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ARTIFICIAL INTELLIGENCE IN RADIOLOGY: SYSTEMATIC REVIEW

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ABSTRACT

Introduction*: Radiology, integral to modern medicine since the discovery of X-rays, has evolved to integrate AI and machine learning, reshaping healthcare. This review explores their impact on radiology, aiming to guide discussions among clinicians, researchers, and policymakers for improved patient outcomes and future directions in AI-driven radiology.*

Methods*: The researchers in this study followed the 2020 Preferred Reporting Items for Systematic Review and Meta-Analysis (PRISMA) guidelines to ensure that their work met the required standards. This was done to ensure the precision and reliability of the conclusions derived from the research.*

Result*: Our search produced 17 results. After looking at the titles and summaries, we discovered 10 papers that fit our criteria after excluding several articles because they did not fit into criteria. But after reading the full papers carefully, we included five papers in our final analysis. These papers included a retrospective observational study and several case reports.*

Conclusion*: Overall, these studies and trials illustrate the promising potential of AI in healthcare, particularly in radiology, while underscoring the need for continued research, larger-scale studies, and addressing limitations to harness its full benefits and ensure patient-centered, effective, and ethical integration into medical practices.*

Keyword: *artificial intelligent, machine learning, radiology*

INTRODUCTION

From its inception, radiology has embarked on a transformative journey, profoundly influencing modern medicine. Starting with the discovery of X-rays and progressing to the integration of artificial intelligence (AI) and machine learning (ML), this diverse field continually evolves, reshaping itself and the healthcare system it supports.[1,2]

This comprehensive review examines how AI and ML intersect with radiology, delving into their core principles, historical development, practical applications, inherent challenges, and ethical considerations.[3] By enhancing our understanding of how AI and ML contribute to radiology, the review aims to stimulate insightful discussions among clinicians, researchers, and policymakers, guiding the field's trajectory and improving patient outcomes. It explores the foundational aspects of AI and ML, their expanding influence in radiology, strategies for practical integration, and case studies spanning various medical domains. Additionally, it addresses challenges such as data quality, ethical dilemmas, and contemplates potential future directions in AI-driven radiology.[4,5]

Radiology, focused on employing imaging techniques for disease diagnosis and treatment, has become integral to modern medicine. Beyond just identifying diseases, modalities like CT, MRI, PET, ultrasound, and X-rays aid immediate interventions, treatment monitoring, and provide a visual narrative of a patient's health.[6] These insights significantly impact patient care by tailoring treatments, improving outcomes, and minimizing side effects. The journey from Roentgen's X-ray discovery in 1895 to current advanced imaging technologies showcases the relentless advancement in medical imaging. CT's introduction in 1973 marked a leap to 3D imaging, while ultrasound's non-ionizing nature found broad application in various clinical fields. MRI, developed in the 1970s, provided detailed soft tissue images, transforming medical imaging.[7] Moving from film-based to digital radiography and the advent of PACS streamlined image acquisition and sharing. Functional imaging like PET and SPECT shed light on biological processes. 3D and 4D imaging enhanced spatial understanding and real-time monitoring of physiological processes. Hybrid imaging like PET/CT and SPECT/CT merged strengths to offer comprehensive diagnostic information. Interventional radiology reshaped healthcare through minimally invasive procedures guided by imaging.[8,9]

The integration of virtual/augmented reality (VR/AR) and AI foresees a transformative era in medical imaging. VR/AR aids training and enhances diagnosis and treatment planning. AI and machine learning elevate image analysis, potentially surpassing human capabilities. Computer-aided diagnosis tools incorporating radiology, pathology, and genomics data promise improved diagnostics. However, the integration of AI and VR/AR faces technical hurdles, demanding integration into existing workflows.

METHODS

Protocol

The researchers in this study followed the 2020 Preferred Reporting Items for Systematic Review and Meta-Analysis (PRISMA) guidelines to ensure that their work met the required standards. This was done to ensure the precision and reliability of the conclusions derived from the research.

