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REVIEW ARTICLE

Current Trends and Future Prospects of Artificial Intelligence in Transforming Radiology

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Abstract

Artificial intelligence (AI) has rapidly transformed numerous industries, including medicine, with radiography standing to benefit significantly from its capabilities. AI enhances diagnostic accuracy, reduces errors, and improves patient care by leveraging large datasets from digital radiographs commonly used in medical and dental practices. Despite these advantages, the impact of AI on image acquisition and radiographer workflows remains underexplored in radiography literature. This review aims to evaluate the effects of AI on radiographic practices, address regulatory challenges, and explore its integration into educational frameworks for radiologists and radiographers. It highlights AI's role in automating tasks, enhancing diagnostic precision, and improving clinical decision-making. A systematic literature search was conducted using PubMed and Google Scholar up to December 2024, with terms including "artificial intelligence," "machine learning," "deep learning," "radiography," and "diagnostic imaging." Seventy-seven peer-reviewed articles and conference papers focusing on AI applications in digital dental radiography were analyzed to extract data on AI methodologies and their potential applications. The findings reveal that AI-powered solutions enhance efficiency in complex imaging tasks, such as lesion identification and triage in mammography, and real-time assessments in cross-sectional imaging, reducing the need for re-scans and increasing patient throughput. However, widespread adoption faces obstacles related to ethical and legal concerns, including data privacy, algorithmic bias, and the need for transparency. While AI demonstrates significant potential to automate workflows, improve diagnostic accuracy, and optimize patient care in radiography, challenges related to human oversight, professional adaptation, and regulatory compliance must be addressed. Further research is needed to fully understand AI′s impact on radiography and to maximize its clinical utility.

Keywords: Artificial Intelligence (AI), Radiography, Machine Learning, Diagnostic Imaging, Medical Practice, Deep Learning, AI in Diagnostic Imaging, etc.

INTRODUCTION

Artificial intelligence (AI) encompasses technologies that enable computers to replicate human intelligence, performing tasks such as learning, problem-solving, and decision-making autonomously. Machine learning (ML), a subfield of AI, focuses on developing algorithms that can identify patterns in data and improve their performance over time without requiring explicit task-specific programming. Deep learning, an advanced subset of ML, employs artificial neural networks inspired by the human brain to model complex patterns in data. These distinctions are critical for radiology, where AI methodologies have shown significant potential in processing large imaging datasets with precision, facilitating diagnostic workflows, and enhancing decision-making accuracy (Hosny et al., 2018; Do et al., 2020).

AI technologies such as virtual assistants, image recognition systems, and search engines have profoundly influenced daily life and healthcare, assisting medical professionals in tasks ranging from illness detection to treatment planning (Jiang et al., 2017). In radiology, the

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shift toward digital imaging, including computed tomography (CT), panoramic radiographs, and cone-beam CT, has resulted in extensive data repositories. These datasets provide a foundation for AI applications, enabling objective, quantitative, and efficient data processing to automate tasks and improve diagnostic accuracy (Thrall et al., 2018). Furthermore, AI facilitates the analysis of complex clinical data, contributing to tailored patient care and better therapeutic outcomes (Joda et al., 2021).

The transformative potential of AI in radiology has fueled considerable research interest. Advances in AI methodologies, particularly in deep learning, have enabled applications in areas such as lesion detection, tumor segmentation, and disease progression monitoring. Dental and maxillofacial radiography have also benefited, with AI-driven systems enhancing diagnostic capabilities and standardizing imaging protocols (Soffer et al., 2019; Hung et al., 2020). Despite these advancements, the practical adoption of AI faces significant challenges, including issues of data privacy, algorithmic bias, and the interpretability of AI models (Nensa et al., 2019; Bluemke et al., 2020).

While AI applications in radiology have demonstrated promise, several critical research gaps persist. Data standardization across imaging modalities remains a challenge, as inconsistent data formats hinder the development of robust, generalizable AI models (Do et al., 2020). Algorithmic bias, resulting from imbalanced training datasets, raises concerns about the equity of AI-driven diagnoses, particularly for underrepresented populations (Thrall et al., 2018). Furthermore, the interpretability of AI models—essential for building trust among clinicians—requires innovative approaches to make complex neural network decisions more transparent (Kuo et al., 2019).

Integrating AI into existing healthcare workflows is another significant hurdle. AI systems must align with regulatory frameworks, such as the Ionising Radiation (Medical Exposure) Regulations, which mandate human oversight for medical imaging (Hall, 2019). This regulatory landscape complicates the automation of radiological tasks and necessitates careful consideration of ethical and legal implications (Langlotz, 2019). Additionally, data privacy concerns and the high costs associated with AI infrastructure pose barriers to widespread adoption, especially in resource-constrained healthcare settings (Khalighi et al., 2024).

The current body of literature underscores the potential of AI in radiology but highlights notable gaps. For instance, while substantial progress has been made in automating image analysis, there is limited research on the integration of AI into clinical workflows, including how it complements decision-making by radiologists. Additionally, the lack of standardized protocols for training and validating AI models impedes the development of robust systems capable of generalizing across diverse clinical settings (Bluemke et al., 2020; Hung et al., 2020). Addressing these gaps is essential for maximizing the clinical utility of AI and ensuring its ethical and equitable adoption.

This study seeks to address these research gaps by exploring the application of AI in radiology, with a particular focus on its integration into clinical workflows, challenges in implementation, and potential solutions. By categorizing AI applications, analyzing current methodological advancements, and highlighting unresolved issues such as data standardization and algorithm transparency, this research aims to contribute to the ongoing discourse on optimizing AI for clinical radiology. Ultimately, this study aspires to provide a foundation for future research and practical guidelines that support the ethical and effective adoption of AI in radiology, advancing diagnostic accuracy and improving patient outcomes.

MATERIALS AND METHODS

A comprehensive and systematic literature search was conducted using PubMed and Google Scholar to identify relevant studies on artificial intelligence (AI) applications in radiology. The search covered publications up to September 2024 without restricting the publication year to ensure an extensive inclusion of research on AI's advancements over time. The search targeted studies focused on general AI technologies and specific applications in digital radiography, ensuring representation across various radiographic modalities, including intraoral, extraoral, panoramic, cone-beam computed tomography (CBCT), and computed tomography (CT). This approach aimed to capture the breadth of AI's impact in both dentistry and broader radiology contexts.

