Results: DAP and mAs increase as BMI increased. A significant mean difference was found for mean DAP (Gy.m^2) between the virtual grid and physical grid (128.1, < 0.04) with 95% CI [5.5, 250]. The VG has far lower mean DAP values than the conventional grid (3425Gy.m^2) and (16265 Gy.m^2), respectively. The mean effective dose of VG was (0.030.02 mSv) and PG (0.200.15 mSv).

Conclusion: By comparison to PG, VG software promises to lower radiation dose levels in terms of DAP value and effective dose.

DIGITAL TECHNOLOGIES POSTER PRESENTATIONS

P100 Radiographer acceptance of a virtual reality tool for patients prior to MRI

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Background: A key part of a radiographers role within MRI is providing the required emotional support to help patient succeed with a scan. Many patients present with anxiety and concern which can present as claustrophobia due to the nature of the scan equipment. This can impact on patient outcomes as well as operational efficiency. Being informed is important to patients and despite use of information leaflets and videos, these are limited in their representation. This is where preparation using virtual reality could be beneficial. As part of a feasibility study looking at the use of a virtual scan experience for patients prior to MRI, the views of practitioners were sought to see how effective this might be and how best to implement its use in clinical practice.

Methods: 9 radiographers attended two focus group sessions to see the tool, undergo a virtual experience, complete a technology acceptance survey and participate in a discussion about its use.

Results: Perceived usefulness, ease of use, attitude and intention to use were all positive towards the virtual scan tool. All practitioners saw value in such a tool and how it could be implemented within practice, with insights into areas for improvement and development gained.

Conclusion: From a practitioner perspective, access to such a virtual scan experience could be of use to better prepare and support those patients needing extra support before a real scan. Acknowledgement of having time to discuss patient concerns was noted and this could provide a means of doing so away from busy scanning lists.

P101 A systematic literature review of clinical decision support systems utilised for radiology requesting

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Background: The impact of unnecessary imaging on healthcare systems is widely recognised. Interventions to reduce this include clinical decision support (CDS). We conducted a systematic literature review to evaluate the best evidence on the effectiveness of CDS for radiology requests.

Method: A systematic Boolean search in IEE Explore, MEDLINE, CINHL, Scopus, ProQuest, and Embase was performed, following the PRISMA framework. Studies reporting CDS interventions used within radiology requests, and outcomes including the number of examinations, positive yield rate, waiting times, and experiences were included. CDS as a teaching tool, or where the clinical decision rule was a simple tick box were excluded. Screening and quality appraisal were evaluated independently by two reviewers. Data extraction and synthesis were performed.

Results: The study is still in progress, a complete analysis is expected by May 2023. Thus far 60 articles have been identified. Studies are grouped by clinical indication or body area; most commonly pulmonary embolism (N=13), mild head trauma (N=7), appendicitis (N=4), and lumbar spine (N=4), with validated clinical decision rules embedded within the CDS. The predominant study design was before and after (n=23). The rationale of studies centered on high usage and a need to lower radiation dose.

Conclusion: Preliminary findings show referrer's attitudes factor in the success of CDS. Change management, experiences, and perceptions may impact effectiveness. Successful implementation can be affected when users are given the opportunity to override the computer decision, or when the computer decision is final, clinicians may view this negatively on their autonomy and be time-wasting.

P102 Knowledge, perceptions, and expectations of Artificial intelligence in radiography practice: A global radiography workforce survey

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Introduction: Artificial Intelligence (AI) technologies have already started impacting clinical practice across various settings worldwide, including the radiography profession. This study is aimed at exploring a world-wide view on AI technologies in relation to knowledge, perceptions, and expectations of radiography professionals.

Objectives: Findings from this study could provide an insight to regional differences in terms of expectations, knowledge, and level of skills of the workforce, helping to formulate a globally informed, integrated guidance for a customised implementation of AI in radiography practice.