Criteria for Eligibility

For inclusion in the study, published articles had to meet particular requirements. They had to be research papers written in English, focusing on artificial intelligent in radiology. The studies had to meet the following criteria: they needed to have been published after 2018 but within the applicable timeframe for this systematic review. Articles falling into categories like editorials, lacking a DOI, review articles that were already published, or duplicating previously published journal papers were excluded from the assessment.

Search Strategy

We conducted a comprehensive literature search using PubMed and Google Scholar, focusing on studies published from 2018 to 2023. The search terms employed were as follows: ("artificial intelligence"[MeSH Terms] OR ("artificial"[All Fields] AND "intelligence"[All Fields]) OR "artificial intelligence"[All Fields]) AND ("radiology"[MeSH Terms] OR "radiology"[All Fields] OR "radiography"[MeSH Terms] OR "radiography"[All Fields] OR "radiology s"[All Fields]). Moreover, we performed cross-referencing of relevant articles to reveal additional research. The evaluation of study quality, methodology, interventions, and results was undertaken independently by the researchers, resolving any differences through discussion and agreement. Furthermore, both researchers collected and compared discoveries from all studies, considering the potential for conducting a meta-analysis if deemed feasible.

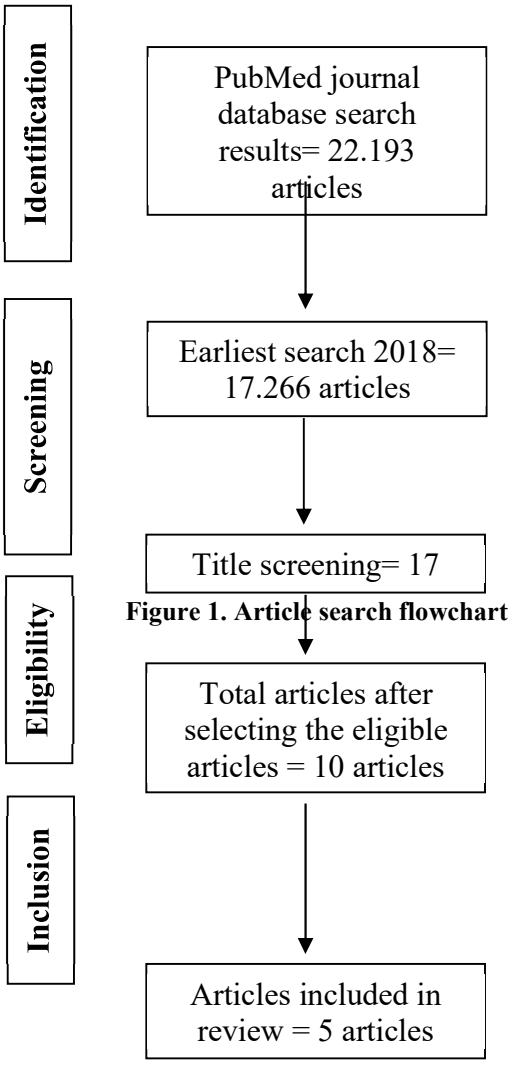

Figure 1. Article search flowchart

Inclusion and exclusion criteria

Inclusion criteria for the studies were as follows: (1) original research that assesses the use of artificial intelligent in radiology field; (2) Randomized Controlled Trials (RCTs) or observational studies (cohort or case-control studies); (3) availability of relevant data. Exclusion criteria were as follows: (1) ongoing studies or studies without available data; (2) duplicate publications. In cases of duplicate publications, the most recent article was chosen; (3) Non-English language studies were excluded.

Data Retrieval

The authors conducted a thorough examination of relevant studies, specifically selecting those that met precise inclusion criteria. They focused on original, unpublished papers in English to ensure a refined and high-quality selection. The analysis covered essential information, such as study particulars, authors, publication dates, locations, and research methodologies, aligning with the study's objectives.