The search strategy incorporated a robust set of keywords, including "artificial intelligence," "machine learning," "deep learning," "convolution neural network," "automated," "computer-assisted diagnosis," "FDA," "radiography," "diagnostic imaging," and "medical." These terms were selected to reflect the diverse spectrum of AI technologies relevant to radiology, from core computational techniques (e.g., deep learning and convolutional neural networks) to regulatory aspects (e.g., FDA approval processes), which are pivotal for understanding the adoption of AI in clinical settings. To enhance the comprehensiveness of the search, additional terms such as "algorithmic models," "predictive analytics," "image segmentation," and "classification algorithms" were included to ensure the coverage of AI methodologies relevant to image analysis and clinical implementation. These terms were derived from established frameworks and guidelines on AI applications in medical imaging (Bluemke et al., 2020; Kuo et al., 2019).

The selection process began with screening article titles and abstracts for relevance, followed by a detailed review of the full text. Studies were included if they focused on AI applications in radiology, either broadly or specific to digital radiography, presented original research, systematic reviews, or meta-analyses, were published in peer-reviewed journals or reputable conference proceedings, and provided full-text availability. Conversely, studies were excluded if they were limited to abstract-only publications or lacked accessible full texts, did not directly address AI applications in radiology or digital radiography, or lacked methodological transparency, particularly in reporting details on the AI algorithms used. This rigorous approach ensured the inclusion of high-quality and relevant studies for the review.

Manual searches were also conducted by examining the reference lists of the included studies and complementary web searches to identify additional relevant papers. This iterative process ensured the inclusion of high-quality and pertinent research.

The final dataset comprised 77 studies, which were thoroughly analyzed for details on the types of data, AI algorithms, and radiographic modalities addressed. The studies were categorized based on their primary AI methodologies, such as deep learning architectures (e.g., convolutional neural networks) or other machine learning models, and their application in diagnostic imaging, image quality assessment, and clinical decision support (Esses et al., 2018; Looney et al., 2018). This categorization facilitated an in-depth understanding of AI's current capabilities and limitations in radiology.

IMPACT OF AI ON RADIOGRAPHIC PRACTICE

Radiographic technology has included AI since the invention of autonomous exposure systems in the 1980s (Localio & Stack, 2015). Despite their limitations, these devices were able to optimise exposure, which improved efficiency and picture quality by limiting the final mAs value required for optimum exposure (van Lent *et al.*, 2012). The early influence of AI on radiography practice was shown by this technology, even though radiographers still maintained substantial control (Hardy & Harvey, 2020). Especially in situations where the patient's body form impacted picture quality, radiographers swiftly embraced these devices for their capacity to enhance image quality while reducing needless exposure (Tariq *et al.*, 2020). To handle any discrepancies and guarantee patient safety, however, human oversight was still necessary (Walsh *et al.*, 2004).

Systems that can analyse picture quality and recommend ideal acquisition settings for complicated imaging modalities like CT and MRI have recently been launched using AI technology. As an example, AI has been used to improve mammography's lesion identification and triage capabilities, enabling radiographers to assign priority to critical cases according to AI's first evaluation (Mendelson, 2019). According to Rahman *et al.* (2023), AI may improve cross-sectional imaging in real time, which means fewer re-scans are needed. This is supported by a clinical trial conducted by Wu *et al.* (2019), which showed that AI can speed the process. The use of AI-powered tools has revolutionised ultrasonography by facilitating the capture of standardised views. This has had a positive impact on diagnostic accuracy by decreasing variability (Geras *et al.*, 2019). Improved radiography processes and more time for patients are two outcomes of AI in action, as shown in these instances (Putra *et al.*, 2022).

There are regulatory issues about the incorporation of AI with radiography, in addition to operational efficiency. The rules that are in place now aren't always suitable for AI-driven systems that take over decision-making responsibilities that were previously handled by humans (Hall, 2019). For instance, current regulations such as the Ionising Radiation (Medical Exposure) Regulations (2017) need human verification and supervision of imaging procedures, which restricts the level of AI automation that may be used in clinical settings. Algorithmic bias, data privacy, and accountability are some of the specific concerns associated with AI, and regulatory agencies will need to adapt to meet these challenges as the technology develops. The advancement and implementation of completely autonomous AI systems in healthcare settings might be impeded in the absence of revised legislation (Nensa *et al.*, 2019).

The possible advantages of AI must be weighed against the dangers of less human supervision by healthcare facilities. If we want to make sure that using AI boosts departmental efficiency without jeopardising patient safety, we need to do risk assessments and manage responsibility. On top of that, radiologists will have to learn how to supervise AI-powered systems, combining their knowledge in radiography with new abilities in AI cooperation and supervision (Figure 1).

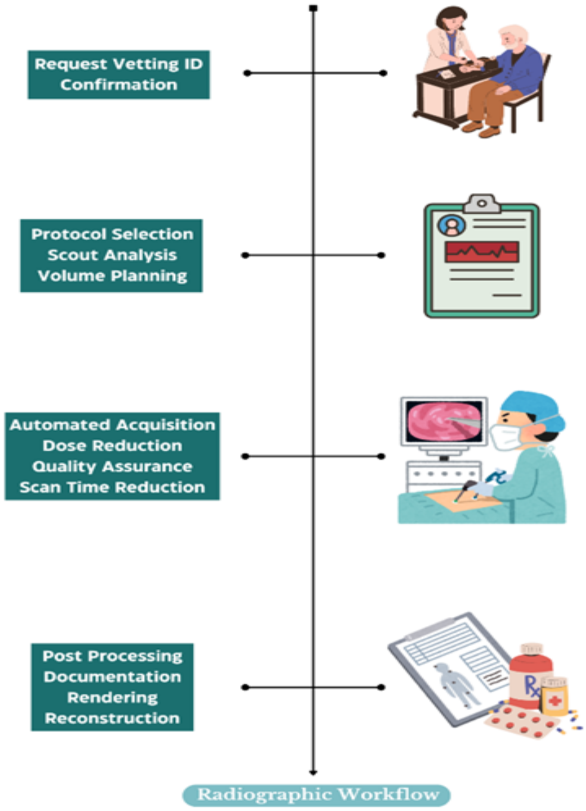

Figure 1. Possible AI-influenced workflow areas in cross-sectional radiography

The radiographer's perspective on the professional challenges posed by the widespread use of AI and the growing automation of image capture has been conspicuously absent from professional and industry literature up until very recently (Murphy & Liszewski, 2019). Comparatively speaking, this stands in sharp contrast to the heated discussions and debates that erupted among radiologists over diagnostic AI when the idea was first mooted as a possible automated solution to radiology reporting backlogs (French & Chen, 2019). Whether this is due to professionals' inability to fathom the magnitude of AI's potential impact, their learnt resistance to change, or their fear of the unknown is unclear (Bluemke *et al.*, 2018). There has been a meteoric rise in the number of articles published in radiology journals addressing artificial intelligence (AI) since 2015. This is likely due to the fact that radiologists have been quick to address initial fears of AI's potential extinction by presenting AI automation in a positive light, arguing that it is an enabling technology rather than a threat to their jobs (Thrall *et al.*, 2018). While some may point to role preservation and protectionism as causes of the recent surge in radiologist interest and debate, it is also fair to say that it has helped to make the case for the importance of human workers in the imaging chain, something that is all too often neglected in the push for better service and lower costs (Langlotz, 2019).