Methodology: An online survey (hosted on Qualtrics) on key AI concepts was open to radiography professionals worldwide (August 1st to December 31st, 2020). The survey sought both quantitative and qualitative data on topical issues relating to knowledge, perceptions, and expectations in relation to AI implementation in radiography practice.
Results: A total of 314 valid responses were obtained with a fair geographical distribution. Of the respondents, 54.1% (157/290) were from North America and were predominantly clinical practicing radiographers (60.5%, 190/314). The findings broadly relate to different perceived benefits and misgivings/shortcomings of AI implementation in radiography practice. The benefits relate to enhanced workflows and optimised workstreams. The shortcomings revolve around de-skilling and impact on patient-centred care due to over-reliance on advanced technology following AI implementation.

Conclusion: Radiographers are key in the integration of AI in clinical practice, working on the interface between technology and patient care, to facilitate a smooth transition for the benefit of the patients. As both theoretical knowledge and clinical uptake of AI in radiography are still under development, opinions of radiographers globally appear divided.

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P103 An evaluation of a checklist in Musculoskeletal (MSK) radiographic image interpretation when using Artificial Intelligence (AI)

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Background: AI is being used increasingly in image interpretation tasks. There are challenges for its optimal use in reporting environments. Human reliance on technology and bias can cause decision errors. Trust issues exist amongst radiologists and radiographers in both over-reliance (automation bias) and reluctance in AI use for decision support. A checklist, used with the AI to mitigate against such biases, may optimise the use of AI technologies and promote good decision hygiene.

Method: A checklist, to be used in image interpretation with AI assistance, was developed. Participants interpreted 20 examinations with AI assistance and then re- interpreted the 20 examinations with AI and a checklist. The MSK images were presented to radiographers as patient examinations to replicate the image interpretation task in clinical practice. Image diagnosis and confidence levels on the diagnosis provided were collected following each interpretation. The participant perception of the use of the checklist was investigated via a questionnaire.

Results: Data collection and analysis are underway and will be completed at the European Congress of Radiology in Vienna, March 2023. The impact of the use of a checklist in image interpretation with AI will be evaluated. Changes in accuracy and confidence will be investigated and results will be presented. Participant feedback will be analysed to determine perceptions and impact of the checklist also.

Conclusion: A novel checklist has been developed to aid the interpretation of images when using AI. The checklist has been tested for its use in assisting radiographers in MSK image interpretation when using AI.

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P105 The role of the radiographer in radiomics studies

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Background: Radiomics is the process of extraction of quantitative information from medical images with the aim of developing useful clinical biomarkers to improve diagnosis, disease monitoring and clinical decision making. Recent advances in machine learning and high-performance computing have increased interest in the potential of radiomics, particularly in the field of oncology (1). Multidisciplinary expertise is required for data and image curation, segmentation, feature extraction and model building, evaluation and validation (2). However, to date, there has been little reference to and understanding of the role and contribution made by diagnostic radiographers. Radiographers have the appropriate domain specific knowledge and skills and are therefore ideally placed to substantially contribute to successful delivery of radiomics studies.

Purpose: The development of a radiomics signature requires carefully curated clinical data, image processing and model development. This work provides the core information that a radiographer needs to know about radiomics and highlights the importance of radiographer involvement. Our local radiomics workflow is presented with particular emphasis on the radiographer role. We use examples of two oncology radiomics studies (involving germ cell tumours and sarcoma) to illustrate the workflow.

Summary of contents: This work will use 2 exemplars to illustrate a typical radiomics study, with an emphasis on radiographer involvement.

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P106 A practical introduction to preparing a clinical radiography department for artificial intelligence

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Background: Implementation of artificial intelligence (AI) in imaging is increasing [1] and requires large, curated datasets with known, reliable ground truth for AI development and performance testing. Evidence based information is becoming available relating to frameworks, ethics, legalities, platforms, programs and teaching of radiographers [2]. However, there is no practical introduction for radiographers on preparing a clinical department for future implementation of AI and optimising current practices to facilitate retrospective data collection.

