraints in MRI efficacy by examining developments in artefact reduction, noise attenuation, and resolution enhancement.

The aim of the review is to synthesize current progress with a particular emphasis on the reduction of artefacts, minimization of noise, and enhancement of image resolution in MRI, providing insights into how these techniques have evolved and their effectiveness in addressing key challenges in the field. This review is intended to provide researchers with a comprehensive overview of current state-of-the-art AI algorithms in MRI image processing, summarize key achievements to date, and highlight existing research gaps for future investigation.

The review aims to address the following key research questions:

- What significant advancements in MRI enhancement techniques have been achieved over time to improve image quality by reducing artefacts, minimizing noise, and enhancing resolution?
- How do deep learning methodologies enhance MRI image quality?

## Methodology

The study methodology is a scoping review examining MRI Image Processing by systematically searching multiple scientific databases and patent repositories over specified years using defined keyword strategies designed and refined with librarian and team input, following established protocols to identify relevant literature and patents. The framework utilized for this scoping review follows the PRISMA-ScR (Preferred Reporting Items for Systematic reviews and Meta-Analyses) framework recommended by (Tricco et al. 2018). The method employed involved an examination of peer-reviewed journal publications spanning the years 2019 to 2024, and reviewed patents from 2015 to 2024.

### **Database selection and search strategy**

The data was selected by using the keywords "Image quality" and "MRI" and ("denoising" or "super resolution" or "artefact reduction" or "motion correction" or "enhancement" or "deep learning for Image Enhancement and Correction in Magnetic Resonance Imaging" ). The ScienceDirect database filters used were published date: 2019-2024, subject areas: medicine and dentistry, biochemistry, genetics and molecular biology, nursing and health professions, article type: review articles, language: English. The CINAHL complete database filters selected were peer reviewed, academic journals from January 1, 2019 to July 31, 2024. PubMed database with filters selecting review, systematic review from January 1, 2019 to July 31, 2024 were also used. Patents are searched using Patent Search Key word: " medical Image quality " and "MRI" and ("denoising" or "super resolution" or "artefact reduction" or "motion correction" or "enhancement" or "MRI image enhancement" or "noise reduction" or "artefact correction" or "deep learning" or "convolutional

neural networks" or "generative adversarial networks") from Lens.org. The patents retrieved were granted patents published from January 1, 2016 to July 31, 2024. A PRISMA-ScR diagram elucidating the process is presented in Figure 1. The search strategies were drafted by an experienced librarian Susanna Rossi and further refined through team discussion by the authors. The final search results were exported into Rayyan AI and duplicates were removed by the authors.

Articles that lacked an abstract pertinent to MRI image enhancement or failed to address the intricacies and challenges associated with the implementation of deep learning methodologies were systematically excluded from the scope of this review. At the full-text screening stage, 14 of the 52 articles and 9 of the 16 patents were excluded for the following reasons: (1) lack of sufficient data or results related to image quality enhancement or correction methods in MRI; (2) failure to meet

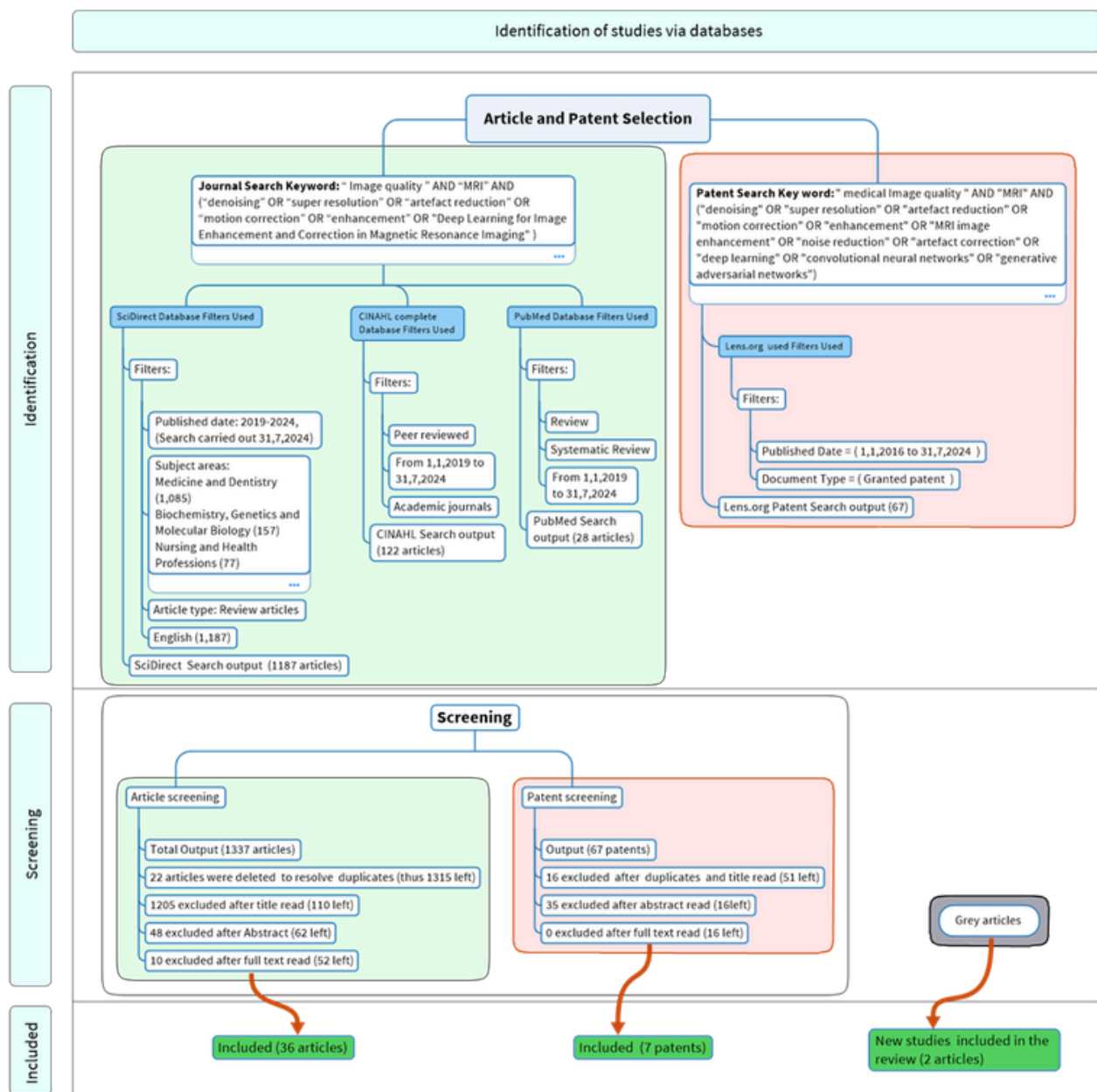


Figure 1. PRISMA diagram of the article collection process adapted from PRISMA2020 (Tricco et al. 2018).

predefined inclusion criteria for methodology, such as absence of empirical validation or appropriate quantitative metrics; and (3) focus on irrelevant topics outside the scope of MRI image enhancement, such as segmentation or diagnostic classification without enhancement techniques. This left 38 articles and 7 patents for final inclusion in the scoping review. These exclusions ensured alignment with the review's objectives under PRISMA-ScR guidelines (Tricco et al. 2018). The PRISMA-ScR-guided review diagram includes two grey literature studies recommended by a medical radiation physicist. These were included to capture emerging non-peer-reviewed insights on MRI image enhancement, enhancing the review's comprehensiveness alongside peer-reviewed sources.

### ***Selection of the articles***

To uphold the integrity and trustworthiness of the information presented in this review, the 38 articles and 7 patents included have undergone an evaluative process. This evaluation included the examination of research design, methodological approaches, data analysis strategies, and the overall quality of the studies. Additionally, the review addressed the limitations and potential biases inherent in the studies while recognizing existing gaps and discrepancies within the current body of literature.

Furthermore, to maintain the rigor and dependability of the information outlined in this review, the literature search and selection process involved a collaborative effort among four authors. The four authors conducted independent screening in Rayyan AI's blind mode, with differences limited to few articles on inclusion criteria interpretation and interpretations of methodological rigor thresholds. Team discussions ensured final consensus without majority voting. This ensured a transparent and unbiased article selection process in the manuscript (Ouzzani et al. 2016). Additionally, all the included articles were read by at least two authors for data extraction and synthesis.

### ***Quality Assessment***

The reliability and validity of the findings presented in this scoping review have been ensured through a quality assessment process. The research team employed the Mixed Methods Appraisal Tool (MMAT), a recognized instrument designed specifically for evaluating the methodological quality of scoping reviews that include qualitative, quantitative, and mixed methods studies (Hong et al. 2018).

The MMAT assessment focused on several key aspects of the review process, including the clarity of the research question, the comprehensiveness of the literature search strategy, the criteria for study selection, data extraction procedures, risk of bias evaluation, and the appropriateness of the analytical methods employed.

Each included study was independently assessed by two members of the research team. Any discrepancies between their evaluations were resolved through discussion and consensus. The overall quality of the review (in the supplementary file, Table S1) was determined based on MMAT ratings. Total points were attributed to each article and a relevance to study score was computed. All articles with scores from 6-10 were included in the study and those with scores of 5 and below were excluded from the study (Pluye et al. 2011). Patents were not appraised.

### ***Data Extraction and Synthesis***

A data-charting form was jointly developed by four authors to determine which variables to extract. The four authors discussed the results and continuously updated the data-charting form in an iterative process. Then an in-depth review of relevant articles was conducted, collecting ideas and insights that addressed the research questions. Full texts of included studies were procured to enable comprehensive thematic analysis. The research team collectively extracted crucial information from each study, including study design, MRI enhancement techniques examined, evaluation methods used, and reported performance metrics. The team analysed trends, common methodologies, and emerging approaches across the included studies.