ROLES OF AI IN RADIOGRAPHY

There has been a lot of written on AI's capabilities in medical picture interpretation, but the field of radiography will be drastically changed by this technology and how radiographers operate (Ranschaert *et al*., 2019). In this part, we will delve into the important ways in which AI is changing radiography, along with the effects on clinical processes and the training of radiographers..

Pre-examination assessment

Patients spend a lot of time with radiographers before, during, and after imaging operations. Here, it's crucial to do things like confirm the patient's identification and brief them about the treatment (Pakdemirli, 2019). Robots can't take the position of human radiologists when it comes to patient care, but they can help with paperwork (GE Healthcare, 2019). Artificial intelligence (AI) has many potential applications in healthcare, such as confirming patients' identities via EHR integration, checking referrals, and using patients' medical histories to choose the most appropriate imaging modality (Lakhani *et al*., 2018). Artificial intelligence enables a more effective workflow by automating these pre-exam processes, freeing up radiographers to concentrate on patient care rather than administrative duties. Radiologists must keep an eye on electronic health record data integrity and check that AI-generated suggestions are correct and consistent.

Examination planning

According to Santini *et al*. (2018), radiographers are tasked with situating patients accurately and choosing imaging settings according to the clinical necessity during examination planning. Image quality variability and patient dose mistakes might be reduced with the use of AI-driven solutions that automate tasks like isocentric placement and protocol changes in CT and MRI (Feng *et al*., 2017; Santini *et al*., 2018). As an example, AI has the ability to assess each patient's unique characteristics and recommend the best amount of contrast and injection rate, which might lead to a decrease in the use of contrast media and be in line with personalised treatment (Tong *et al*., 2018; Lou *et al*., 2019). More consistent picture quality with fewer retakes might result from this automation, which would improve production efficiency. Deep learning algorithms have the ability to auto-segment tumours and personalise radiation doses in therapeutic radiography. This might lead to better treatment accuracy and fewer side effects (Teeuwisse *et al*., 2007).

Image acquisition

Another important duty of radiographers is to choose the right imaging methods. On the other hand, diagnostic precision might be compromised due to inconsistent procedure selection (Foley *et al*., 2012). AI may improve consistency across different contexts by automatically suggesting protocols based on patient data (Sammy *et al*., 2017). Improved patient safety and picture quality may be achieved by the use of AI-powered dose reduction algorithms in mammography, CT, and PET/CT (McFadden *et al*., 2013). An area that has long relied on human operators, ultrasonography may now benefit from AI's ability to automate foetal measurements, kidney function assessments, and positioning tools (Brown & Marotta, 2018). Throughput and patient care are both enhanced by these innovations, which enable radiographers to do evaluations more rapidly and precisely.

Image processing

Recent advances in artificial intelligence (AI) have focused on improving image post-processing in radiology, leading to improvements in modality throughput and examination time reduction (Liu et al., 2018). Artificial intelligence algorithms have advanced to the point that they can automatically segment organs, super-resolve pictures (Esses *et al*., 2018), , and even create synthetic modalities, such CT-equivalent images from MR scans (Humphries *et al*., 2019; Looney *et al*., 2018). Radiographers might get high-quality, standardised photos faster with these innovations, cutting down on the requirement for many imaging sessions and improving workflow efficiency (Ahn *et al*., 2019).

Future Implications for Radiographer Training and Careers

There will be a need for radiographers who are skilled in AI technologies since the field is expected to be transformed by AI's growing influence in radiography. To better educate radiographers for jobs that include supervising and evaluating AI-driven activities, future training programs could have to include AI literacy, data management, and ethical issues. As new AI tools and methodologies are developed, radiographers will also need ongoing education on the subject. Aside from streamlining workflows, AI also presents radiographers with chances to hone their technical abilities, positioning them as vital players in the future of AI-driven radiography.

PROSPECTS FOR RADIOLOGISTS

The future of radiology, particularly the roles and responsibilities of radiologists, will be significantly influenced by the increasing integration of AI-driven diagnostic imaging technologies (Wu *et al*., 2017). Historically, radiologists have adapted well to technological advancements, especially when they provide clear benefits for patient health and align with ethical standards (Kuo *et al*., 2019). While large-scale clinical impact studies are limited, AI′s rapid evolution suggests it will soon be widely adopted in radiology. Radiologists must therefore prepare to embrace these new opportunities while maintaining their core commitment to patient care (Yoon *et al*., 2015).

Patient-Radiologist Relationship and Trust-Building

Radiologists have new difficulties in establishing and sustaining trusting connections with their patients as AI becomes more self-reliant. Artificial intelligence technologies fall short of human doctors when it comes to providing the comfort and understanding that patients need. As automation speeds up the referral and screening procedures, the radiologist's role in giving informed consent and talking about radiation hazards and imaging advantages will becoming even more important (Nie *et al*., 2016). To maintain openness and trust with their patients in the face of automation's ability to cut down on patient engagement times, radiologists may have to shift their focus to patient-centered communication. Radiologist shortages are making this change all the more important in countries like the UK, where staffing levels are already low and patient contacts are already constrained (Akkus *et al*., 2018). According to Wang *et al*. (2019), radiologists will most likely continue to be held legally responsible for the operational elements of medical imaging as the "operators" under IR(ME)R laws. As a result, radiologists are under increasing pressure to provide guidelines for the safe and effective use of semi-automated systems in healthcare (NHSx Artificial Intelligence, 2019).

Limitations and Ethical Challenges of AI in Diagnosis

Radiologists must seriously confront the limits of AI, even if it has the potential to increase diagnostic accuracy. According to the Society and College of Radiographers (2019), AI systems may have trouble handling complicated or uncommon instances, which might result in diagnostic mistakes that harm patient results. The use of contextual judgement is essential for AI to recognise subtle abnormalities or unusual presentations, for example. The use of AI in diagnosis is complicated by ethical considerations, such as the possibility of bias in AI algorithms and problems with transparency. Artificial intelligence's dependability in critical contexts is called into doubt when it fails to identify subtle diseases, which may result in missed or delayed diagnosis (Health Education England, 2019). Therefore, radiologists should have a balanced view, appreciating AI for what it can do but being wary of its shortcomings (Royal College of Radiologists, 2019). Spencer (2003) and Roberts *et al.* (2022) are two recent studies that highlight the need of strong ethical frameworks in radiology for addressing these dangers and promoting safe AI integration.