Purpose: Primary learning outcome:

*Early awareness of future requirements for AI to build into the routine change cycle in a clinical department. Informative: * For commissioning new scanners and imaging information systems, planning staff education, research and harmonisation across sectors. SUMMARY Scanners: * review AI packages available and assess what is useful for your department * consider (for example), auto align to increase consistency and reproducibility * schedule testing program to identify new artefacts, even in product packages, plus ongoing quality assurance Harmonisation: * sequences, sequence and protocol names across scanners, hospital and regions * reduce unnecessary variation while maintaining clinical expertise and patient specific care Data recording: * complete, comprehensive, in best format and location to create minable data Research: * AI trials require understanding of detailed imaging parameters as these images will also be interrogated by an algorithm that does not view images visually * early optimisation of workflow, even in the absence of immediate AI installation, will facilitate retrospective studies, especially multi-centre Education: * importance of consistency, while not reducing radiographer autonomy or clinical expertise * benefits to daily working life through good change management

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P107 Evaluation of renal cortical stiffness in patients with type 2 diabetes mellitus (DM) by Point Shear Wave Elastography

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Introduction: Point shear wave elastography (pSWE) is an emerging quantitative imaging technique that can be used in the assessment of renal disease. Patients with type 2 diabetes mellitus (DM) are more likely to develop nephropathy. This study aimed to investigate the feasibility of pSWE to assess renal cortical stiffness (CS) in Type 2 diabetes mellitus (DM) patients compared to healthy subjects.

Method: This study comprised of 31 Type 2 diabetic patients (9 males, 22 females and mean age 58 ±14) and 31 healthy control group (15 males, 16 females and mean age 29 ± 11). In addition to routine renal ultrasound, CS was measured using pSWE. The measurements were obtained using ElastPQ (EPQ; Philips Healthcare, Bothell, WA). Three different valid measurements in each kidney were recorded. Ultrasound scanning and measurements were carried out by two certified experienced sonographers.

Result: The cortical stiffness measurements in the patients was significantly higher than the control group with 12.21 ± 12 kPa vs. 8.46 ± 43 kPa; p<0.02). The mean renal length in both patients and healthy were 10.53 ± 1.2 and 10.86 ± 1.3 cm, respectively (p = 0.61). CS was lower in patients than in healthy control, but with no significant difference; 7.2 mm vs 8.31 mm; p = 0.23).

Conclusion: This study revealed that assessment of renal CS using pSWE is feasible. DM patients have higher cortical stiffness measurements compared to healthy control. It is recommended that pSWE measurement of the renal CS should be used as part of routine screening in diabetic patients.

P109 Accuracy of the radiological protocols in detecting scaphoid fractures, a retrospective study

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Early and accurate diagnosis of scaphoid fractures is vital for improving patient outcomes. However, there is no international agreement on the optimal imaging examination for diagnosing suspected scaphoid fractures. This study aimed to assess the different imaging examinations of scaphoid fractures at three major hospitals in Najran, Saudi Arabia. Radiological strategies for imaging suspected scaphoid fracture were determined using a short cross-sectional survey. The accuracy of the different imaging techniques was compared, and the number of patients with a scaphoid fracture who underwent examination at these hospitals in the past year preceding the start of this study was also investigated. The results showed that a plain x-ray was the first line of imaging examination for suspected scaphoid fracture at the three hospitals. When the initial plain x-ray could not rule out scaphoid fracture, a repeated x-ray (10--14 days) was used as second-line imaging in two hospitals, while computed tomography (CT) was used as a third line of imaging. In the third hospital, a CT scan was used as the second line of imaging, while magnetic resonance imaging (MRI) was used as the third line of imaging. A total of 122 112 patients sustained scaphoid fractures in the three hospitals. Initial plain x-ray was able to diagnose 72% of all cases as the first imaging line. Repeated X-rays identified 60% of the fractures that were not detected on the initial plain radiograph, while CT scans identified 88% of the fractures that were not detected on the first plain radiograph.

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P110 Diagnostic accuracy study of a machine-learning algorithm in the detection of abnormalities on chest X-Rays of emergency department and hospital patients

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Background: Chest X-rays (CXRs) are the most common imaging examination worldwide and the first line investigation for individuals with respiratory symptoms. Several artificial intelligence (AI) algorithms detect abnormalities on CXRs. We assess the diagnostic accuracy of Lunit Insight CXR, a CE marked AI, at detecting 10 common CXR abnormalities from emergency department and hospital ward patients. These are typically challenging to interpret as they are often technically suboptimal due to patients being acutely unwell.