Author	Origin	Method	Sample Size	Result
Barreiro-Ares et al., 2023.[10]	Spain	Analytical study; questionnaire.	Total 281 students.	Two hundred and eighty-one students correctly responded the questionnaire; 79.3% of them claimed that they knew what AI is. However, their objective knowledge about AI was low but acceptable. Only 24.9% would choose radiology as a specialty, and only 40% of them as one of their first three options. The applications of this technology were valued positively by most students, who give it an important Support Role, without fear that the radiologist will be replaced by AI (79.7%). The majority (95.7%) agreed with the need to implement well-established ethical principles in AI, and 80% valued academic training in AI positively.
Muehlematter et al., 2021.[11]	Switzerland.	Analytical study.	22 AI/MLbased medical devices approved by the FDA and 240 AI/ML-based CE-marked medical devices in Europe.	The search identified 15 525 sources of interest. Our final study cohort included 222 AI/ML-based medical devices approved by the FDA and 240 AI/ML-based CE-marked medical devices in Europe. 202 (91%) of 222 of the included US devices were identified using medical device database searches and 150 (63%) of 240 of the included European devices were identified using medical device database searches (figure 1, appendix pp 3–37). 124 AI/ML-devices were commonly approved in the USA and Europe.
May, et al., 2019. [12]	US.	Retrospective study	250 full-field digital mammograms between January 1, 2013, and March 31, 2013,	The evaluation encompassed the false-positive marks per image (FPPI) of both systems, along with the count of cases devoid of any marks. All findings demonstrated notable and statistically significant decreases in false marks when utilizing AI-CAD compared to CAD (confidence interval = 95%), without compromising sensitivity. Overall, employing AI-based CAD led to a 69% reduction in FPPI compared to CAD, comprising an 83% decrease in calcification-related FPPI and a 56% decrease in mass-related FPPI. Almost half (48%) of cases exhibited no AI-CAD markings, whereas only 17% showed no conventional CAD marks. AI-CAD showcased a substantial reduction in FPPI for masses and calcifications across all tissue densities compared to CAD. The documented 69% FPPI decrease could potentially translate into a 17% reduction in radiologist reading time per case, drawing from previous literature on CAD reading times.
Lee et al., 2018.[13]	Oxford, UK.	Prospective study.	Prospective growth data were recorded at 12 months for 94 patients. Of these, growth data were further recorded at 24 months in 79 patients.	Prospective growth data were recorded at 12 months (360 49 days) in 94 patients. Of these, growth data were further recorded at 24 months (718 81 days) in 79 patients. The average growth in AAA diameter was 3.4% at 12 months, and 2.8% per year at 24 months. The algorithm predicted the individual's AAA diameter to within 2 mm error in 85% and 71% of patients at 12 and 24 months.
Nam et al., 2023.[14]	South Korea	Single-center,	1226 participant.	A total of 10,476 participants (median age, 59 years [IQR, 50–66 years]; 5121 men) underwent

	pragmatic, open-label randomized controlled trial.	randomization into either the AI group (n = 5238) or the non-AI group (n = 5238). The trial achieved the predefined primary outcome, revealing an enhanced detection rate of actionable nodules in the AI group compared to the non-AI group (0.59% [31 out of 5238 participants] vs 0.25% [13 out of 5238 participants], respectively; odds ratio, 2.4; 95% CI: 1.3, 4.7; P = .008). The detection rate for malignant lung nodules was higher in the AI group compared to the non-AI group (0.15% [eight out of 5238 participants] vs 0.0% [0 out of 5238 participants], respectively; P = .008). Both the AI and non-AI groups exhibited comparable rates of false-referral (45.9% [56 out of 122 participants] vs 56.0% [56 out of 100 participants], respectively; P = .14) and positive-report rates (2.3% [122 out of 5238 participants] vs 1.9% [100 out of 5238 participants]; P = .14).