AI-Focused Education and Training

According to Culpan *et al.* (2019), radiologists will need to acquire new abilities in order to take advantage of AI's efficiency advantages in service delivery. Society and College of Radiographers (2019) states that radiologists will need technology-interfacing and cross-modality abilities to supervise different imaging procedures and manage intricate AI-driven workflows due to the increasing patient volumes. In order to prepare students to securely use AI, ML, and DL, radiography programs should make sure that students comprehend the basics. Topol (2019) recommends major changes to healthcare education that would allow doctors and nurses to learn from one another's experiences and adjust their methods to new technologies (Nair *et al.*, 2018). Further education in the statistical foundations of AI is required for radiologists so that they can evaluate AI results with objectivity and put these findings into practice. In order to train a diverse workforce that can manage the changing role of AI in radiology, there must be a change in educational practices (Annarumma *et al.*, 2019).

Radiographer Reporting

Reporting by radiographers is already commonplace in the UK, especially in fields like mammography and projection radiography; however, this practice might be taken to the next level with the help of AI (Culpan *et al.*, 2019). Combining the knowledge of radiographers with the efficiency of AI might solve reporting backlogs and enhance screening turnaround times, especially for high-volume imaging such as mammography and lung screening (Ritchie *et al.*, 2016). Further streamlining of these procedures via research into radiographer-led reporting services helped by AI might make radiology departments more robust to workload demands and personnel shortages (Annarumma *et al.*, 2019). The importance of radiographers in guaranteeing the accuracy of AI-driven imaging cannot be overstated, since human assessment is still required under IR(ME)R standards notwithstanding AI recommendations (Royal College of Radiologists, 2018).

FDA-CLEARED AI TOOLS

The main objective of radiology AI systems that have been authorised by the FDA is to improve healthcare delivery via more efficient and accurate imaging and interpretation of diagnostic data. Reliability in clinical settings is ensured since each instrument has been through extensive assessment to satisfy FDA safety and efficacy criteria. Some of these AI systems detect anomalies in X-ray and magnetic resonance imaging (MRI) scans, while others aid in the analysis of genetic data and the prediction of patient outcomes. By facilitating individualised treatment regimens, speeding up diagnosis, and reducing room for human mistake, these technologies show great potential to improve patient care (Tariq *et al.*, 2020).

Building on this, further research has shown that these AI technologies can perform as well as human radiologists in certain situations, if not better. Consider the following examples: Tschandl *et al.* (2021) demonstrated in a meta-analysis that AI tools for skin lesion detection were just as effective as dermatologists, and Larson *et al.* (2022) cited particular cases where AI-assisted reads of chest radiographs consistently found subtle findings more so than human readers alone. Nevertheless, there are studies that show situations when human supervision is still necessary, which shows that the AI tools' efficiency varies depending on the clinical setting.

Table 1
List of FDA-approved companies

Company	AI Tool (s)
Quantib	Quantib Brain
RADLogics	AI Medical Imaging (AIMI) Platform
Vital Images	Vital CT Lung Density Analysis; Vital CT Brain Perfusion
Koios Medical	Koios DS for Breast
Zebra Medical Vision	HealthCCS; HealthCXR; HealthICH; HealthPNX; HealthVCF
iCAD	PowerLook Tomo Detection V2 Software
Imaging Biometrics	IB Neuro; IB Stone Checker
AIDOC	AIDOC-Briefcase-ICH; AIDOC-Briefcase-CSF; AIDOC-Briefcase-PE; AIDOC-Briefcase-LVO
Subtle Medical	SubtleMR; SubtlePET

Clinical trials using AI tools licensed by the FDA have shown encouraging outcomes in terms of diagnostic efficiency and accuracy, with the tools often reducing the time to diagnosis and helping to lessen the proportion of false positives and negatives. As an example, AI-powered stroke diagnosis on CT scans has greatly improved workflow efficiency, leading to speedier treatments and ultimately better patient outcomes. Also, radiologists are using AI more and more in their practice, albeit not everyone is on board with it. Scepticism about AI tools is starting to fade as these technologies prove to be reliable and operate well with current processes. Continuous validation studies and open performance reporting in real-world settings are crucial for gaining the medical community's confidence and promoting wider clinical usage.

AI POWDERED CARCINOMA MANAGEMENT IN NEUROLOGY SECTION

There are several obstacles in neuro-oncology that patients encounter at different points in their treatment, but AI shows potential as a game-changing tool. Artificial intelligence (AI) has the ability to change the way brain tumours are managed. It can speed up MRI scans, spot anomalies, improve workflows, measure accurately, analyse massive volumes of imaging data, and spot patterns that humans would miss. Neuroimaging and a thorough physical examination are the standard procedures for patients suspected of having a brain tumour. Surgical excision or a sample for histology and molecular analysis may follow a tumor's confirmation. In order to bolster the diagnosis and treatment strategy, additional biomarker testing of serum or cerebrospinal fluid (CSF) may be carried out if necessary. After the clinical team considers the patient's comorbidities, potential toxicity, available clinical trials, and standard care recommendations, they choose the best course of therapy (Villanueva-Meyer et al., 2017).

The complex process involved in neuro-oncology–which includes neurosurgeons, neuroradiologists, molecular pathologists, and neuropathologists–could be aided by artificial intelligence (AI) by integrating data from different imaging and biomarker sources. Nevertheless, neuro-oncology presents a number of obstacles to the use of AI. There are still some technological hurdles to overcome, such as the need for more sophisticated imaging algorithms that can capture the diverse and intricate features of tumours, which are often affected by genetic diversity and the brain tissue around them. Current therapies, such as surgery, radiation, and chemotherapy, might harm nearby healthy tissue due to the vulnerability of brain tissue (Khalighi et al., 2024).

Additional challenges to using AI in clinical neuro-oncology include costs and the need for specialised infrastructure. For smaller healthcare institutions, the continuing expenditures for data storage and processing, as well as the acquisition, maintenance, and upgrading of AI platforms, might be too much to bear. These expenses could make AI less accessible outside of high-resource environments and delay its broad adoption.

As a last point, getting practitioners on board is a big deal since changing clinical procedures is required to include AI technologies into everyday practice. Because of concerns regarding AI dependability, many neuro-oncologists may be hesitant to rely on AI-driven suggestions, particularly in complicated situations that need nuanced judgement. Transparency in decision-making and interpretability to reassure doctors of validity are crucial for AI systems to gain greater adoption. More study and clinical trials are needed to prove the safety, effectiveness, and influence of AI applications in neuro-oncology in order to alleviate these worries (Monsour et al., 2022).