### ***Results***

The study characteristic sample is presented in Table 1 which is the first four rows of a larger dataset, serving as a sample of the full set of study characteristics. The complete table, referred to as Table S3\_Study Characteristics, can be found in the supplementary section. This excerpt is intended to illustrate the format and content of the full dataset, which provides detailed information for all included studies. The supplementary Table S3\_Study Characteristics has 38 studies and 7 patents included in the scoping review, which were organised according to the PICOS framework. These studies collectively address a wide range of challenges in medical imaging, particularly in the field of MRI, such

as noise reduction, motion artifact correction, image reconstruction, and image quality enhancement. Generally, the interventions involve the application of advanced machine learning and DL techniques, including CNNs, GANs, and patient-specific models, for tasks like denoising, super-resolution, and automated quality control. Comparisons are typically made against conventional imaging methods, traditional machine learning approaches, or pre-intervention image quality. The outcomes consistently focus on improvements in image quality, diagnostic accuracy, SNR, and overall workflow efficiency. The study designs span a spectrum from experimental and retrospective analyses to prospective studies, technical method descriptions, and comprehensive literature reviews. This diversity highlights both the rapid technological advancements in the field and the breadth of clinical and technical problems being addressed, providing a robust foundation for understanding current trends and future directions in AI-driven medical image quality improvement.

The overview illustrated in Figure 2 sets the stage for the exploration of the evolving landscape of MRI technology and its implications for both clinical and research applications by addressing the results from individual studies.

### **Exploring Noise reduction, Image Quality Enhancement and Artefact Reduction**

MRI image quality is improved using various advanced methods. Traditional transform-based techniques often require manual tuning and are affected by noise and artifacts. Optimization methods use iterative algorithms to enhance images but need more computing power. Deep learning with convolutional neural networks (CNNs) automatically improves resolution and reduces noise and artifacts better than Traditional transform-based techniques like Wiener filtering and Block-Matching 3D Filtering (BM3D) denoising . (Ahishakiye et al. 2021.)

Table 1. Sample of Study Characteristic: Key Variables from the Full Dataset.

Autho (Year) Publication forum: Title	Population/Problem	Intervention	Comparison	Outcome	Study Design
Abbasi, H. et al. (2023) Neuroscience Informatics: Automatic Brain Ischemic Stroke Segmentation with Deep Learning: A Review	Patients with suspected or confirmed acute ischemic stroke	Deep learning models for automatic segmentation of stroke lesions	Manual or threshold-based methods, other ML techniques	Segmentation accuracy (Dice, sensitivity, specificity)	Review
Ahishakiye, E. et al. (2021) Intelligent Medicine: A Survey on Deep Learning in Medical Image Reconstruction	Medical image reconstruction with incomplete data	Deep learning techniques (CNNs)	Traditional and compressed sensing-based methods	High-quality image reconstructions	Literature Review
Allen, T.J. et al. (2023) Tomography (Ann Arbor, Mich.): Evaluation of a Deep Learning Reconstruction for High-Quality T2-Weighted Breast MRI	Patient images with noise	Patient-specific deep learning network for denoising	Conventional denoising methods	Improved image quality, reduced noise	System/ method description
Almansour, H. et al. (2022) Academic Radiology: Accelerated 3D T2-Weighted Turbo-Spin-Echo Sequences...	Patients with pelvic pathologies, pelvic MRI at 1.5T	Novel 3D T2-TSE with inner-volume excitation & iterative denoising	2D T2-TSE sequences	Image quality, lesion detection, faster acquisition	Prospective

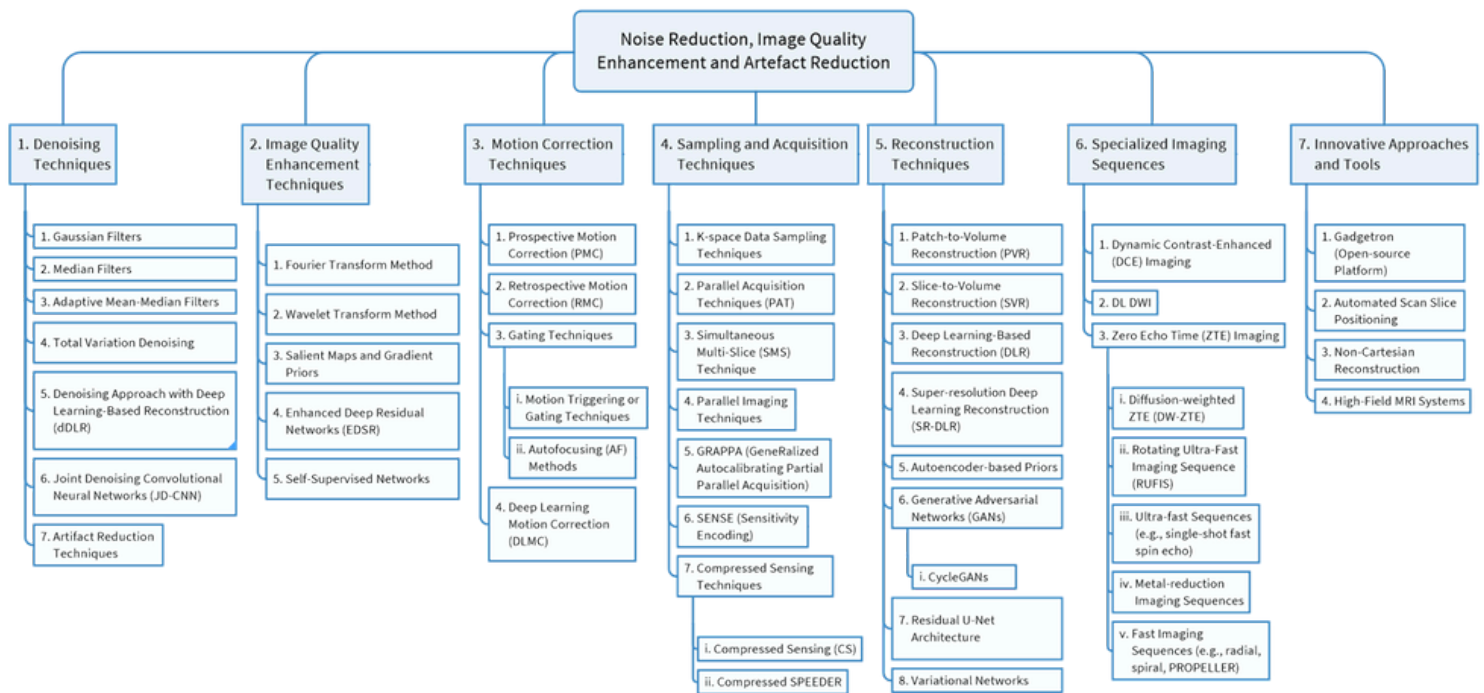


Figure 2 Overview of Artefact Reduction, Noise Reduction and Image Quality Enhancement

### Denoising Techniques

Traditional filtering techniques, such as Gaussian filters, median filters, and adaptive filters, have long been employed to reduce noise in medical images. They rely on predefined mathematical operations to reduce noise based on local pixel statistics. In contrast, deep learning methods automatically learn complex noise patterns from large datasets, enabling superior restoration performance and adaptability across diverse imaging conditions. (Shedbalkar et al. 2021.) Gaussian filters are computationally simple and effective at eliminating Gaussian noise by averaging pixel values with a Gaussian kernel. However, they often blur edges and high-frequency components, which can compromise critical image details (Shedbalkar et al. 2021). Median filters, on the other hand, excel at mitigating salt-and-pepper noise by replacing pixel values with the median of neighbouring values. While they preserve edges better than linear filters, iterative application can result in the loss of fine details and increased computational complexity due to sorting operations. (Shedbalkar et al. 2021.)

Adaptive filtering techniques, such as adaptive mean-median filters and bilateral filters, offer improvements over linear methods by adjusting parameters based on local image characteristics. These methods preserve edges and high-frequency details while reducing noise but require careful parameter tuning for optimal performance. (Shedbalkar et al. 2021.) For example, bilateral filtering reduces noise while preserving edges by analysing intensity variations within the intensity domain. Despite their advantages, traditional filtering methods are limited in their ability to address non-Gaussian noise types and often result in blurring of high-resolution images, which is particularly problematic in MRI (Uetani et al. 2021). Digital filters Sharpen-1 (F1) and Sharpen-2 (F2) enhance medical images by emphasizing density transitions, making anatomical boundaries more distinct. These filters visualize anatomical structures better. (Montesinos et al. 2019.)

DLR utilizes CNNs trained on large datasets of high-quality images to adaptively remove noise. This helps challenges associated with long scan durations, for example, with patients with Parkinson's disease .

However, the effectiveness of DLR depends on the quality of training data and the availability of vendor-specific implementations. (Oshima et al. 2023.) Additionally, DLR methods have reduced artefacts while preserving diagnostic integrity, marking a shift toward automated approaches that enhance MRI image quality and manage noise and artefacts in clinical practice (Barrett et al. 2024; Higaki et al. 2018). Advanced Intelligent Clear-IQ Engine (AiCE), is a DLR tool integrated into MRI protocols. AiCE reduces noise without compromising image contrast and has shown significant enhancements in MRI image quality, particularly when paired with Compressed SPEEDER (Ueda et al. 2021).

Other innovative techniques include iterative denoising algorithms, which enhance image quality through a bank of thresholded orthogonal Fourier Transforms applied after parallel-imaging processing. These algorithms utilize quantitative noise maps for spatially adapted wavelet thresholding. Additionally, inner-volume excitation improves image quality by focusing on specific regions of interest during acquisition, thus minimizing artefacts. (Almansour et al. 2022.)

Joint Denoising Convolutional Neural Networks (JD-CNN) represent another innovative approach that enhances high-field diffusion-weighted imaging (DWI). JD-CNN outperforms conventional methods like Total Variation (TV) denoising and BM3D by retaining more details and enhancing image boundaries. However, JD-CNN requires extensive training datasets with high-quality images and is prone to over-denoising, which can result in the loss of important image details. (Wang et al. 2019.)

Innovative artefact reduction techniques have further improved MRI image quality. For instance, iterative denoising algorithms integrated into imaging sequences have reduced scan times while enhancing image quality. Automated systems leveraging computer vision can facilitate artefact identification and correction, ensuring efficient processing of high-quality images while addressing operational challenges inherent in manual adjustments. (Almansour et al. 2022.)

The evolution from traditional filtering methods to advanced machine learning-based approaches reflects ongoing efforts to enhance medical imaging quality while preserving critical details. While

traditional techniques continue to play a role in specific applications, modern approaches like dDLR and JD-CNN offer significant advantages in terms of efficiency, accuracy, and diagnostic utility (Hokamura et al. 2024; Nazir et al. 2024; Wang et al. 2019).