RESULT

Our search produced 17 results. After looking at the titles and summaries, we found 10 papers that fit our criteria. At first, we excluded several articles because they were written in review style. But after reading the full papers carefully, we included five papers in our final analysis. These papers included a retrospective observational study and several case reports.

In *Barreiro-Ares* et al, the study relied on an anonymous online questionnaire distributed among medical students during the 2021–2022 academic year. From 283 responses collected, 281 were valid for analysis. These respondents were categorized into different age groups: Group 1 (21–22 years old, 42.34%), Group 2 (≤20 years old, 34.16%), and Group 3 (≥23 years old, 23.48%). Gender distribution revealed 71.17% women and 28.83% men. The majority of participants, 97.86%, originated from the University of Santiago de Compostela.[10]

Participants were distributed across various academic grades: 25.62% in the 6th grade, followed by 17.80% each in the 2nd and 5th grades, 13.52% in the 1st year, 12.81% in the 3rd year, and 12.45% in the 4th year. Additionally, respondents mainly hailed from the University of Santiago de Compostela (97.86%), while smaller percentages represented other institutions.[10]

About 75.09% of participants expressed no interest in choosing radiology as a specialty. Age seemed to correlate with the likelihood of selecting radiology. A significant portion (79.36%) demonstrated familiarity with AI. Most respondents (81.14%) recognized AI's integration in daily life, predominantly through media sources.[10]

More than half of the participants believed that AI enhanced human capabilities. There was notable uncertainty regarding AI's potential influence on human autonomy and decision-making. However, a substantial portion anticipated AI's impact on radiology, with 91% foreseeing changes in radiologists' work processes.[10]

While most agreed that AI would alter radiology, the majority felt its role should support rather than replace radiologists. Participants believed AI could enhance patient care and reduce the need for professionals while upholding ethical principles.[10]

A majority (80%) advocated for students' training in AI, recognizing its potential benefits. The drawbacks highlighted by respondents encompassed AI's limitations in interpreting patients' holistic clinical contexts, associated high implementation costs, privacy concerns, and the need for professional training in AI management.[10]

This study delved into various aspects of respondents' demographics, perceptions of AI, its perceived impact on radiology, ethical considerations, and identified drawbacks, providing insights into how medical students perceive and engage with AI in their academic journey.[10]

In Muehlematter et al (2021) exploration yielded 15,525 pertinent sources. Within our study group, 222 medical devices leveraging AI/ML garnered FDA approval, while 240 similar devices secured CE marking in Europe. Of the 222 US-approved devices, 202 (91%) were identified through medical device database searches, while for the 240 European devices, 150 (63%) were identified via similar searches.[11]

The FDA approvals for AI/ML-based medical devices exhibited a notable rise—from nine in 2015, escalating annually to 77 by 2019, and culminating in 24 approvals between January 1 and March 31, 2020 (Figure 2). A significant majority

(92%) of the 222 devices obtained approval through the 510(k) pathway, 7% through the de-novo pathway, and 1% via the premarket approval pathway (Figure 3). Radiology dominated the application domain for FDA-approved devices, showing steady growth from six approvals in 2016 to 47 in 2019. [11]

Among these FDA-approved devices, 85% were geared for healthcare professionals' use, with a majority manufactured by small companies, largely originating from the USA (57% of 222 devices), followed by Israel, Sweden, England, and France. Notably, a statistical association was observed between the FDA regulatory pathway and device medical specialty ($p=0.011$), particularly evident in the prevalence of molecular genetics devices approved via the de-novo pathway ($p=0.008$). [11]

Regarding CE-marked devices in Europe, the numbers increased annually, reaching 100 in 2019, with an additional 19 devices CE-marked between January 1 and March 31, 2020 (Figure 2). Radiology remained a dominant application domain, peaking at 59 approvals in 2019. Among these CE-marked devices, 82% were intended for healthcare professionals' use, with 80% manufactured by small companies. [11]