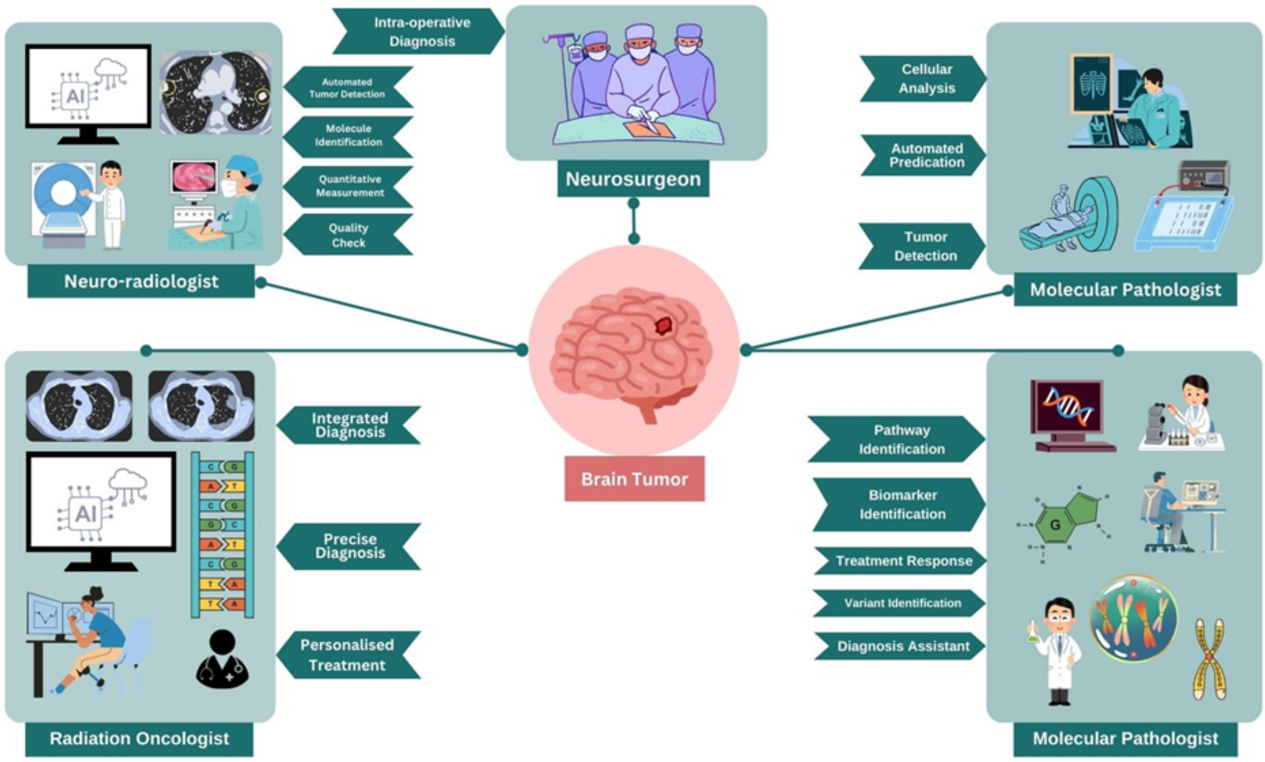

Figure 2. Artificial Intelligence in neuro-oncology. AI aids neuro-oncologists/radiation-oncologists by allowing integrated diagnosis, providing deeper disease insights, predicting outcomes, and stratifying patients to customize treatment strategies. AI helps neuroradiologists detect and segment tumors, identify molecular subtypes, quantify tumors, distinguish them from necrotic regions, and perform automated quality checks using MRI images. AI helps neurosurgeons monitor surgical margins and provide real-time diagnosis and advice, improving surgical accuracy and patient outcomes. AI helps neuropathologists analyze fresh/FFPE samples by automating feature measurement, tumor classification and grading, tumor identification, and histo-molecular categorization of cellular and tissue structures.AI helps molecular pathologists identify biomarkers, pathways, treatment responses, variants, and diagnoses using mutation data, single-cell data, methylation patterns, RNA sequencing, and more (Khalighi et al., 2024).

CONCLUSIONS

Radiography stands to benefit greatly from the imminent advent of AI, which has the ability to automate and improve diagnostic procedures, leading to more efficiency, accuracy, and the possibility of individualised patient treatment. There are several concerns that arise with the incorporation of AI. For example, there is a concern that conventional radiographer positions may be reduced and that strict human control is necessary to ensure quality and patient safety. To successfully monitor AI-driven operations, radiologists must prioritise patient-centered care while embracing these changing technologies and adapting their training to embrace AI capabilities.

The next step in getting physicians to completely trust AI-generated outcomes is for researchers to work on making AI algorithms that are more interpretable and transparent. It is equally crucial to increase clinical involvement in AI research so that tools may be made that fit the practical demands of radiographers and radiologists and are in line with real-world clinical procedures. A more efficient and patient-centered radiography practice, where the benefits of AI are balanced with the essential human aspects of healthcare, will be possible if these areas are addressed.

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Ethics approval and consent to participate

No ethical approval form was taken from any institute for this review article.

Competing/Conflict of interests Statement

The authors declare no conflict of interest

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Authors' contributions

Rezwan Ahmed Mahedi & Sadia Afrin: Web-Analysis Design, Supervised the Data Collection Process, And Checked Writing, Approved Methodology, Manuscript Editing and Supervised All Steps;

Raiyan Azmee, Marzan Azmee & Fatiha Jakir: Researched Literature, Questionnaire Design, And Coordinate and Monitor the Process, Wrote the First Draft of The Manuscript;

Hrishik Iqbal & Nikolaus Syrmos: Final Paper Revision;

Mufassir Ahmad Nishan: Organizing and Data Arrangement, Checked Writing;

Mohammed Burhan Uddin: Final Editing, Reviewing.

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Availability Of Data And Materials

The article and supplementary materials contain the original contributions discussed in the study. Original datasets are available upon reasonable request from the corresponding author.

REFERENCES

Ahn, C. K., Jin, H., Heo, C., & Kim, J. H. (2019). Combined low-dose simulation and deep learning for CT denoising: Application of ultra-low-dose cardiac CTA. In T. G. Schmidt, G.-H. Chen, & H. Bosmans (Eds.), *Medical Imaging 2019: Physics of Medical Imaging* Article 1094846 (Progress in Biomedical Optics and Imaging - Proceedings of SPIE; Vol. 10948). SPIE. https://doi.org/10.1117/12.2513144

Akkus, Z., Kostandy, P. M., Philbrick, K. A., & Erickson, B. J. (2018). Extraction of brain tissue from CT head images using fully convolutional neural networks. In E. D. Angelini & B. A. Landman (Eds.), *Medical Imaging 2018: Image Processing* Article 1057420 (Progress in Biomedical Optics and Imaging - Proceedings of SPIE; Vol. 10574). SPIE. https://doi.org/10.1117/12.2293423