### ***Image Quality Enhancement Techniques***

The Fourier Transform method aids in noise reduction via low pass filtering in the frequency domain but is limited for non-stationary signals like medical images. Conversely, the Wavelet Transform method is particularly effective in localizing both time and frequency components, reducing noise by removing high-frequency components according to predefined rules. However, this approach may cause blurring in high-resolution MRI applications. (Uetani et al. 2021.) Salient maps and gradient priors utilize gradient information to minimize errors between estimations and ground truth, thereby improving image quality; however, their performance can be inconsistent across different applications (Li et al. 2021).

Enhanced Deep Residual Networks (EDSR) utilize residual blocks to improve structural normalization, effectively reducing artefacts and enhancing image quality (Li et al. 2021). Self-supervised networks demonstrate strong denoising capabilities and improve image resolution while reducing the reliance on labelled data, though they may not match the performance of fully supervised methods. DL enables image-to-image translation and segmentation tasks, generating specific sequences like fat-suppressed T2-weighted images. (Vrettos et al. 2024.)

### ***Motion Correction Techniques***

Motion correction in MRI is a critical aspect of ensuring high-quality imaging, as motion artefacts can significantly degrade diagnostic accuracy. These artefacts arise from various sources, including physiological movements such as breathing and cardiac pulsations or involuntary patient motion (Chang et al. 2023; Tripathi et al. 2024; Zhou et al. 2024). Motion correction techniques are broadly categorized into prospective motion correction (PMC) and retrospective motion correction (RMC) approaches, with each offering distinct advantages and limitations (Chang et al. 2023; Chen et al. 2023; Levac et al. 2022).

PMC operates during the imaging process itself by dynamically adjusting radio frequency (RF) pulses and

magnetic field gradients in response to real-time motion data. This is achieved using external tracking devices or navigators that measure subject movement during scanning. Self-navigation methods have also been developed to extract motion information directly from repeated k-space measurements. However, due to the time constraints of real-time estimation, PMC is typically limited to correcting dominant motions, such as respiratory movements along the foot-head direction. (Zhou et al. 2024.) While PMC compensates for real-time motion, it requires additional hardware and can prolong scan times (Chang et al. 2023).

In contrast, RMC focuses on correcting motion artefacts after image acquisition using post-processing algorithms. RMC does not require additional hardware or real-time motion estimation, making it particularly suited for complex motion correction tasks. Many deep learning-based methods fall under this category, leveraging advanced reconstruction techniques to improve image quality. DL plays a critical role in retrospective motion correction, using extensive datasets to identify and remove motion artefacts without requiring explicit motion information. (Levac et al. 2022.) However, RMC is computationally intensive and cannot guarantee data quality if significant motion artefacts are present during acquisition (Chang et al. 2023; Zhou et al. 2024).

Deep Learning Motion Correction (DLMC) has emerged as a promising retrospective approach. DLMC eliminates the need for extra hardware and can manage complex motion patterns by learning mappings between motion-corrupted images and their artefact-free counterparts. Despite its potential to enhance resolution and quality, DLMC relies heavily on large training datasets and robust regularization to prevent overfitting. (Chang et al. 2023; Tripathi et al. 2024.)

Hybrid approaches that combine PMC and RMC aim to leverage the strengths of both techniques while addressing their limitations. For example, hybrid methods can use PMC for real-time adjustments during acquisition and RMC for refining image quality post-scan. However, these methods may introduce complexity and compatibility issues in clinical workflows. (Chang et al. 2023.) More also, supervised deep learning models like the Residual U-Net architecture have shown great promise in correcting motion-related artefacts and enhancing image quality

by learning complex data patterns. For example, U-Net has been successfully applied to brain MRI for artefact correction and segmentation accuracy improvement. (Abbasi et al. 2023.)

Several artefact mitigation strategies complement these correction techniques. Physical stabilization methods, such as immobilization or sedation, can prevent bulk movement but are often impractical in clinical settings. Physiological motions like breathing and cardiac pulsations are addressed through gating techniques that synchronize data acquisition with specific respiratory or cardiac cycles. (Zhou et al. 2024.) Advanced reconstruction techniques also play a vital role in motion correction. Motion-corrected reconstruction aims to restore artefact-free images from corrupted k-space data with or without additional motion information. These methods have been extended to handle non-rigid body motion using local autofocusing approaches. (Zhou et al. 2024.)

Although traditional and deep learning-based methods have advanced, challenges persist. Gating techniques struggle to fully address non-periodic movements, such as cardiac pulsations (Bopp et al. 2018; Rohkohl et al. 2010). Mathematical algorithms for iterative artefact removal can be computationally expensive and time-consuming. Moreover, DL-based approaches require extensive datasets for training and may struggle with generalization if training data do not adequately represent real-world scenarios. (Tripathi et al. 2024.)

### **Sampling and Acquisition Techniques**

K-space data sampling techniques are widely used to reduce blurring and ghosting by overlapping partial samples (Ljungberg et al. 2021; Singh et al. 2023). However, these methods are not universally effective for all types of artefacts. For example, volume censoring can identify motion-affected areas but may not fully eliminate motion artefacts, often resulting in some loss of image data (Barrett et al. 2024; Chen et al. 2023). Periodically Rotated Overlapping Parallel lines with Enhanced Reconstruction (PROPELLER) MRI employs k-space sampling to correct spatial inconsistencies while rejecting motion-corrupted data. Despite its effectiveness, this approach is complex and unsuitable for all MRI scan types (Chang et al. 2023; Singh et al. 2023; Tripathi et al. 2024). To address artefacts associated with prolonged scans, partial k-space acquisition can be utilized. This technique combines fully sampled reference data

with partial data for reconstruction, which enhances efficiency but may introduce grafting artefacts such as high-frequency distortions. (Aamir et al. 2023; Chatterjee et al. 2024; Singh et al. 2023.)

Compressed sensing techniques is a good tool for maintaining SNR while reducing scan times. These methods reconstruct images from undersampled data by exploiting sparsity in the transform domain. (Tripathi et al. 2024.) One prominent commercial application of this technique is Compressed Speed Enhancement by Exploiting Data Redundancy (SPEEDER), which combines compressed sensing with parallel imaging. This method enhances image quality by undersampling k-space data and reconstructing images through multiple sensitivity maps and wavelet transforms, ensuring data fidelity and promoting sparsity for effective denoising. (Ueda et al. 2021.) However, it's important to note that compressed sensing techniques may introduce global ringing artefacts if not managed properly (Uetani et al. 2021).

Parallel imaging techniques are widely used to reduce scan times by acquiring multiple data sets simultaneously through multiple receiver coils. This method typically result in a reduced SNR, they offer significant time savings (Uetani et al. 2021). SENSitivity Encoding (SENSE) and GeneRALized Autocalibrating Partially Parallel Acquisition (GRAPPA) are two prominent parallel imaging methods that enhance SNR by suppressing noise-like artefacts during unaliasing of simultaneously acquired slices. Furthermore, regularized image domain split slice-GRAPPA combines advantages from both SENSE and GRAPPA to significantly reduce noise in DWI. (Zhang et al. 2024.)

A DL module trained on both fully sampled and grafted data can effectively predict and alleviate such artefacts while preventing under sampling issues (Chatterjee et al. 2024). Patient compliance during MRI scans is critical factor influencing image quality. These challenges can result in lower image quality, increased motion artefacts, or incomplete examinations. Traditional acceleration methods such as parallel acquisition techniques (PAT) and compressed sensing (CS) have been employed to address these issues. However, PAT reduces the SNR in proportion to the square root of the PAT factor, while CS can produce overly smoothed images that limit diagnostic utility. (Gohla et al. 2024.)

Advancements in simultaneous multi-slice (SMS) imaging have significantly reduced acquisition times by enabling the simultaneous acquisition of multiple slices. This technique is particularly beneficial for cystic fibrosis (CF) patients who may struggle with prolonged scan durations. When combined with motion correction (Moco), SMS further enhances image quality by aligning and combining multiple repetitions from different diffusion directions and weightings, thereby improving SNR. Importantly, motion correction is integrated directly into the scanner's reconstruction process, streamlining workflow and reducing post-processing requirements. (Glutig et al. 2022.)

### **Reconstruction Techniques**

Traditional methods like Patch-to-Volume Reconstruction (PVR) and Slice-to-Volume Reconstruction (SVR) benchmark 2D-to-3D conversion, improving image quality despite limitations: PVR's narrow field of view misses detailed anatomy, and SVR yields lower quality than super-resolution volumes. Deep learning advances, such as Generative Adversarial Networks (GANs), surpass these by markedly enhancing quality and curbing artifacts. (Liu et al. 2021.)

By employing CNNs, DLR effectively reduces noise while preserving fine structural details across various MRI sequences. It also suppresses truncation artefacts by estimating high-frequency k-space data and enhances resolution through direct reconstruction from k-space using CNNs (Kim et al. 2023). However, DLR has limitations, such as its inability to depict small structures not captured in the original images and its reduced effectiveness in mitigating motion or magnetic susceptibility artefacts. Additionally, further validation in diverse clinical scenarios is required to establish its general applicability. (Uetani et al. 2021.)

Super-resolution deep learning reconstruction (SR-DLR) offers a specialized approach to improving MR image quality, particularly in magnetic resonance angiography (MRA). This method integrates three key processes: deep learning-based denoising, zero-padding interpolation (ZIP) for resolution enhancement, and artefact removal using neural networks. SR-DLR enhances spatial resolution while preserving vascular structural details, accelerates scan durations, and improves SNR, CNR, and image

sharpness. Despite its promise, further validation across different MRI sequences and clinical settings is necessary to confirm its robustness. (Hokamura et al. 2024.)

Autoencoder-based priors have also been explored for image enhancement. These models encode both super-resolution images and ground truth into a low-dimensional space, optimizing features for similarity. Autoencoders (AEs), whether supervised or unsupervised, are effective at correcting sequence artefacts, reducing noise, and enhancing image quality. Variational Autoencoders (VAEs) are particularly beneficial for addressing motion artefacts but may fall short of GANs in preserving fine details due to their inherent limitations in feature representation. (Chen et al. 2023; Li et al. 2022.)