Distinct associations were noted between the classification of CE-marked devices and the countries of manufacturer, medical specialty, and manufacturer size ($p<0.001$). Notably, certain countries showed significantly higher counts than expected, such as England-based and Israel-based devices under specific classifications. However, no association was established between device classification and intended use by healthcare professionals. [11]

Among the identified AI/ML-based medical devices, 124 were commonly approved by both the FDA in the USA and CE-marked in Europe. These devices, predominantly used in radiology, showcased varied approval timelines between the two regulatory bodies. Additionally, a larger proportion of commonly approved devices hailed from large companies compared to those solely approved by either the FDA or CE-marked in Europe. Multivariate regression indicated a median time difference between CE marking and 510(k) approval of 166 days ($p<0.001$). Sensitivity analyses corroborated these findings, shedding light on the nuanced timeline discrepancies between CE marking and FDA approvals for these commonly approved devices[11]

A retrospective study by Mayo et al. (2019) was performed on a set of 250 two-dimensional (2D) full-field digital mammograms (FFDM) collected from a tertiary academic institution based in the USA which specializes in cancer healthcare There were 21 recalled cases (BI-RADS 0) out of the 245 cases included, resulting in an 8.6% recall rate. The tissue density distribution stood at 3% fatty, 46% scattered, 48% heterogeneously dense, and 2% extremely dense. All three cancer cases were accurately identified by both CAD and AICAD, marking a sensitivity rate of 100% for both. CAD exhibited false marks on 200 of the 242 non-cancer cases (83%) and had no markings on 42 cases (17%). On the other hand, AI-CAD presented false marks on 126 of the 242 non-cancer cases (52%) and had no marks on 116 cases (48%). This translates to 37% fewer cases with false marks and simultaneously 64% more mark-free cases with AI-CAD compared to CAD.[12]

The overall False Positive Marks per Image (FPPI) reduction with AI-CAD compared to CAD was 69%. AI-CAD outperformed CAD for both masses and calcifications, showcasing an 83% reduction in FPPI for calcifications and a 56% reduction for masses. The FPPI for masses was higher than for calcifications for both systems.

The overall FPPI for AI-CAD was 0.29, with a 95% confidence interval (CI) range of 0.21–0.35. In contrast, CAD's overall FPPI was 0.92, well beyond the 95% CI. Specifically, for calcifications, AI-CAD's FPPI was 0.07 (95% CI: 0.041–0.11) compared to CAD's FPPI of 0.42. For masses, AI-CAD's FPPI was 0.22 (95% CI: 0.18–0.26) compared to CAD's FPPI of 0.50. Once again, there was a 69% reduction in overall FPPI with AI-CAD compared to CAD, with AI-CAD showcasing better performance for both mass and calcification cases. [12]

The reduction in false-positive markings per image was consistent across all tissue densities, ranging from fatty to extremely dense with AI-CAD. The FPPI reduction with AI-CAD was demonstrated for both mass and calcification categories. For ultimately benign cases, CAD showed no marks in 39 out of 242 cases, while AI-CAD showed no marks in 113 cases. This resulted in a specificity of 16% for CAD and 47% for AI-CAD. Out of the 21 cases categorized as BI-RADS 0 and recalled from screening with CAD, 18 cases (86%) turned out to be false-positive recalls confirmed as benign through biopsy or long-term follow-up of 2 years or more. Among these, 15 cases had CAD marks, whereas only 8 had AI-CAD marks. [12]

This research by Lee et al (2018) is grounded in a prospective study involving patients diagnosed with AAAs (Oxford Abdominal Aortic Aneurysm Study, OxAAA). All participants provided written consent to join the study, which was ethically approved under reference SC/0250/13. The National Health Service (NHS) AAA surveillance program provided the AAA size data, measured by the anteroposterior diameter (APD) via ultrasound. Additionally, the study assessed brachial artery flow-mediated dilation (FMD) as an extra research evaluation. The annual AAA % growth was computed using the formula (DAPD/APD at baseline)/(number of days elapsed/365 days). [13]