Annarumma, M., Withey, S. J., Bakewell, R. J., Pesce, E., Goh, V., & Montana, G. (2019). Automated triaging of adult chest radiographs with deep artificial neural networks. *Radiology, 291*(1), 196–202. https://doi.org/10.1148/radiol.2018180921

Bluemke, D. A., Moy, L., Bredella, M. A., Ertl-Wagner, B. B., Fowler, K. J., Goh, V. J., Halpern, E. F., Hess, C. P., Schiebler, M. L., & Weiss, C. R.. (2020). Assessing Radiology Research on Artificial Intelligence: A Brief Guide for Authors, Reviewers, and Readers–From the Radiology Editorial Board. *Radiology*, *294*(3), 487–489. https://doi.org/10.1148/radiol.2019192515

Brown, A. D., & Marotta, T. R. (2018). Using machine learning for sequence-level automated MRI protocol selection in neuroradiology. *Journal of the American Medical Informatics Association, 25*(5), 568–571. https://doi.org/10.1093/jamia/ocx125

Culpan, G., Culpan, A. M., Docherty, P., & Denton, E. (2019). Radiographer reporting: A literature review to support cancer workforce planning in England. *Radiography (London, England: 1995), 25*(2), 155–163. https://doi.org/10.1016/j.radi.2019.02.010

Department of Health. (2017). *The Ionising Radiation (Medical Exposure) Regulations*. Retrieved from http://www.legislation.gov.uk/uksi/2017/1322/contents/made

Do, S., Song, K. D., & Chung, J. W. (2020). Basics of deep learning: A radiologist's guide to understanding published radiology articles on deep learning. *Korean Journal of Radiology, 21*(1), 33–41. https://doi.org/10.3348/kjr.2019.0312

Esses, S. J., Lu, X., Zhao, T., Shanbhogue, K., Dane, B., Bruno, M., & Chandarana, H. (2018). Automated image quality evaluation of T2-weighted liver MRI utilizing deep learning architecture. *Journal of Magnetic Resonance Imaging, 47*(3), 723–728. https://doi.org/10.1002/jmri.25779

Feng, S. T., Zhu, H., Peng, Z., Huang, L., Dong, Z., Xu, L., Huang, K., Yang, X., Lin, Z., & Li, Z. P. (2017). An individually optimized protocol of contrast medium injection in enhanced CT scan for liver imaging. *Contrast Media & Molecular Imaging, 2017*, 7350429. https://doi.org/10.1155/2017/7350429

Foley, S. J., McEntee, M. F., & Rainford, L. A. (2012). Establishment of CT diagnostic reference levels in Ireland. *The British Journal of Radiology, 85*(1018), 1390–1397. https://doi.org/10.1259/bjr/15839549

French, J., & Chen, L. (2019). Preparing for artificial intelligence: Systems-level implications for the medical imaging and radiation therapy professions. *Journal of Medical Imaging and Radiation Sciences, 50*(4), S20–S23. https://doi.org/10.1016/j.jmir.2019.09.002

GE Healthcare. (2019). No matter how you slice it, this AI tech is changing MR neuro imaging. Retrieved from http://newsroom.gehealthcare.com/this-ai-tech-is-changing-mr-neuro-imaging/

Geras, K. J., Mann, R. M., & Moy, L. (2019). Artificial intelligence for mammography and digital breast tomosynthesis: Current concepts and future perspectives. *Radiology, 293*(2), 246–259. https://doi.org/10.1148/radiol.2019182627

Hall, M. (2019). Artificial intelligence and nuclear medicine. *Nuclear Medicine Communications, 40*(1), 1–2. https://doi.org/10.1097/MNM.0000000000000937

Hardy, M., & Harvey, H. (2020). Artificial intelligence in diagnostic imaging: Impact on the radiography profession. *The British Journal of Radiology, 93*(1108), 20190840. https://doi.org/10.1259/bjr.20190840

Health Education England. (2019). *The Topol Review: Preparing the healthcare workforce to deliver the digital future*. Retrieved from https://topol.hee.nhs.uk/

Hosny, A., Parmar, C., Quackenbush, J., Schwartz, L. H., & Aerts, H. J. W. L. (2018). Artificial intelligence in radiology. *Nature Reviews Cancer, 18*(8), 500–510. https://doi.org/10.1038/s41568-018-0016-5

Humphries, T., Coulter, S., Si, D., Simms, M., & Xing, R. (2019). Comparison of deep learning approaches to low dose CT using low intensity and sparse view data. In H. Bosmans, G.-H. Chen, & T. Gilat Schmidt (Eds.), *Medical Imaging 2019: Physics of Medical Imaging* (p. 156). SPIE.

Hung, K., Montalvao, C., Tanaka, R., Kawai, T., & Bornstein, M. M.. (2020). The use and performance of artificial intelligence applications in dental and maxillofacial radiology: A systematic review. *Dentomaxillofacial Radiology, 49*(1), 20190107. https://doi.org/10.1259/dmfr.20190107

Jiang, F., Jiang, Y., Zhi, H., Dong, Y., Li, H., Ma, S., Wang, Y., Dong, Q., Shen, H., & Wang, Y.. (2017). Artificial intelligence in healthcare: past, present and future. *Stroke and Vascular Neurology, 2*(4), 230–243. https://doi.org/10.1136/svn-2017-000101

Joda, T., Yeung, A. W. K., Hung, K., Zitzmann, N. U., & Bornstein, M. M. (2021). Disruptive innovation in dentistry: What it is and what could be next. *Journal of Dental Research, 100*(5), 448–453. https://doi.org/10.1177/0022034520978774

Khalighi, S., Reddy, K., Midya, A., Pandav, K. B., Madabhushi, A., & Abedalthagafi, M. (2024). Artificial intelligence in neuro-oncology: Advances and challenges in brain tumor diagnosis, prognosis, and precision treatment. *NPJ Precision Oncology, 8*(1), 80. https://doi.org/10.1038/s41698-024-00575-0

Kuo, C.-C., Chang, C.-M., Liu, K.-T., Lin, W.-K., Chiang, H.-Y., Chung, C.-W., Ho, M.-R., Sun, P.-R., Yang, R.-L., & Chen, K.-T. (2019). Automation of the kidney function prediction and classification through ultrasound-based kidney imaging using deep learning. *NPJ Digital Medicine, 2*(1). https://doi.org/10.1038/s41746-019-0104-2

Lakhani, P., Prater, A. B., Hutson, R. K., Andriole, K. P., Dreyer, K. J., Morey, J., Prevedello, L. M., Clark, T. J., Geis, J. R., Itri, J. N., & Hawkins, C. M. (2018). Machine learning in radiology: Applications beyond image interpretation. *Journal of the American College of Radiology, 15*(2), 350–359. https://doi.org/10.1016/j.jacr.2017.09.044

Langlotz, C. P. (2019). Will artificial intelligence replace radiologists? *Radiology: Artificial Intelligence, 1*(3), e190058. https://doi.org/10.1148/ryai.2019190058

Liu, F., Jang, H., Kijowski, R., Bradshaw, T., & McMillan, A. B. (2018). Deep learning MR imaging-based attenuation correction for PET/MR imaging. *Radiology, 286*(2), 676–684. https://doi.org/10.1148/radiol.2017170700

Liu, J., Zarshenas, A., Wei, Z., Yang, L., Fajardo, L., Suzuki, K., & Qadir, A. (2018). Radiation dose reduction in digital breast tomosynthesis (DBT) by means of deep-learning-based supervised image processing. In E. D. Angelini & B. A. Landman (Eds.), *Medical Imaging 2018: Image Processing* (Vol. 7, p. 14). SPIE.