GANs have changed MRI reconstruction by generating high-quality synthetic images that closely align with real data distributions. Conditional GANs excel in image-to-image translation tasks by adding previously unobservable details to original images. Specifically, CycleGANs (with its ability to learn mappings between two image domains without requiring paired training data, compared to traditional GAN that typically needs matching image pairs) have been proposed for generating isotropic super-resolution volumes from anisotropic 2D T2-weighted turbo spin echo (T2w-TSE) and single-shot fast spin echo (ssFSE) images. This approach preserves high-frequency details often lost during traditional 3D reconstructions and enables the mapping of unpaired datasets, overcoming the limitations of supervised learning models. (Liu et al. 2021.) However, GAN-generated SR images may exhibit weak correlations with ground-truth images, posing challenges for clinical applications where accuracy is critical. Additionally, GANs require meticulous hyperparameter tuning and are computationally demanding, with risks such as mode collapse limiting their variety of outputs. (Li et al. 2022; Liu et al. 2021.)

Dense convolutional networks have also been utilized for stroke detection and artefact correction, further enhancing diagnostic quality by addressing motion-related issues (Abbasi et al. 2023). Unsupervised models like GANs excel in noise reduction while preserving anatomical details across diverse noise types (Guerreiro et al. 2023). Variational networks extend compressed sensing techniques by enforcing data consistency and leveraging CNNs to learn prior

information from undersampled k-space data. These networks significantly improve image quality by combining traditional principles with modern deep learning capabilities. (Lin et al. 2023.)

Super-resolution techniques, improve the spatial resolution of MRI images, preserving high-frequency details that are often lost during traditional reconstruction methods. CycleGANs are particularly effective in generating high-resolution 3D images from lower-resolution 2D data without requiring matched pairs, which is beneficial for sequences like T2-weighted and ssFSE images. (Li et al. 2021.)

### **Specialized Imaging Sequences**

Specialized imaging sequences in MRI have been developed to address challenges such as metal-induced artefacts, motion artefacts, and acoustic noise, while improving image quality and diagnostic accuracy. Among these, dynamic contrast-enhanced (DCE) imaging is particularly useful in cases of severe metal artefacts in the pelvis. Although DCE imaging without fat suppression may reduce lesion conspicuity and introduce chemical shift artefacts, it serves as a reliable "safety net" for lesion detection and overall image quality. Techniques like fat suppression and increasing receiver bandwidth further minimize chemical shift artefacts, enhancing diagnostic outcomes. Compared to echo-planar imaging diffusion-weighted imaging (EPI-DWI), DCE imaging is less affected by susceptibility artefacts, making it a valuable alternative. (Barrett et al. 2024.)

DWI has particularly benefited from the integration of SMS and Moco techniques. Studies have shown that DWI with SMS and Moco is 32% faster than standard DWI while providing superior image quality. This combination delivers clearer images with improved visualization of mesenteric lymph nodes, even in patients with reduced compliance. These advantages make it a valuable tool for abdominal imaging in paediatric and adolescent CF patients. The technique offers a safe, efficient, and non-invasive method for evaluating therapies in young CF patients while maintaining high diagnostic accuracy. (Glutig et al. 2022.) DL in DWI enables artefact and noise reduction, producing clearer, higher-quality images from under-sampled data, as seen with models like DWI U-Net and CNN-based denoising, which enhance signal-to-noise ratio and surpass traditional methods, offering improved diagnostic accuracy and clinical decision-making (Aamir et al. 2023; Chen et al. 2023). DL also enhances segmentation and data

augmentation, crucial for diagnostic and therapeutic procedures (Vrettos et al. 2024).

Zero Echo Time (ZTE) imaging represents an innovative advancement in MRI technology. With a nominal echo time (TE) of zero, ZTE captures short-lived signals from tissues that are often invisible on conventional MRI. Its 3D radial sampling improves motion robustness, while ultra-short repetition times enable fast and efficient scanning. The Rotating Ultra-Fast Imaging Sequence (RUFIS), foundational to ZTE silent imaging, accelerates data acquisition and reduces gradient switching. Additionally, ZTE's high pixel bandwidth mitigates chemical shift off-resonance effects, and diffusion-weighted ZTE (DW-ZTE) provides comparable diffusion metrics to DW-EPI with reduced distortions in some cases. (Ljungberg et al. 2021.)

Multi-echo ZTE offers further advantages by reducing geometric distortions caused by magnetic susceptibility variations and mitigating motion and eddy current artefacts. The high SNR free induction decay (FID) image at TE = 0 serves as a distortion-free reference for spatial normalization of gradient echoes and supports quantitative T2\* mapping and quantitative susceptibility mapping (QSM). Interleaved acquisition strategies enable retrospective motion correction by reconstructing motion navigators during data acquisition. These features make ZTE particularly promising for neuroimaging, where its ability to reduce acoustic noise improves patient comfort, alleviates anxiety, and enhances communication between radiographers and patients. Moreover, ZTE reduces susceptibility artefacts near metallic implants or electrodes, further enhancing its diagnostic utility. (Ljungberg et al. 2021.)

Ultra-fast sequences like ssFSE significantly reduce acquisition times but produce low-resolution images requiring post-processing through super-resolution techniques. Similarly, 3D volumetric scans offer faster acquisition compared to multi-plane 2D scans but are more susceptible to motion artefacts and exhibit weaker T2 contrast, necessitating additional processing for quality enhancement. (Liu et al. 2021.)

Metal-reduction imaging sequences (MARS) are critical for addressing the severity of metal-related susceptibility artefacts, which depend on the size, composition, and location of metallic implants. Scanning at 1.5T is less prone to susceptibility distortions than at 3T. Specific sequences that

oversample the central k-space region effectively reduce artefacts in EPI-DWI and turbo-spin echo T2-weighted sequences. T2 mapping has also emerged as a robust alternative to EPI-DWI-derived apparent diffusion coefficient (ADC) maps, especially for patients with hip replacements. Additionally, air-related susceptibility artefacts may be mitigated by positioning patients supine, although evidence supporting this approach remains limited. (Barrett et al. 2024.)

Additionally, fast imaging sequences or motion-insensitive sampling trajectories—such as radial, spiral, or PROPELLER—can minimize distortions caused by motion (Zhou et al. 2024).

In conclusion, advancements like ZTE imaging and specialized metal-reduction sequences represent significant progress in MRI technology. These techniques address limitations of conventional sequences by enhancing image quality, reducing distortions and artefacts, and improving patient comfort. Their versatility makes them valuable tools in both clinical practice and research settings for applications ranging from neuroimaging to diffusion imaging and MR angiography. (Ljungberg et al. 2021.)

### ***Innovative Approaches and Tools***

Efforts by researchers to develop open-source platforms, such as Gadgetron (Hansen & Sørensen 2013; Xue et al. 2015), aim to incorporate machine learning frameworks directly into MRI scanners. However, widespread clinical adoption of DL-based methods necessitates large-scale validation studies and further refinement to ensure robustness and reliability in clinical practice (Montalt-Tordera et al. 2021).

Advanced DL algorithms have shown the ability to process imaging data more efficiently than traditional methods, offering solutions for challenges such as operator variability and imaging artefacts. For instance, automated scan slice positioning, explored since the early 2000s, leverages artificial intelligence (AI) to standardize scan protocols and minimize operator dependency. Additionally, Non-Cartesian Reconstruction techniques employ Non-Uniform Fast Fourier Transform (NUFFT) to convert irregularly sampled data into Cartesian representations, effectively reducing imaging artefacts. Super-resolution methods further enhance MRI resolution using DL models without extending scan times. (Potočnik et al. 2023.)

### **Commercial Solutions in MRI Image Enhancement**

The landscape of MRI image quality enhancement is characterized by a confluence of commercial innovations and investigative research. The potential of advanced algorithms and machine learning techniques is pivotal in transforming clinical imaging practices. Patient-related factors such as bulk motion or rectal spasms can impact imaging quality; however, respiratory motion artefacts varies depending on the anatomic location. (Barrett et al. 2024; Lin et al. 2023; Tripathi et al. 2024.)

Deep Resolve Boost employs advanced DL algorithms to reconstruct MR images with high SNR and anatomical detail through combined parallel imaging and simultaneous multislice acceleration. AIR Recon DL, a prototype from a vendor (GE HealthCare), enhances T2-weighted MRI through denoising and interpolation; however, its application may be limited in emergent clinical situations due to prolonged offline reconstruction times. (Lin et al. 2023.) It leverages CNNs to produce high-fidelity images from raw k-space data, effectively mitigating noise and artefacts while preserving spatial resolution. Although conventional reconstruction methods utilizing intensity filters can diminish noise, they may compromise spatial resolution. (Kim et al. 2023.) Canon Medical Systems' Advanced Intelligent Clear IQ Engine utilizes DL algorithms for noise reduction while maintaining contrast in images (Tajima et al. 2021). Furthermore, simultaneous multislice techniques employ multiband radio-frequency pulses to enhance spatial resolution and decrease acquisition time (Zhang et al. 2024). Major vendors such as GE, Philips, and Siemens have widely adopted DL techniques that not only reduce scan times but also maintain or enhance image quality.

### **The performance of MRI Enhancement Techniques**

The evaluation of MRI image enhancement techniques has demonstrated substantial advancements in image quality, leveraging various metrics and methodologies to achieve better diagnostic outcomes. Among these, the SSIM, Peak SNR (PSNR), RMSE, and SNR have emerged as pivotal tools for assessing the efficacy of these techniques. SSIM, for instance, is instrumental in quantifying structural fidelity, with higher values indicating superior preservation of anatomical details. Advanced methods, such as Fast Spin Echo (FSE) aware motion simulation models, have achieved SSIM scores of 0.851 compared to 0.730 for FSE agnostic models, showcasing their capability to enhance

structural features. (Levac et al. 2022.) Similarly, PSNR is widely used to evaluate noise reduction and structural preservation, with modified sub-pixel convolution (MSPC) yielding the highest PSNR values for 3D brain MRI images (Li et al. 2021).

Techniques like DLR have demonstrated superior performance in enhancing grey-white matter sharpness and lesion conspicuity. For example, DLR images achieve higher Likert scale ratings for sharpness and overall quality compared to conventional methods, confirming interobserver consistency in evaluating motion artefacts and noise. (Kim et al. 2023.)

Quantitative metrics such as RMSE and Normalized RMSE (NRMSE) are critical for assessing pixel-wise intensity differences. Studies have reported significant RMSE reductions with DL methods, such as a 63.77% reduction when PVR was applied alongside Super-Resolution techniques (Liu et al. 2021). Similarly, advanced motion correction models like DLMC, trained with physics-informed acquisition dynamics like FSE, achieved significantly higher SSIM scores and lower NRMSE compared to FSE-agnostic models (Chang et al. 2023; Levac et al. 2022).