Methods: 110 adult CXRs were collected retrospectively via consecutive sampling. All CXRs were reviewed by a thoracic radiologist to confirm the ground truth diagnosis to which the Lunit algorithm was assessed against. The algorithm provides a continuous probability score for the presence of each of the ten abnormalities, which we utilised for ROC analysis. Three cut-off values (15, 30, 45) were utilised for sensitivity and specificity analysis.

Results: The algorithm showed high accuracy at detecting all the abnormalities with an AUROC >0.9 ($p<0.0001$). Average sensitivities for each cut-off; 92% (15), 81% (30), 69% (45). Average specificities; 91% (15), 96% (30), 98% (45). Average positive predictive values; 77% (15), 86% (30), 91% (45). Average negative predictive values; 98% (15), 94% (30), 91% (45).

Conclusion: Our results demonstrate that the Lunit algorithm is highly accurate at detecting the specified ten CXR abnormalities in this cohort of patients even with the presence of multiple abnormalities on the same film. Going forward, we will assess the ability of the algorithm as a diagnostic aid for clinicians who interpret CXRs.

P111 Black box no more: A survey to explore knowledge and perspectives on AI governance in radiography in the UK

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Background: AI adoption in medical imaging is highly dependent on staff training, knowledge, and confidence about AI solutions. In addition, rigorous AI governance frameworks should be in place to facilitate effective validation and evaluation of AI tools, monitor their clinical effectiveness, and guide professionals throughout the models' life cycle. This study aims to assess the status quo around AI governance from the perspectives of medical imaging professionals in the UK.

Method: An online survey was built on Qualtrics and was administered to medical imaging professionals, AI vendors, and AI experts in the UK via email and the researchers' social media. Electronic informed consent was obtained from all participants, and data analysis was performed on the SPSS, employing both descriptive and inferential statistics.
Results: A total of 245 valid responses were received. Self-guided, online training was mostly reported. Many of them (42.1%) were not sure about using any AI governance frameworks, however, they generally comply with informed consent (41.5%) and data security (53.4%) protocols. Locally developed frameworks (35.8%) are often used for AI validation. Expected costs are routinely assessed before procurement (45.4%). Development of specific guidance on AI validation/evaluation, robust AI governance frameworks, and AI-related training were reported as top priorities for a successful AI adoption.

Conclusion: This study highlights the need for a robust AI governance framework to guide safe and successful AI adoption in medical imaging in the UK. The importance of AI-related training is also paramount, with medical imaging professionals eager to learn more on these technologies.

P112 Inter-operator precision of the bindex system for measuring fragility fracture risk based on measurements of the wrist and tibia

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Background: The Bindex is a quantitative ultrasound scanner and provides a bone mineral density index based on cortical bone thickness at the radius, proximal and distal tibia, which is an indicator of osteoporosis(NICE, 2021). The current DXA waiting list is highly variable(NHS, 2022) and Bindex might serve as an alternative for indicating osteoporosis(NICE, 2017). This study aims to explore the inter-operator precision errors for the combination of the radius, distal and proximal tibia using the Bindex.

Method: Thirty-seven participants were recruited. All three anatomical sites of each participant were scanned by two operators. A bone index was calculated for each patient based on wrist and tibia results obtained by each operator. Interclass correlation coefficient (ICC), root mean squared coefficient of variation (RMSCV), and the least significant change (LSC) were calculated to assess the reliability and agreement of measurements between operators.

Results: Inter-operator agreement was excellent (ICC = 0.954; $p<0.001$). The RMSCV was 2.73%, resulting in a LSC of 7.5%.

Conclusion: The high inter-operator reliability shows that Bindex allows reliable measurements between trained practitioners to diagnose osteoporosis. The LSC is higher than reported for DXA(Lewiecki *et al.*, 2016), indicating that it might not be suitable for treatment monitoring purposes. However, with simplicity in design, no ionising radiation, shorter scan time and being logistically convenient, Bindex could be a good compliment with DEXA for osteoporosis diagnosis. The small sample size and limited demographics of participants are limitations to this study as well as the leg and arm measurement marks remaining visible for the second operator.