The study recorded prospective growth data at 12 months (360 49 days) for 94 patients, with further records at 24 months (718 81 days) for 79 patients. The average AAA diameter growth stood at 3.4% after 12 months and 2.8% per year at the 24-month mark. ROC curves were plotted using the thresholds of "stable/no growth" (defined as 0%/year growth) or "fast growth" (defined as the upper tertile of growth within the group) at both 12 and 24 months, showcasing discrimination based on FMD, AAA diameter, and the prediction of future growth rates against these predefined thresholds. Utilizing the described machine learning techniques, individual AAA diameter predictions were accurate within a 2 mm error for 85% and 71% of patients at 12 and 24 months, respectively. This prediction showed a root mean square error of 1.7 and 2.4 at 12 and 24 months, respectively. [13]

Gong Nam et al in 2020-2021 conducted a pragmatic, randomized controlled trial at a health screening center linked to a tertiary referral hospital. All individuals visiting the center for chest radiography during the health checkups between June 2020 and December 2021 were included and randomized into either the intervention arm (AI group) or control arm (non-AI group) in a 1:1 ratio. Exclusions were made for individuals under 18 years old. Radiologists in the AI group interpreted chest radiographs aided by AI-based CAD, while those in the non-AI group interpreted chest radiographs without AI-based CAD results (refer to Fig 1). Most interpretations were conducted by three designated board-certified radiologists (E.H.L., H.J.K., and M.N., with 36, 27, and 13 years of chest radiography reading experience, respectively) at our health screening center. The allocation was known to the radiologists, physicians at the health screening center, and outcome assessors (single blinded). [14]

A total of 10,478 participants were enrolled in AI-PACS, with two participants under 18 years old excluded. The final analysis included 10,476 participants (median age: 59 years [IQR: 50–66 years]; 5121 men) split into the AI (n = 5238) and non-AI (n = 5238) groups (Fig 1). Within the cohort, 11% (1138 of 10,476 participants) were current smokers, 25% (2633 of 10,476 participants) were former smokers, 0.6% (n = 59) had a history of lung cancer, and 10% (n = 1038) had a history of other malignancies (see Table 1). There were no observable differences in baseline characteristics between the two groups (P = .15–.91). [14]

Among the 10,476 participants, 2% (n = 222) had chest radiographs indicating nodules. Older age, a history of lung cancer or pulmonary tuberculosis, and the absence of prior chest radiographs were associated with positive results. The positive-report rates varied among the reporting radiologists (see Table S1). Of the participants, 47% (n = 4886) underwent chest CT within three months after chest radiography, and 0.3% (n = 30) had pathologic evaluation of lung nodules. Factors like age, gender, smoking status, and prior chest radiograph influenced the likelihood of undergoing chest CT.

The AI group exhibited a higher detection rate for actionable lung nodules on chest radiographs compared to the non-AI group (0.59% [31 of 5238 participants] vs 0.25% [13 of 5238 participants], respectively; odds ratio [OR], 2.4; 95% CI: 1.3, 4.6; P = .008) (see Table 2), achieving the primary outcome of the trial (see Table 1). However, there was no significant difference in the positive-report rate of chest radiography between the AI and non-AI groups. The false-referral rates were comparable between the AI and non-AI groups among participants with positive chest radiographs. [14]

Notably, despite chest CT being performed for nearly half the participants irrespective of chest radiography results (mostly for health checkup purposes), several actionable lung nodules were initially identified at CT. The diagnostic performance of chest radiography was better in the AI group, especially among participants who underwent chest CT, showing higher sensitivity, positive predictive value, and negative predictive value in detecting actionable lung nodules compared to the non-AI group. [14]