Noise reduction techniques have further enhanced MRI quality. The Contrast-to-Noise Ratio (CNR) is employed to assess contrast improvements between different tissues in MRI images. Results indicated substantial enhancements in CNR values following various enhancement techniques, facilitating better tissue differentiation crucial for accurate diagnosis. (Foley et al. 2021; Uetani et al. 2021.) Block-Matching and 3D Filtering (BM3D) denoising has demonstrated significant improvements in SNR and CNR, particularly in applications like thoracic MRI and women's pelvic imaging where diagnostic accuracy is critical. For instance, BM3D increased the SNR of thoracic MRI images from an average of 54.71 to 193.80 post-denoising while preserving signal integrity. (Astari et al. 2022.) Additionally, DL-based denoising applied to low-excitation neuromelanin-sensitive MRI achieved a 1.5-fold improvement in SNR and CNR while reducing scan times from 16 minutes to just over three minutes (Oshima et al. 2023).

Subjective evaluations complement these quantitative assessments. Radiologists consistently prefer enhanced images due to improved perceived quality and artefact reduction. Likert scores indicate

that super-resolution volumes achieve ratings above three for overall quality and individual criteria, suggesting good to excellent delineation in images. (Liu et al. 2021.) Comparative analyses between SVR and Super-Resolution techniques showed PSNR improvements of 72.41%, RMSE reductions of 17.44%, and SSIM increases of 7.5%, highlighting SVR's efficacy in enhancing image quality. Qualitative assessments by radiologists using scoring systems revealed that enhanced images were generally preferred over non-enhanced counterparts, with significant improvements noted in perceived image quality and artefact reduction across multiple studies. (Allen et al. 2023; Foley et al. 2021; Hokamura et al. 2024.) Radiologist Likert Scores indicated that super-resolution volumes achieved scores above 3 on a scale of 1 to 4 across overall image quality and individual assessment criteria, suggesting good to excellent delineation in the images (Liu et al. 2021).

CNN models can achieved mean PSNR values of 35.21 dB and SSIM scores of 0.974, outperforming traditional methods like U-Net and MoCoNet (Zhao et al. 2022). In specialized applications such as paediatrics imaging or free-breathing protocols for patients with Tuberous Sclerosis Complex, advanced techniques have effectively addressed motion artefacts while significantly reducing scan times without compromising diagnostic clarity or sharpness scores (Balza et al. 2019; Cui et al. 2023).

DL surpasses traditional interpolation methods by reducing artefacts and improving perceptual indices, Root Mean Square Error (RMSE), and SSIM (Li et al. 2021). DL applications extend to brain and cardiac imaging, where simulated low-resolution images are used for model training. Architectures like CNNs and GANs are adapted for MRI super-resolution tasks, with densely connected networks showing improvement over baseline CNNs and GAN variants. (Li et al. 2021.)

### **Challenges of Implementing DL in MRI Quality Improvement**

Implementing DL techniques for MRI quality improvement presents several challenges, including data availability, algorithm generalizability, computational demands, and integration with existing clinical workflows. These challenges collectively hinder the widespread adoption of these advanced methodologies in clinical practice.

**Generalizability and Data Requirements:** DL models in medical imaging struggle with generalization due to a lack of data and computational demands necessitating the use of GPUs for timely completion of training tasks. Overfitted models often fail to perform well across scanners, systems, or protocols. Lack of specific image priors restricts DL applicability across medical imaging. (Liu et al. 2021.)

Limited or misaligned data makes it difficult to accurately restore details in super-resolution images (Liu et al. 2021). Techniques like CycleGAN use unpaired data but still require high-quality ground-truth for effective training, highlighting the need for domain adaptation, transfer learning, and standardized evaluation (Singh et al. 2023). The computational expense of DL limits clinical adoption as these methods require substantial resources for training and inference, limiting accessibility (Ahishakiye et al. 2021; Tripathi et al. 2024). Despite reducing trainable parameters, the need for large datasets remains a challenge (Tripathi et al. 2024).

### **Motion Correction and Data-Driven Methods:**

Advancing motion correction for MRI using data-driven methods presents challenges, such as obtaining paired corrupted and ground truth images for training. Self-supervised and weakly supervised learning approaches can help. Assessing the accuracy and fidelity of estimated motion fields is also challenging, with issues like topology folding resulting in unrealistic motion estimates. (Zhou et al. 2024.)

### **Image Fidelity and Algorithm Limitations:**

DL reconstruction techniques often face criticism for their inability to effectively depict small structures and for not adequately addressing certain artefacts, such as motion and magnetic susceptibility distortions. These limitations detract from the diagnostic utility of MRI images. (Chang et al. 2023; Lin et al. 2023; Uetani et al. 2021.) However, advancements like super-resolution and motion correction tools offer solutions. These methods enhance image quality by improving resolution and reducing artefacts, thereby enhancing diagnostic utility. Biases inherent in AI algorithms can affect performance if training datasets do not adequately represent diverse patient demographics. (Potočnik et al. 2023.)

**Privacy and Data Collection:** The challenge of data availability is compounded by privacy concerns surrounding large-scale data collection, essential for training robust models. Inadequate or biased datasets can lead to suboptimal performance and limit the generalizability of DL models across different scanner types and clinical environments. Furthermore, clinical validation remains crucial; current regulatory processes may not be equipped to handle the continuous evaluation required for AI algorithms capable of transfer learning and domain adaptation. (Chen et al. 2023.) Efficient data collection and promoting data sharing are essential for developing robust and accurate DL models. Many machine learning studies face limitations due to small datasets, often stemming from restricted access to patient data or limited diagnostic procedures. (Chen et al. 2023; Lin et al. 2023; Singh et al. 2023; Zhang & Sejdíć 2019.)

**Denosing and Feature Reconstruction:** DLR software offers varying degrees of denoising, with higher levels potentially causing "over-smoothing" of images, increasing the likelihood of false positives (Barrett et al. 2024; Cui et al. 2023). Incorporating feature reconstruction loss aims to ensure perceptual similarity to the ground truth but may not enforce an exact match, which can be problematic in medical applications (Guerreiro et al. 2023). Over denoising, where DL models excessively reduce noise, can compromise important image features. This issue can be mitigated by integrating regularizers, such as edge-preserved indices, into the network's loss function (Wang et al. 2019). Variability of noise patterns presents additional complications. Models like JD-CNN may perform poorly if the noise encountered during application diverges significantly from the training data. (Wang et al. 2019.)

**False Classifications and Workflow Integration:** DL applications in MRI often encounter false classifications that undermine the reliability of image quality assessments and subsequent diagnostic decisions (Chatterjee et al. 2024; Foley et al. 2021). Integrating DL into clinical workflows is challenging, meaning images are not always available in real-time, and variability in image quality due to different machines, protocols, and patient factors further complicates this integration (Chang et al. 2023).

**Integration with Existing Technologies:** Combining DL with existing MRI technologies can be complex and impractical in clinical applications (Chang et al. 2023). The need for diverse datasets further complicates this integration, particularly in specialized applications such as breast MRI, where anatomical variability must be accounted for (Allen et al. 2023).

**Continuous Model Maintenance:** Maintaining model performance requires repetitive adjustments and fine-tuning, which can be resource-intensive and time-consuming (Hsieh, Avinash, et al. 2018). These frequent modifications are necessary to ensure optimal results but can detract from overall efficiency in clinical settings.

**Economic and Clinical Balance:** Achieving a balance between providing optimal medical care and ensuring economic efficiency remains a persistent challenge. The growing demand for expensive treatments, longer life expectancies, and rapid advancements in diagnostic technologies highlight the need for sustainable solutions that address both economic and clinical aspects of healthcare delivery. (Gohla et al. 2024.)

**Adversarial Training with GANs:** Adversarial training using GANs can generate realistic but artificial patterns, posing a risk of misinterpretations or erroneous conclusions in medical imaging (Guerreiro et al. 2023). This highlights the need for caution and further refinement to ensure both visual realism and clinical accuracy.

**Reliability and Interpretability:** The "black-box" nature of DL algorithms makes it difficult for clinicians to understand how decisions are made, leading to distrust and limiting clinical adoption (Chang et al. 2023; Waisberg et al. 2024).

### **Patent Claims Related to MRI Enhancement Technologies**

This section provides an overview of patent claims related to MRI enhancement technologies, highlighting their significance within the reviewed literature. By examining these claims, we aim to elucidate the innovative advancements and legal protections that shape the development of MRI image enhancement methodologies.

#### *Apparatus Claims and Motion Correction*

Apparatus claims related to MRI enhancement technologies encompass various innovative techniques aimed at improving image quality and reducing artefacts. Motion detection and correction are pivotal, with claims utilizing a similarity measure between adjacent MR images to minimize motion artefacts, thereby enhancing the diagnostic utility of MRI images. The apparatus is designed to identify transformation interval images during motion, applying transformation matrices that specifically target intervals where motion occurs, facilitating effective motion artefact correction. Additionally, motion-free intervals can be excluded from correction processes to preserve image quality. (Lee & Park 2018.)

User input for selecting reference MR images is another significant feature, crucial for accurate image registration and minimizing artefacts during processing. The controller's capability to calculate differences between the centres of mass or intensity of adjacent MR images aids in detecting motion effectively, which is essential for addressing motion-related artefacts. (Lee & Park 2018.)

#### *DL Technologies*

The adaptability of DL methodologies extends beyond MRI, allowing application to other imaging modalities and classification problems (Foley et al. 2021). Artefact correction through DL modules has also been proposed, involving grafting processes that effectively remove high-frequency artefacts from MRI images (Chatterjee et al. 2024). Moreover, methods for accelerating MRI examinations by training DL models on fully sampled and partial k-space data have been claimed to enhance artefact prediction and removal. A smart loss function within these modules adjusts weights based on relevance during training, improving the efficacy of artefact prediction networks. (Chatterjee et al. 2024.)

The application of DL extends to the extraction of task-based metrics from image data, enhancing the evaluation of image quality and reducing false classifications (Hsieh, Gopal, et al. 2018). This approach not only improves reliability in image quality assessments but also supports ongoing learning and evaluation processes that can lead to enhanced system performance (Hsieh, Gopal, et al. 2018).

#### *Motion Score Data and Denoising Techniques*

The use of motion score data can facilitate the classification and localization of medical conditions in MRI scans. If a motion score exceeds a defined threshold, a rescan can be initiated to improve image quality and reduce patient recall rates. The effectiveness of machine learning models in managing image quality issues has been emphasized as a critical advancement in this domain. (Polzin et al. 2022.)