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P113 Radiomics: A quantitative approach to improve screening for breast cancer

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Background: Breast cancer prognosis improves if it is detected early. However, it can be challenging to identify breast lesions due to factors such as breast density and overlapping structures. To improve the accuracy of breast cancer screening, researchers are using AI algorithms, including radiomics. Radiomics involves using advanced mathematical analysis to extract data from medical images.

Purpose: The importance of early detection in breast cancer survival. The use of radiomics to optimize breast cancer screening accuracy and reduce false positives and negatives.

Summary of content: A radiomics model was tested on mammograms to detect breast cancer from ≈30,000 women and reduced false positives by 5.7% in the US and 1.2% in the UK, and false negatives by 9.4% in the US and 2.7% in the UK. It also reduced the workload of the second reader by 88%. Another radiomics model was used in a study of 222 patients and reduced false-positive results from 66 to 20 while maintaining a sensitivity of 98%. The radiologist had a specificity of 74.2% and sensitivity of 91.8%. In a study of 50 female patients with BI-RADS 4/5 on mammography, an expert radiologist had an accuracy of 97% and ROC AUC of 95.9%, whereas two radiomics models had ROC AUCs of 84.2% and 85.1% in differentiating malignant from benign lesions. However, it is noted that the expert's performance surpasses the average radiologist. These studies suggests that incorporating a radiomics model with the work of a radiologist may improve the effectiveness and accuracy of breast cancer screening.

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P114 Exploring the impact of different image reconstruction methods on the performance of iterative metal artefact reduction algorithm to improve the CT image quality of metal implants

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Metal artefacts resulting from implants such as knee prosthesis are one of the most common artefacts that affect Computed Tomography (CT) image quality. The artefact appears as dark and bright streaks across the image and obscures anatomical structures surrounding the implant. The aim of this study is to explore which combination of iterative metal artefact reduction (iMAR) algorithm and CT convolution kernel gives the best metal artefact reduction. Methods An in-house developed total knee replacement phantom was scanned twice using CT (Biograph, Siemens, Germany), the first with a metal prosthesis inserted in the phantom (artefact scan) and the second without metal insertion (reference scan). The artefact scan with metal artefacts was corrected using iMAR and reconstructed using 13 different CT kernels to produce 13 different images which were subtracted from the reference scan using MATLAB. On the difference images, 4 periprosthetic ROIs were drawn away from streaks while 8 ROIs were drawn on the streak artefacts around the prosthesis and the mean pixel value and the standard deviation from all ROIs were measured. These values were compared to find the best iMAR-kernel combination that gave results closest to the reference scan. Results The highest mean pixel value in ROIs away from streaks was with the Br36 kernel while the lowest was with the Br59 kernel. The highest mean pixel value in streak ROIs was with the Br36 kernel while the lowest was with the Br49 kernel. Conclusion iMAR with sharper kernels improves the overall CT image quality.

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P115 Missed lung cancers on CXR: A human audit

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Background: Lung cancer (LC) is the most common cause of cancer death in the UK. Since there are no specific signs or symptoms that reliably differentiate LC from a non-neoplastic chest pathology, radiography is usually the initial modality used in the investigation. To reduce time to diagnosis and improve overall care, high standards of reporting are imperative to detect LC at the earliest stage. A RCR audit template was used to assess the accuracy of human reporters prior to introducing an artificial intelligence (AI) programme.
Method: Current data uses 6 months. Final audit will include all 2022 patients. The sample included all patients referred to the lung MDT with a confirmed diagnosis of primary LC between July and December 2022. A retrospective review was performed of all chest x-ray (CXR) reports in the 12 months prior to formal diagnosis. All 'no lesion identified' reports were reviewed to determine whether the carcinoma was visible.
Results: Of 151 patients diagnosed with LC: 78 patients met the inclusion criteria. 24 reports were categorised as 'no lesion identified'. On expert review, 11 lesions were 'not visible' and 13 were 'missed cancers'. On review of the 'missed cancers', the most common overlooked areas included the right apex and para-tracheal region.
Conclusion: All 'missed cancers' and 'missed follow-ups' were fed back to reporting clinicians in line with departmental discrepancy policy. All 'missed cancers' will be assessed by the AI programme to compare human and AI accuracy. The audit cycle will be repeated to assess the impact of AI on lesion detection.