A small percentage of participants (0.28%; 30 of 10,476) underwent pathologic evaluation for lung nodules, and the proportions were similar between the AI and non-AI groups. Detection rates of malignant lung nodules and lung cancer on chest radiographs were higher in the AI group; however, no significant differences were observed in logistic regression analyses. The impact of AI-based CAD on actionable lung nodule detection remained consistent across various subgroups, showing no significant interactions for several factors such as age, sex, smoking status, history of lung cancer, or reporting radiologists. Specific factors like age and sex displayed borderline significance (P = .06 and P = .05, respectively). Additionally, characteristics of lung nodules like size, location, and overlapping structures did not affect the sensitivity of chest radiography (see Tables 4, S3, S4, and S5).[14]

DISCUSSION

The majority of surveyed students demonstrated awareness of AI, recognizing its applications in daily life, evident through their self-perception and the objectively measured correctness of True/False questions related to fundamental knowledge, showing an acceptable percentage of accurate responses.[10]

Interestingly, most participants favored academic training in AI, perceiving it as beneficial for their careers. The absence of such education might influence students' readiness to work with these technologies in fields like radiology post-graduation. While students recognized the positive value of AI applications, about half saw it as a tool enhancing human capabilities while impacting decision-making autonomy. [10]

Regarding the future of AI in healthcare, students believed it would significantly shape medical care, especially in radiology, yet there were divided opinions about whether AI would replace radiologists entirely. Most students believed AI would revolutionize radiology, augmenting radiologists' efficiency rather than replacing them, while some anticipated a reduction in radiologist numbers due to AI advancements. [10]

The inability of AI to comprehend patients in a comprehensive clinical context, along with implementation costs, privacy concerns, and the necessity of professional AI training, were highlighted as major limitations of AI in medicine. While AI could detect pathologies in radiological exams, students recognized its limitation in establishing definitive diagnoses, emphasizing the indispensable role of radiologists. [10]

The count of AI/ML-based medical devices in the USA and Europe has risen steadily since 2015. Europe has more (240) compared to the USA (222), possibly more due to a lack of a complete database. Only a small fraction falls into the high-risk category (1%). Most devices in both regions are for radiological purposes, likely due to the vast imaging data available and declining reimbursements. However, the sheer count of approvals doesn't confirm their actual use. Some devices might be used internally without official approval. [11]

Lack of transparency and limited data make assessing safety and performance of AI/ML devices challenging. Efforts like the upcoming Eudamed database aim to improve transparency. In the USA, more detailed information about approved devices, especially AI/ML-based ones, is necessary for clear identification. Identifying approved AI/ML-based devices is tough due to different terminologies used. This could lead to underestimating their count. [11]

The radiologist's final BIRADS assessment is influenced by CAD marks. Reducing false-positive assessments is a priority in mammography software. Our study found 83% of false-positive BIRADS 0 cases had CAD marks; only 56% had AI-CAD marks. AI-CAD significantly reduces FPPI, potentially lowering false recalls and costs. These recalls impact patients psychologically and financially. [12]

CAD marks impact radiologist efficiency. Cases with CAD marks take longer to read. AI-CAD could reduce reading time by 64% compared to CAD. AI-CAD, trained with benign and malignant cases, assigns a NeuScore to assess lesion suspiciousness. This score is unavailable in CAD. AI-CAD marks benign findings less often than CAD. As AI-CAD learns, it's expected to improve this distinction. NeuScore™ may aid radiologists' decisions. Interactive quantitative CAD with scoring doesn't increase reading time.[12]

Economically, AI-CAD could save 375 hours of radiologist time annually, potentially allowing 10% more screenings. This could generate $1,488,362 in increased revenue yearly. However, this study's retrospective nature and small sample size warrant further sensitivity analysis. Unlike CAD, AI-CAD is vendor-agnostic, user-friendly, and can operate on processed images. It doesn't need raw DICOM data or calibration with imaging equipment. Its deep learning capabilities offer additional benefits like NeuScore™ and lesion probability assessment.[12]