Denoising techniques are essential for enhancing image sharpness by reducing noise during deconvolution operations. Spatial filtering algorithms smooth out insignificant patches within images without compromising spatial resolution. The management of residual noise is discussed in terms of its random characteristics and how varying initial solutions can lead to different outcomes regarding spatial noise distribution. This invention demonstrates broad applicability across various medical imaging modalities where residual noise poses challenges. (Reusch 2020.)

#### *DL for Image Denoising*

A DL approach for image denoising in medical imaging involves a computer-implemented method aimed at improving image quality through an advanced denoising framework (Tang et al. 2021). The approach begins by processing an image of a patient and introducing controlled noise to create a noisy input image. This initial step allows the model to effectively learn the noise characteristics. Thereafter, the patient's image is transformed from a thin slice volume to a thick slice volume, minimizing noise within the image even before the controlled noise is added, hence enhancing the overall quality of the input data. (Reusch 2020.) A DL network is then trained using the noisy input image to identify the introduced noise. Once trained, the network is deployed as a secondary model to process a second image of the same patient, identifying and removing noise from the second image, resulting in a denoised output suitable for clinical purposes. (Tang et al. 2021.) Several refinements ensure that the training data is consistent and reliable by introducing noise derived from either phantom scans or simulations during the training process. Additionally, the level of introduced noise can be scaled dynamically based on feedback, allowing for greater adaptability in various imaging scenarios. Before removing the noise identified in the second image, the model performs additional checks and refinements to ensure accuracy and reliability. (Demesmaeker et al. 2020.)

#### *Investigative technique for Motion Artefacts Reduction*

Parikh and Dimmer (2016), presents a novel approach to reducing motion artefacts in medical imaging systems by utilizing real-time localization data and advanced image processing techniques. The method begins with the acquisition of time-varying localization data from a sensor array communicating with several active markers placed within the patient's body. These markers are positioned in a predefined geometric arrangement, and the sensor array, located outside the patient, collects localization data based on this known geometry.

Simultaneously with localization data acquisition, the imaging system scans a specific volumetric portion of the patient's body, generating raw image data that includes details about the volumetric region where the active markers are located. The raw image data is then processed into individual image frames using a specialized algorithm. These frames are subsequently grouped, or binned, based on a designated time window corresponding to the real-time localization data, providing precise timestamps and spatial coordinates for accurate alignment of the image frames. (Parikh Parag & Dimmer Steven 2016.)

To address motion artefacts, the system produces motion-compensated image data by selecting and processing a specific subset of the binned image frames, ensuring that the final images are of high quality with reduced motion-induced distortions. Moreover, the system continuously monitors the localization data to detect any shifts in the position of the volumetric portion being scanned. If a shift is identified, the processing algorithm is dynamically recalibrated to adapt to these changes, maintaining accuracy and compensating for any motion that might affect image quality. (Parikh Parag & Dimmer Steven 2016.)

This method offers a robust solution for mitigating motion artefacts in medical imaging, resulting in high-quality, motion-corrected images crucial for accurate diagnostic analysis (Parikh Parag & Dimmer Steven 2016).

#### *Iterative Image Reconstruction*

A neural network-based system for iterative image reconstruction assigns image quality scores at each iteration of the reconstruction process, guiding the optimization of cost functions to ensure convergence toward high-quality images. It also guides the criteria

to stop the iteration process and adjust reconstruction parameters, allowing for adaptive optimization. (Demesmaeker et al. 2020.)

#### *Multi-Contrast Imaging and Data Augmentation*

A novel approach for improving image quality by integrating multi-contrast imaging, data augmentation, and DL has been proposed. Denoising of the input image is performed using non-local means (NLM) filtering and multi-contrast information. This is followed by applying patch-based data augmentation to the images, where model parameters are adapted to approximate high SNR and high-resolution reference images for denoising and enhancement. Lastly, the augmented images are input into a DL network, which includes residual learning and CNNs, to further enhance reconstruction. This approach has proved effective in improving SNR and enhancing resolution, especially for Arterial Spin Labelling (ASL) MRI. (Zaharchuk et al. 2021.)

### **Discussion**

This scoping review addressed two key research questions: (1) What are the major advancements in MRI enhancement techniques? and (2) What role does deep learning play in improving MRI image quality? The Results show traditional methods (denoising, motion correction, optimized sampling) reduced artefacts and noise while enhancing resolution. Advanced sequences (e.g., parallel imaging, compressed sensing) and tools improved diagnostic quality for anatomical and pathological visualization. Deep learning outperformed traditional approaches in noise suppression and artefact mitigation, especially in low-field MRI and accelerated scans (Chen et al. 2023; Gohla et al. 2024; Singh et al. 2023), confirming progress on both questions.

The results as seen in section 5.2 shows that no single technique universally outperforms others across all scenarios. For instance, while denoising techniques such as NLM Filtering show promise in minimizing noise without sacrificing critical image details, they may not be as effective in scenarios involving significant motion artefacts. Conversely, motion correction techniques have demonstrated substantial improvements in dynamic imaging situations but can introduce their own complexities during implementation (Levac et al. 2022; Tripathi et al. 2024; Zhou et al. 2024). Deep learning methods have improved MRI by speeding acquisition, boosting

signal-to-noise ratio, and enhancing diffusion-weighted imaging. However, challenges like validation across diverse clinical cases and ensuring model generalizability remain. Furthermore, the reliance on proprietary algorithms may limit access to cutting-edge techniques for some facilities (Abbasi et al. 2023; Chen et al. 2023; Potočník et al. 2023; Z. Zhang & Sejdić 2019). Understanding benefits and limitations is beneficial for radiographers, clinicians and researchers aiming to optimize MRI imaging for diagnostic purposes (Montalt-Tordera et al. 2021; Y. Zhang et al. 2024).

Looking ahead, there is a need for continued research into hybrid approaches that combine traditional MRI techniques with emerging deep learning technologies. For example, integrating patent claims related to innovative imaging sequences with DL could pave the way for novel solutions that address current limitations (Chen et al. 2023; Wang et al. 2019). This hybrid approach can leverage the strengths of both traditional methods and DL to enhance MRI quality further. This combination can provide more reliable and effective results, as traditional techniques can complement the DL models and address the data limitation challenges (Moummad et al. 2022).

Additionally, ongoing exploration into the inner workings of deep learning models is vital to understanding how they can better enhance MRI quality (Montalt-Tordera et al. 2021; Singh et al. 2023). While deep learning has improved MRI images, its complex algorithms often operate as a "black box" - their decision-making is not transparent. To fully leverage deep learning for MRI enhancement, it is beneficial to gain a deeper understanding of how these models function and the factors influencing their performance. This transparency will allow researchers, clinicians, and developers to optimize the application of deep learning, tailoring the models to specific clinical needs and refining them to overcome limitations. By demystifying the mechanisms of deep learning, its transformative power in MRI enhancement can be maximized.

Classifying patents related to MRI as either purely investigative techniques or commercially viable technologies presents a significant challenge due to several factors. The primary difficulty stems from the limited visibility into the actual implementation and impact of patented MRI technologies. Often, the details provided in patent applications do not fully

reveal whether a technology is practically applicable or remains largely theoretical. To address this classification problem, further research is essential. Specifically, in-depth studies of white papers and technical documentation associated with these patents could provide additional clarity. These documents often contain detailed descriptions of the technology, experimental results, and potential applications, which are not always apparent from the patent text alone. Therefore, it is recommended that future studies focus on analysing the supplementary materials related to MRI patents to gain a more accurate understanding of their nature and potential impact. This approach would enhance the ability to differentiate between investigative techniques and commercially relevant technologies in the field of MRI.

This scoping review employed a comprehensive search strategy across multiple databases, using specific keywords related to MRI enhancement techniques to ensure the identification of relevant articles and patents. The adherence to the PRISMA guidelines and the inclusion of a PRISMA diagram further enhanced the transparency, reproducibility, and clarity of the study. Additionally, the application of structured database filters helped to refine the search results, focusing on high-quality, relevant studies that aligned with the review's objectives, thus minimizing the inclusion of irrelevant data and enhancing the precision of the findings.

The review has several limitations. First, it only considered articles published in English, which may result in a language bias and the exclusion of valuable research in other languages. Second, while the review spanned multiple databases and included patents from 2015 to 2024, it focused primarily on review articles from 2019 to 2024, which may not capture earlier foundational research or ongoing developments beyond the specified period. Finally, the reliance on indexed databases could overlook grey literature or unpublished studies that could provide additional insights, although the inclusion of patents helps mitigate this limitation to some extent.

Despite these limitations, the systematic and structured approach used in this review ensures that the findings are robust and reproducible, providing a valuable contribution to the understanding of MRI enhancement techniques. The methodology's strengths, particularly the comprehensive search strategy and adherence to PRISMA guidelines,

enhance the reliability and validity of the conclusions drawn from this review.

Analysis of the 45 (Table S3\_Study Characteristics, can be found in the supplementary section) items from the included studies reveals a clear predominance of research originating from high-income countries, which account for approximately 71% (32/45) of the geographic entries. The United States leads with 13 entries (29%), primarily linked to advanced MRI infrastructure and AI integration, followed by Germany (6 entries, 13%) focusing on high-resource systems for diffusion-weighted imaging and glioblastoma protocols. Japan and China each contribute 5 entries (11%), highlighting super-resolution techniques and growing AI applications in high-resource and middle-high income Asian contexts, respectively.

European high-income nations show substantial representation, with the UK (2), Netherlands (1), Switzerland (2), France (2), Portugal (1), and Greece (1) totalling 9 entries (20%), often emphasizing machine learning reconstruction and specialized MRI applications suited to advanced healthcare settings. Middle-income countries are less prevalent at 13% (6/45), including Iran (1), Indonesia (1), Brazil (1), and India (2), where studies address emerging challenges in denoising and motion correction relevant to developing MRI expertise.

Limited contributions from low- and middle-income countries appear in only 2 entries (4%), from Rwanda/South Africa, targeting constrained MRI availability. Canada features in 3 entries (7%) with broad AI reviews applicable across contexts. This distribution underscores the concentration of MRI image quality and deep learning research in regions with robust technological infrastructure, potentially limiting generalizability to resource-poor settings.