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P116 Automated progression monitoring of pulmonary nodules across follow-up lung CT scans

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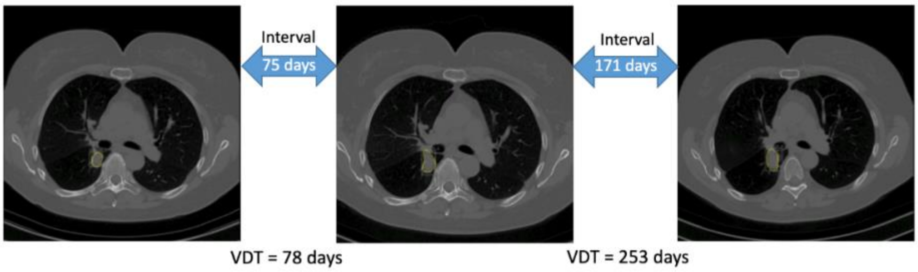
Background: Tracking the progression of nodule is a key practice in early detection of lung cancer. This study was conducted to assess the potential of a automated detection and monitoring algorithm to track and assess growth of clinician identified nodule.

Methods: 114 patients with the nodules at baseline and with at least one follow-up were included. A radiologist with 5-year experience identified the nodules and annotate the entire boundary in all slices. In follow-up scans the radiologist focussed on the same nodules and marked the boundary if present. A deterministic algorithm was used to calculate the volume of the nodule from the radiologist's marking. All follow-up scans were processed by our algorithm which comprise of the deep learning and image-based registration method. VDT of radiologist and our algorithm are compared.

Result: The radiologist identified 282 nodules at baseline. All 282 nodules persisted at first follow-up. Among the patients with two follow-ups, 63 nodules were present at baseline. Our algorithm correctly tracked 256 of the 282 nodules out of which 207 of the 219 nodules in first follow-up scan and 52 of the 63 nodules in both the first and second follow-up. There are 76 nodules which have VDT < 400 days in the ground truth, out of which our algorithm is able to pick up 54 nodules which have VDT < 400 days.

Conclusion: Our algorithm can automate nodule tracking and help radiologist to monitor progression of nodules



which may become malignant in follow-ups, thereby increase performance and improve patient management.

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P117 Using artificial intelligence (AI) to diagnose pathology on chest x-rays

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Although Artificial intelligence (AI) has been around for decades, due to the recent advances in technology interest and use continues to expand in clinical practice. From the introduction of radiological imaging being digitised and stored electronically, it has advanced the construction of deep learning (DL) models by collecting datasets and ground truth labelling. This in theory could aid health professionals to reach a diagnosis promptly when there is a lack of radiology expertise to assist. Chest x-rays are one of the most useful tools for diagnosis due to fast turnaround, however, due to a shortfall in expected workforce, DL could prove to be beneficial in alleviating reporting turnaround time pressures. From a radiographer's perspective, AI has the potential to assist with clinical decision making, enhance education and extend radiography led research. Using a narrative literature review, this poster demonstrates a basic introduction into AI for chest x-ray image interpretation. It provides a brief explanation into the construction of a DL model and performance measurement. Plus, highlighting advantages and disadvantages of this being applied into clinical practice. This poster contains nine sections (including references) summarising a literature review of five articles on the topic.

RADIOTHERAPY SERVICE DEVELOPMENT POSTER PRESENTATIONS

P118 Pain flare following palliative radiotherapy for bone metastases: A systematic literature review

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Background: External Beam Radiotherapy (EBRT) is an effective treatment for palliation of symptomatic bone metastases (Spencer et al, 2018). One potential side effect of EBRT is pain flare, a transient increase of pain in the treated area, with varying incidence. This review aimed to determine the incidence and timing of pain flare following EBRT for bony metastatic disease, and whether this toxicity could be predicted, improving informed consent.

Method: A systematic search and critical review of published literature was performed. Electronic databases searched included PubMed, CINAHL complete and the Cochrane library using keywords including 'pain flare', 'palliative radiotherapy' and 'bone metastases'. Primary studies written in English, published between January 2005 and December 2020 were eligible for inclusion. Additional inclusion criteria comprised studies conducted in adult humans