Liu, S., Wang, Y., Yang, X., Lei, B., Liu, L., Li, S. X., Ni, D., & Wang, T. (2019). Deep learning in medical ultrasound analysis: A review. *Engineering (Beijing, China), 5*(2), 261–275. https://doi.org/10.1016/j.eng.2018.11.020

Localio, A. R., & Stack, C. B. (2015). TRIPOD: A new reporting baseline for developing and interpreting prediction models. *Annals of Internal Medicine, 162*(1), 73–74. https://doi.org/10.7326/M14-2423

Looney, P., Stevenson, G. N., Nicolaides, K. H., Plasencia, W., Molloholli, M., Natsis, S., & Collins, S. L. (2018). Fully automated, real-time 3D ultrasound segmentation to estimate first trimester placental volume using deep learning. *JCI Insight, 3*(11), e120178. https://doi.org/10.1172/jci.insight.120178

Lou, B., Doken, S., Zhuang, T., Wingerter, D., Gidwani, M., Mistry, N., Ladic, L., Kamen, A., & Abazeed, M. E. (2019). An image-based deep learning framework for individualizing radiotherapy dose. *The Lancet Digital Health, 1*(3), e136–e147. https://doi.org/10.1016/S2589-7500(19)30058-5

McFadden, S. L., Hughes, C. M., & Winder, R. J. (2013). Variation in radiographic protocols in paediatric interventional cardiology. *Journal of Radiological Protection, 33*(2), 313–319. https://doi.org/10.1088/0952-4746/33/2/313

Mendelson, E. B. (2019). Artificial intelligence in breast imaging: Potentials and limitations. *AJR. American Journal of Roentgenology, 212*(2), 293–299. https://doi.org/10.2214/AJR.18.20532

Monsour, R., Dutta, M., Mohamed, A. Z., Borkowski, A., & Viswanadhan, N. A. (2022). Neuroimaging in the era of artificial intelligence: Current applications. *Federal Practitioner, 39*(Suppl 1), S14–S20. https://doi.org/10.12788/fp.0231

Murphy, A., & Liszewski, B. (2019). Artificial intelligence and the medical radiation profession: How our advocacy must inform future practice. *Journal of Medical Imaging and Radiation Sciences, 50*(4 Suppl 2), S15–S19. https://doi.org/10.1016/j.jmir.2019.09.001

Nagi, R., Aravinda, K., Rakesh, N., Gupta, R., Pal, A., & Mann, A. K. (2020). Clinical applications and performance of intelligent systems in dental and maxillofacial radiology: A review. *Imaging Science in Dentistry, 50*(2), 81–92. https://doi.org/10.5624/isd.2020.50.2.81

Nair, A., Screaton, N. J., Holemans, J. A., Jones, D., Clements, L., Barton, B., Gartland, N., Duffy, S. W., Baldwin, D. R., Field, J. K., Hansell, D. M., & Devaraj, A. (2018). The impact of trained radiographers as concurrent readers on performance and reading time of experienced radiologists in the UK lung cancer screening (UKLS) trial. *European Radiology, 28*(1), 226–234. https://doi.org/10.1007/s00330-017-4903-z

Nensa, F., Demircioglu, A., & Rischpler, C. (2019). Artificial intelligence in nuclear medicine. *Journal of Nuclear Medicine, 60*(Suppl 2), 29S–37S. https://doi.org/10.2967/jnumed.118.220590

NHSx. (2019). *Artificial intelligence: How to get it right. Putting policy into practice for safe data-driven innovation in health and care*. Retrieved from https://www.nhsx.nhs.uk/assets/NHSX_AI_report.pdf

Nie, D., Cao, X., Gao, Y., Wang, L., & Shen, D. (2016). Estimating CT image from MRI data using 3D fully convolutional networks. *Deep Learning and Data Labeling for Medical Applications: First International Workshop, LABELS 2016, and Second International Workshop, DLMIA 2016, Held in Conjunction with MICCAI 2016, Athens, Greece, October 21, 2016, Proceedings*, 170–178. https://doi.org/10.1007/978-3-319-46976-8_18

Pakdemirli, E. (2019). Artificial intelligence in radiology: Friend or foe? Where are we now and where are we heading? *Acta Radiologica Open, 8*(2), 2058460119830222. https://doi.org/10.1177/2058460119830222

Putra, R. H., Doi, C., Yoda, N., Astuti, E. R., & Sasaki, K. (2022). Current applications and development of artificial intelligence for digital dental radiography. *Dento Maxillo Facial Radiology, 51*(1), 20210197. https://doi.org/10.1259/dmfr.20210197

Qasim Ali, M., Deb, A., Hasan, M. D. S., Rahman, M., Rahman, H., Afrin, S., Rahman Bhuiyan, M. D. K., Roy, U., Uddin, M. B., Mudhafar, M., Syrmos, N., & Ahmed Mahedi, M. D. R. (2022). Cadmium toxicity in nature generates the cancerous problems. *Pollution Research, 41*(4), 1151–1156. https://doi.org/10.53550/pr.2022.v41i04.002

Rahman Bhuiyan, M. K., Rahman, D. M., Kumar Das, S., Shahidul Islam, D. S. M., Mahmud, D. F., Mukit, A., Malik, J. A., Ahmed Mahedi, M. R., Afrin, S., & Symros, N. (2023). Current aspects of non-Hodgkin lymphoma (NHL) in Bangladesh: A mini review. *Clinical Medicine and Health Research Journal, 3*(1), 312–316. https://doi.org/10.18535/cmhrj.v3i01.130

Ranschaert, E. R., Duerinckx, A. J., Algra, P. R., Kotter, E., Kortman, H. G., & Morozov, S. P. (2019). Advantages, challenges, and risks of artificial intelligence for radiologists. *Artificial Intelligence in Medical Imaging*.