Future research should focus on combining familiar traditional methods (e.g., NLM noise filtering, motion correction) with deep learning (DL) workflows. Key steps for researchers include: (1) using traditional processing upfront to create clear feature maps that track changes and cut DL's "black box" mystery; (2) building flexible setups where DL improves images and traditional physics checks validate results; and (3) requiring standard tests on varied MRI scans to reveal DL choices and compare hybrids against pure DL across sites. To boost reliability across cases, use transfer learning from shared MRI libraries and

create open benchmarks for these hybrids, adding scan shortcuts like compressed sensing. This plan draws straight from our review of each method's strengths and limits.

## Conclusion

This scoping review highlights significant advancements in MRI enhancement techniques, particularly in artefact reduction, noise minimization, and resolution enhancement. Techniques such as MARS and SEMAC have demonstrated effectiveness in reducing artefacts, while silent gradient sequences have improved noise reduction, contributing to clearer and more diagnostically useful images.

DL methodologies have emerged as a transformative force in MRI enhancement, playing a crucial role in improving image quality. These methods enhance image quality by denoising and improving contrast, holding substantial potential for clinical applications such as diffusion-weighted imaging. DL reconstruction techniques are instrumental in enhancing image resolution by reconstructing high-quality images from under sampled data, thereby improving diagnostic accuracy and reducing scan times. Additionally, DL refines the capabilities of traditional techniques by removing noise and preserving anatomical details, leading to more accurate and efficient diagnostic imaging. However, DL also introduces challenges such as obscuring small lesions or introducing artefacts, and its implementation is hindered by data confidentiality issues and limited dataset availability.

Performance metrics such as accuracy, processing speed, and SNR are crucial for evaluating the effectiveness of MRI enhancement techniques. Despite the challenges associated with DL, its integration in MRI has the potential to revolutionize clinical diagnostics by reducing scanning times and improving image quality, thereby enhancing patient care and outcomes.

Future research (elaborated in the discussion section) should focus on addressing these challenges, ensuring that advanced MRI techniques are widely adopted in clinical settings. This includes implementation of evaluation measures for machine learning-based reconstruction methods and addressing ethical concerns related to data privacy. By overcoming these obstacles, MRI can continue to evolve as a powerful diagnostic tool, offering high-

quality imaging that supports precise medical interventions and ultimately enhances patient outcomes.

**Supplementary Materials:** [Figure S1: PRISMA diagram of the article collection process adapted from PRISMA2020](#); [Figure S2: Overview of Artefact Reduction, Noise Reduction and Image Quality Enhancement](#); [Table S1: MMAT appraisal for Advancements in MRI Enhancement Techniques](#).

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## Abbreviations

The following abbreviations are used in this manuscript:

3DT2SPACE	3D T2-weighted Sampling Perfection with Application optimized Contrasts using different flip angle Evolutions
ADC	Apparent Diffusion Coefficient
AE	Autoencoders
AI	Artificial Intelligence
AiCE	Advanced Intelligent Clear-IQ Engine
ASL	Arterial Spin Labelling
BM3D	Block-Matching and 3D Filtering
CF	Cystic Fibrosis
CNN	Convolutional Neural Network
CNR	Contrast-To-Noise Ratio
CS	Compressed Sensing
DCE	Dynamic Contrast-Enhanced
DL	Deep Learning
DLMC	Deep Learning Motion Correction
DLR	Deep Learning-Based Reconstruction
DW	Diffusion-Weighted Imaging
DWI	Diffusion-Weighted
EPI	Echo-Planar Imaging
F1	Sharpen-1 Digital Filter
F2	Sharpen-2 Digital Filter
FSE	Fast Spin Echo
GAN	Generative Adversarial Network
GRAPPA	Generalized Auto calibrating Partially Parallel Acquisition
JD	Joint Denoising
MARS	Metal Artefact Reduction Sequence
MMAT	Mixed Methods Appraisal Tool
MRI	Magnetic Resonance Imaging
NRMSE	Normalized RMSE
PAT	Parallel Acquisition Techniques
PMC	Prospective Motion Correction
PRISMA	Preferred Reporting Items for Systematic Reviews and Meta-Analyses
PROPELLER	Periodically Rotated Overlapping Parallel Lines with Enhanced Reconstruction
PSNR	Peak Snr
PVR	Patch-To-Volume Reconstruction
RF	Radio Frequency
RMC	Retrospective Motion Correction
RMSE	Root Mean Square Error
SEMAC	Slice Encoding for Metal Artefact Correction
SENSE	Sensitivity Encoding
SMS	Simultaneous Multi-Slice
SNR	Signal-To-Noise Ratio
SPEEDER	Speed Enhancement by Exploiting Data Redundancy
SR	Super-Resolution
ssFSE	Single-Shot Fast Spin Echo
SSIM	Structural Similarity Index
SVR	Slice-To-Volume Reconstruction
ZTE	Zero Echo Time

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Note \* indicates the 45 selected references used in the final analysis of the scoping review.

## Radiografiatieteessä tutkitaan ihmislähtöisiä, turvallisia ja laadukkaita kuvantamisen ja sädehoidon palveluja

Lectio praecursoria, esitetty Turun yliopistossa, lääketieteellisessä tiedekunnassa 27.6 2025

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Suomessa tehdään keskimäärin 6,5–7 miljoonaa kuvantamistutkimusta vuodessa. Erityisesti kasvu on viime vuosina ollut vaativimmissa kuvantamistutkimuksissa, kuten tietokonetomografia- ja magneettikuvauksissa. Sädehoitoa puolestaan saa noin puolet kaikista syöpään sairastuneista eli arviolta 17 000 potilasta vuodessa. Kuvantamistutkimusten ja sädehoidon tarve on kasvussa, muun muassa siksi että Suomessa väestö ikääntyy ja samalla tarve näille palveluille kasvaa. Nykyään asiakkaat ovat myös laatumietoisempia, mikä lisää tarvetta kehittää palveluja asiakaslähtöisesti.

Kuvantamistutkimuksia ja sädehoitoa yhdistää se, että ne molemmat katsotaan kuuluvan alaan, jota kutsutaan radiografiaksi. Radiografia alana koskettaa todennäköisesti meitä jokaista jossain elämän vaiheessa, sillä diagnostiset palvelut ovat välttämättömiä lähes kaikilla hoitopoluilla modernissa terveydenhuollossa. Olet siis tutustunut radiografian maailmaan, jos sinulta koskaan on otettu röntgenkuva, olet käynyt ultraääni-, magneetti- tai tietokonetomografiatutkimuksessa tai mammografiaseulonnassa. Tai jos sinun tai läheisesi syövän hoitoon on annettu sädehoitoa. Radiografiassa toimitaan potilaan hoidon ja tekniikan rajapinnalla, röntgenhoitajan ollen usein ainoa terveydenhuollon ammattilainen, jonka potilas kohtaa kuvantamistutkimuksen tai sädehoidon aikana. Radiografia tulee erottaa käsitteenä radiologiasta, joka on lääketieteen erikoisala, jonka ytimessä erilaisten sairauksien diagnosointi niiden kuvien pohjalta, jotka röntgenhoitaja on ottanut.

Käytännön toimintana radiografialla on pitkä historia, joka juontaa juurensa röntgensäteilyn ja radioaktiivisuuden keksimiseen 1800-luvun loppupuolella. Pian säteilyn keksimisen jälkeen havainnoitiin, että sitä voitaisiin käyttää lääketieteessä diagnosoimaan ja hoitamaan sairauksia. Tämän uuden keksinnön ympärille kehittyi myös oma

ammattiryhmä, joka operoi säteilyllä, tuottaen diagnostista informaatiota eri sairauksien hoitoon ja seurantaan lääketieteen eri erikoisaloille kliinikoiden hoitopäätösten tueksi. Tätä ammattiryhmää kutsuttiin aluksi röntgenteknisiksi apulaisiksi, myöhemmin röntgenhoitajiksi. Röntgenkuvantaminen sai ensimmäisen tieteellisen julkaisunsa jo vuonna 1896. Tuon julkaisun ensimmäisessä numerossa todettiin näin: " Tämän uuden taidon kehitys on ollut niin nopeaa, että vaikka professori Röntgenin keksintö on vasta eilinen asia, se on jo ottanut paikkansa hyväksyttynä diagnoosin apuvälineenä ". Nykyään on vaikea kuvitella, miten esimerkiksi leikkauksia suunniteltaisiin ilman mitään käsitystä siitä, millaisia sisäisiä vammoja potilaalla on.

1900-luvun loppupuolella useassa maassa havainnoitiin, että diagnostiikka on kehittymässä vaativammaksi, teknologia kehittyi ja palvelujen tuottaminen vaatii korkeampaa koulutusta. Myös Suomessa röntgenhoitajien koulutus siirtyi korkeakouluun 1990-luvulla. Korkeakoulutukseen siirtymisen myötä tarve alan tutkimustiedolle tunnistettiin paremmin.

Teknologinen kehitys alalla ei osoita hidastumisen merkkejä. Tekoälyn kehittyminen on tuottanut uudenlaisia ratkaisuja, mutta samalla osoittanut puutteita ja eettisiä haasteita. Tutkimuksen tarve radiografian alalla on ilmeinen, sillä ala on jatkuvassa muutoksessa. Niukkenevien terveydenhuollon resurssien myötä, olisi myös tärkeää tunnistaa vaikuttavimmat kuvantamisen ja sädehoidon käytännöt. Vaikuttavien palvelujen tunnistamiseen vaaditaan alan tutkimusta. Alan tutkimusta tarvitaan myös ihmislähtöisen toiminnan kehittämiseen ja kuvaus- ja hoitoprosessien laadun parantamisen tueksi. Unohtamatta alan koulutusta, joka kaipaa tutkimustietoa, jotta tulevilla ammattilaisilla olisi valmistuttuaan tietoa ja osaamista tutkituista ja vaikuttavista käytänteistä, sekä kompetensseja edelleen kehittää alaa.