Ritchie, A. J., Sanghera, C., Jacobs, C., Zhang, W., Mayo, J., Schmidt, H., Gingras, M., Pasian, S., Stewart, L., Tsai, S., Manos, D., Seely, J. M., Burrowes, P., Bhatia, R., Atkar-Khattra, S., van Ginneken, B., Tammemagi, M., Tsao, M. S., Lam, S., & Pan-Canadian Early Detection of Lung Cancer Study Group. (2016). Computer vision tool and technician as first reader of lung cancer screening CT scans. *Journal of Thoracic Oncology, 11*(5), 709–717. https://doi.org/10.1016/j.jtho.2016.01.021

Royal College of Radiologists. (2018). *Standards for interpretation and reporting of imaging investigations* (2nd ed.). Retrieved from https://www.rcr.ac.uk/system/files/publication/field_publication_files/bfcr181_standards_for_interpretation_reporting.pdf

Royal College of Radiologists. (2019). *Clinical radiology: UK workforce census 2018 report*. Retrieved from https://www.rcr.ac.uk/publication/clinical-radiology-uk-workforce-census-report-2018

Sammy, I. A., Chatha, H., Bouamra, O., Fragoso-Iñiguez, M., Lecky, F., & Edwards, A. (2017). The use of whole-body computed tomography in major trauma: Variations in practice in UK trauma hospitals. *Emergency Medicine Journal, 34*(10), 647–652. https://doi.org/10.1136/emermed-2016-206167

Santini, G., Zumbo, L. M., Martini, N., Valvano, G., Leo, A., Ripoli, A., Avogliero, F., Chiappino, D., & Latta, D. D. (2018). Synthetic contrast enhancement in cardiac CT with deep learning. *ArXiv*. https://arxiv.org/abs/1807.01779

Society and College of Radiographers. (2019). Communicating radiation benefit and risk information to individuals under the ionising radiation (medical exposure) regulations (IR(ME)R).

Soffer, S., Ben-Cohen, A., Shimon, O., Amitai, M. M., Greenspan, H., & Klang, E. (2019). Convolutional neural networks for radiologic images: A radiologist's guide. *Radiology, 290*(3), 590–606. https://doi.org/10.1148/radiol.2018180547

Spencer, N. (2003). Re: Can radiographers read screening mammograms? *Clinical Radiology, 58*(11), 902. https://doi.org/10.1016/j.crad.2003.08.002

Sun, Y., Zhu, Z., & Pang, S. (2019). Learning models for acquisition planning of CT projections (Conference Presentation). *Anomaly Detection and Imaging with X-Rays (ADIX) IV*.

Tariq, A., Purkayastha, S., Padmanaban, G. P., Krupinski, E., Trivedi, H., Banerjee, I., & Gichoya, J. W. (2020). Current clinical applications of artificial intelligence in radiology and their best supporting evidence. *Journal of the American College of Radiology, 17*(11), 1371–1381. https://doi.org/10.1016/j.jacr.2020.08.018

Teeuwisse, W., Geleijns, J., & Veldkamp, W. (2007). An inter-hospital comparison of patient dose based on clinical indications. *European Radiology, 17*(7), 1795–1805. https://doi.org/10.1007/s00330-006-0473-1

The Cancer Workforce Plan: Phase 1: Delivering the cancer strategy to 2021. (2017). Retrieved from https://www.hee.nhs.uk/sites/default/files/documents/Cancer%20Workforce%20Plan%20phase%201%20-%20Delivering%20the%20cancer%20strategy%20to%202021.pdf

Thrall, J. H., Li, X., Li, Q., Cruz, C., Do, S., Dreyer, K., & Brink, J. (2018). Artificial intelligence and machine learning in radiology: Opportunities, challenges, pitfalls, and criteria for success. *Journal of the American College of Radiology, 15*(3 Pt B), 504–508. https://doi.org/10.1016/j.jacr.2017.12.026

Tong, N., Gou, S., Yang, S., Ruan, D., & Sheng, K. (2018). Fully automatic multi-organ segmentation for head and neck cancer radiotherapy using shape representation model constrained fully convolutional neural networks. *Medical Physics, 45*(10), 4558–4567. https://doi.org/10.1002/mp.13147

US Food and Drug Administration. Proposed regulatory framework for modifications to artificial intelligence/machine learning (AI/ML)-based software as a medical device (SaMD): Discussion paper and request for feedback.

van Lent, W. A., Deetman, J. W., Teertstra, H. J., Muller, S. H., Hans, E. W., & van Harten, W. H. (2012). Reducing the throughput time of the diagnostic track involving CT scanning with computer simulation. *European Journal of Radiology, 81*(11), 3131–3140. https://doi.org/10.1016/j.ejrad.2012.03.012

Villanueva-Meyer, J. E., Mabray, M. C., & Cha, S. (2017). Current clinical brain tumor imaging. *Neurosurgery, 81*(3), 397–415. https://doi.org/10.1093/neuros/nyx103

Walsh, C., Larkin, A., Dennan, S., & O'Reilly, G. (2004). Exposure variations under error conditions in automatic exposure-controlled film-screen projection radiography. *The British Journal of Radiology, 77*(923), 931–933. https://doi.org/10.1259/bjr/62185486

Wang, S., He, K., Nie, D., Zhou, S., Gao, Y., & Shen, D. (2019). CT male pelvic organ segmentation using fully convolutional networks with boundary sensitive representation. *Medical Image Analysis, 54*, 168–178. https://doi.org/10.1016/j.media.2019.03.003

Wang, S., Su, Z., Ying, L., Peng, X., Zhu, S., Liang, F., Feng, D., & Liang, D. (2016). Accelerating magnetic resonance imaging via deep learning. In *Proceedings of the IEEE International Symposium on Biomedical Imaging* (pp. 514–517). https://doi.org/10.1109/ISBI.2016.7493320

Wu, G. G., Zhou, L. Q., Xu, J. W., Wang, J. Y., Wei, Q., Deng, Y. B., Cui, X. W., & Dietrich, C. F. (2019). Artificial intelligence in breast ultrasound. *World Journal of Radiology, 11*(2), 19–26. https://doi.org/10.4329/wjr.v11.i2.19

Wu, L., Cheng, J. Z., Li, S., Lei, B., Wang, T., & Ni, D. (2017). FUIQA: Fetal ultrasound image quality assessment with deep convolutional networks. *IEEE Transactions on Cybernetics, 47*(5), 1336–1349. https://doi.org/10.1109/TCYB.2017.2671898

Yielder, J., & Davis, M. (2009). Where radiographers fear to tread: Resistance and apathy in radiography practice. *Radiography (London, England: 1995), 15*(4), 345–350. https://doi.org/10.1016/j.radi.2009.07.002

Yoon, Y., Jeon, H.-G., Yoo, D., Lee, J.-Y., & Kweon, I. S. (2015). Learning a deep convolutional network for light-field image super-resolution. *2015 IEEE International Conference on Computer Vision Workshop (ICCVW).*