Radiografian alalle tuottaa tutkimustietoa tieteenala, jota kutsutaan radiografiatieteeksi, joskus myös kliiniseksi radiografiatieteeksi. Kansainvälisesti sillä ei ole vakiintunutta nimeä. Tieteenalassa yhdistyy luonnontieteellinen, tekninen ja humanistinen näkökulma. Tieteenalana se on vielä nuori ja nuoruudesta kertoo myös se, että tieteenalan paradigmaa on tutkittu vähän. Väitöskirjassani tarkastelin radiografiatieteen paradigmaa. Paradigmalla viitataan tieteenalalla vallitseviin näkemyksiin muun muassa siitä, mitä ilmiöitä alalla tutkitaan, millaisiin ongelmiin etsitään vastauksia, mitä menetelmiä tutkimuksessa käytetään, millaista tutkimusta arvostetaan ja miten tutkijat tieteenalalla ymmärtävät todellisuuden ja tiedon luonteen, jonka pohjalta he tekevät oletuksia tutkittavista ilmiöistä. Voidaan sanoa, että paradigma on kuin ikkuna tieteenalan maailmaan. Katselemalla tieteenalaa tuon ikkunan läpi, voimme ymmärtää miten tieteenalan tutkijat tulkitsevat maailmaa ja siinä esiintyviä ilmiöitä, ymmärrämme paremmin, miten tutkimusta tehdään, miten tuloksia suhteutetaan ympäröivään maailmaan ja mitä alalla pidetään oikeana tietona.

Paradigma sitoo tieteenalan myös vahvemmin muuhun akateemiseen yhteisöön. Paradigman avulla tieteenala voi perustella oman olemassaolonsa merkitystä ja auttaa tunnistamaan tieteenalan muista, samankaltaisia ilmiöitä tutkivista tieteenaloista. Radiografiatieteen kohdalla tämä on erityisen merkityksellistä, sillä alalla ei ole tällä hetkellä omaa yliopistokoulusta Suomessa, jossa radiografiatiedettä voisi opiskella oman tieteenalan lähtökohdista ja erityispiirteet huomioiden. On hyvä huomioida, että kaikki röntgenhoitajien tekemä tutkimus ei ole radiografiatiedettä, sillä röntgenhoitajataustaiset henkilöt voivat tehdä tutkimusta myös muilla aloilla.

Kun aloitin väitöskirjatyöni, radiografiatiedettä oli tutkittu jonkin verran jo aikaisemmin. Oli tutkittu esimerkiksi tieteenalan keskeisiä käsitteitä ja tehty tieteenalan tutkimuksen kartoituksia. Aiemmissa tutkimuksissa oli todettu, että röntgenhoitajilla on myönteinen suhtautuminen tutkimukseen, mutta he toimivat harvoin päätutkijana tutkimusprojekteissa. Haasteina tutkimustyölle on tunnistettu muun muassa tutkimustaitojen puute, tutkimuskulttuurin puuttuminen ja rahoituksen puute. Motivaattorina tutkimusuralle on mainittu esimerkiksi halu kehittää alaa, potilaiden hoitoa ja omaa uraa.

Tieteenalan koulutuksen tutkimuksissa oli todettu, että radiografian koulutus ja perinteet vaihtelevat kansainvälisesti paljon, ja yhteisiä näkemyksiä on vaikea löytää. Myös sädehoidon ja kuvantamisen erilaisuutta on korostettu ja monissa maissa niitä tarkastellaan erillisinä aloina. Päätin tarkastella niitä yhtenä radiografiatieteen alana, sillä niillä enemmän yhteneväisyyksiä kuin eroavaisuuksia ja ne ovat jatkuvasti lähentyneet toisiaan. Molemmissa operoidaan säteilyn ja teknologian avulla, ja niissä kohdataan ihmisiä erilaisia elämäntilanteissa. Kuvantamisen puolella annetaan syöpähoitoja esimerkiksi toimenpideradiologian yhteydessä ja sädehoidossa simuloidaan hoitotilanteita kuvantamisen teknologialla, tietokonetomografialla ja magneettikuvauksella.

Voidaan sanoa, että radiografia alana on hyvin samankaltainen riippumatta siitä, missä päin maailmaa ollaan. Kuvantamistutkimuksia tehdään sairauksien diagnosoimiseksi ja hoidon vasteen varmistamiseksi yhtä lailla Suomessa kuin Kanadassa tai Afrikassa. Sädehoito on merkittävässä asemassa syövän hoidossa. Missä vain teknologia sen sallii. Lähtiessäni tätä väitöskirjaa tekemään, minua kiinnosti ajatus siitä, että jos ympäristö, jossa toimitaan ja ilmiöt, joita tutkitaan ovat samanlaisia, eikö tieteenalan näkökulman eli paradigman pitäisi olla kansainvälisesti myös tunnistettavissa? Tein myös havainnon, että radiografiatieteessä ylipäätään on vähän keskusteltu tieteenalan filosofisista lähtökohdista. Mikä on erikoista siitä näkökulmasta, että filosofiset lähtökohdat ovat se perusta, jolle tieteenalan tutkimusta rakennetaan.

Lähdin tutkimaan kansainvälistä aineistoa, tavoitteenani tutkia radiografiatiedettä tieteenalana ja esittää tieteenalalle paradigma. Urakka oli suuri ja lopullista totuutta on vaikea, ellei mahdotonta tavoittaa. Väitöskirjatutkimukseni jälkeen tiedämme radiografiatieteestä kuitenkin paljon enemmän kuin tiesimme ennen kuin tutkimustani aloitin.

Väitöstutkimus eteni kolmessa vaiheessa. Ensimmäisessä vaiheessa tunnistettiin radiografiatieteessä tutkittavat ilmiöt ja tutkittavista ilmiöistä ne, joita pidetään tieteenalalla tärkeimpinä tutkimuskohteina ja keskeisinä käsitteinä. Toisessa vaiheessa keskeiset käsitteet ja niiden väliset suhteet määriteltiin, kuten myös tieteenalan tiedolliset mielenkiinnon kohteet ja minkälaista tietoa

tieteenalalla tuotetaan. Kolmannessa vaiheessa yhdistettiin aiemmin kerätty aineisto ja tarkasteltiin sitä tieteenfilosofi Thomas Kuhnin määrittelemän tieteenalamatriisin kautta ja muodostettiin viitekehys paradigmalle. Tieteenalamatriisissa kuvataan tieteenalan jaetut arvot, symboliset yleistykset, malliesimerkit ja metafysiset oletukset.

Tutkimuksessani osoitin, että radiografiatieteelle on mahdollista määritellä yhtenevä, vallitseva paradigma kansainvälisesti. Vaikka käytännöt ja koulutus vaihtelevat niin kuvantamisessa ja sädehoidossa jonkin verran, on silti mahdollista tunnistaa yhteisiä ilmiöitä, joita tieteenalalla tutkitaan. Radiografiatieteen keskeiset tutkimuskohteet liittyvät radiografian kliinisten käytäntöjen, röntgenhoitajien ammatin, turvallisen ja laadukkaan säteilynkäytön ja radiografian alalla käytettävän teknologian rajapinnoilla tapahtuviin ilmiöihin. Radiografiatieteen tutkimusta tehdään, jotta voisimme tuottaa ihmislähtöisiä, turvallisia ja laadukkaita kuvantamisen ja sädehoidon palveluja ihmisten hyvinvoinnin parantamiseksi.

Väitöstutkimuksen tuloksia voidaan hyödyntää kehitettäessä diagnostisten alojen koulutusta ja tutkimusta. Tuoreessa Sosiaali- ja terveysministeriön julkaisussa hoitohenkilöstön koulutuksesta todettiin, että diagnostiikka-aloille kaivataan omaa perustutkimusta täydentävää koulutusta, sillä muiden alojen koulutukset eivät palvele tätä alaa. Suomessa radiografiatiede on ollut monta vuotta pysähtyneessä tilassa yliopistokoulutuksen puutteen vuoksi. Tutkimusta tehdään jonkin verran ammattikorkeakouluissa mm. erilaisissa hankkeissa. Radiografiatieteellä on oma pieni, mutta aktiivinen tutkimusseura sekä oma tieteenalan julkaisu, mutta tutkimus voisi olla laajempaa ja aktiivisempaa. Yliopistoissa tieteenalan tutkimusta tehdään muiden tieteenalojen alaisuudessa. Tehdessä tutkimusta muiden tieteenalojen alla, radiografiatieteen oma näkökulma voi jäädä vähemmälle huomiolle. Oman yliopistokoulutuksen avulla mahdollistettaisiin tohtoripolut, joissa tutkimusta tehdään oman tieteenalan paradigman lähtökohdista. Tohtorin tutkintoa pidetään edellytyksenä itsenäisen tutkimuksen suorittamiseen. Radiografian alalla on todettu Suomessa ja kansainvälisesti olevan vähemmän tohtorin tutkinnon omaavia, kuin muilla vastaavilla aloilla, esimerkiksi sairaanhoitajien keskuudessa. Yhtenä syynä tähän on pidetty omien tohtoripolkujen puutetta ja vähäisiä mahdollisuuksia edetä kliinisestä röntgenhoitajan työstä tutkijan urapolulle.

Oman koulutuksen avulla tutkimuksen edistäminen ei olisi vain pienen aktiivisen joukon ylläpitämää. Kansainvälisesti radiografiatieteen tutkimus menee eteenpäin nopeasti. Etenkin Euroopassa julkaisutoiminta on kiihtynyt viime vuosina, ja tutkimusten taso on laadullisesti korkeampaa. Riskinä Suomessa on jäädä jälkeen tästä kehityksestä.

Tutkimuksen tulokset ovat merkityksellisiä myös röntgenhoitajien ammattikunnalle. Ammattialan kehitykselle ja autonomiselle asemalle on merkityksellistä, että alalle tuottaa tietoa oma tieteenala, jolla on oma määritelty paradigma.

Tutkimuksen tuloksia voidaan hyödyntää kansainvälisesti kehitettäessä radiografiatieteen tieteenalaa ja pohjana monikansalliselle tutkimukselle. Aiemmissä tutkimuksissa on todettu, että yhteisen paradigman puute hankaloittaa tutkijoiden välistä yhteistyötä ja kun tutkijoilla on yhteinen paradigma, jonka pohjalle tutkimusta voidaan rakentaa, on yhteistyö sujuvampaa. Paradigman avulla myös yksittäiset radiografiatieteen tutkijat voivat suunnata omaa tutkimustaan kohti tieteenalalle merkityksellisiä tutkimusongelmia ja perustella omia näkökulmiaan. Tieteenalan paradigma on muuttuva ja monitahoinen, ja tarkastelemalla sitä säännöllisin väliajoin tieteenala voi kehittyä.

Viime kädessä tämä tutkimus hyödyttää kuvantamisen ja sädehoidon palveluja käyttäviä ihmisiä, sillä tieteenalan kehittyminen tuottaa laadukkaampaa tutkimusta näiden palvelujen parantamiseksi.

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