AAA screening programs are established in the UK, Sweden, and Germany to prevent rupture-related deaths. International guidelines suggest regular ultrasound monitoring for small AAAs (<55 mm) until they reach the 55 mm threshold. Recommendations vary: AAAs between 30-45 mm need annual scans, while those between 45-55 mm need scans every six months. The number of AAAs requiring surveillance in the UK increases annually, leading to a rise in surveillance scans.[13] A survey of AAA patients revealed concerns about monitoring frequency and management explanations. Predicting AAA growth can offer patients insight into their condition's future, allowing personalized surveillance. Using machine learning techniques on existing data, an algorithm predicts individual AAA growth, enabling tailored monitoring intervals. [13]

Real-life AAA surveillance involves multiple operators. This study uses NHS AAA surveillance program measurements to predict AAA growth, accommodating inter-observer variation. The predictive accuracy may reduce with longer forecast durations but remains relatively stable up to 24 months. While this study focuses on biomarkers predicting AAA growth, future research may explore biomarkers for rupture risk. However, studying rupture risk requires observing a prospectively recruited cohort progressing to rupture, posing practical and ethical challenges. Geometric/volumetric AAA measurements, especially via 3D ultrasound, may offer better insights into growth. Future validation work should consider these measurements' impact on prediction algorithms. [13]

In study explored the influence of AI-based CAD on spotting actionable lung nodules in chest radiographs via a randomized trial involving 10,476 adults. The AI-based CAD notably enhanced the detection rate of these nodules without elevating false-referral rates. While the AI group showed higher detection rates of malignant nodules and lung cancer, these results were based on a small incidence, warranting cautious interpretation.[14]

One strength of this trial was its real clinical setting, involving a substantial number of participants. However, the study size fell short of the estimated target, and the prevalence of actionable lung nodules was lower than in retrospective studies. This revealed the limitations of retrospective research, emphasizing the AI's more pronounced effect in low-prevalence scenarios.Yet, the trial couldn't evaluate AI's impact on patient management or decision-making due to a large proportion

undergoing chest CT irrespective of radiography results. Therefore, the study focused on AI's impact on diagnostic performance rather than impacting diagnoses or patient outcomes. [14]

The trial indicated higher sensitivity with AI-based CAD, particularly in older individuals or those with a history of lung cancer or tuberculosis. However, it showed consistent performance across different populations and among radiologists with varying sensitivity levels. However, limitations included assessing only a subgroup due to differing CT rates, the trial's single-institution nature, and unmet estimated sample size. Plus, the study didn't explore AI's standalone performance, its effects on reporting prioritization, or reduction in reporting time. Lastly, the study targeted a specific population, potentially limiting its generalizability. [14]

CONCLUSION

The intersection of AI technology with medicine and radiology has garnered significant attention among students and healthcare professionals. The comprehensive understanding and perceptions among students about AI's role in healthcare, its limitations, and the anticipated impact on radiology present a dynamic landscape for future implementation. Moreover, the rise in AI/ML-based medical devices in both the USA and Europe signifies a growing reliance on technology in the field of radiology. However, challenges persist regarding the transparency and assessment of the safety and performance of these devices, necessitating the development of more comprehensive databases and standardized terminology for identification.

In the realm of radiology, the integration of AI-based CAD has exhibited promising outcomes in improving nodule detection rates while potentially reducing false positives. This advancement presents opportunities to enhance radiologist efficiency and accuracy, albeit with some challenges such as the need for more extensive studies, evaluation of AI's impact on patient management, and considerations for varied populations. Similarly, in AAA screening programs, the integration of machine learning techniques to predict individual AAA growth stands as a promising avenue for personalized surveillance, although further research into biomarkers and geometric/volumetric measurements is warranted for validation and improvement.

Overall, these studies and trials illustrate the promising potential of AI in healthcare, particularly in radiology, while underscoring the need for continued research, larger-scale studies, and addressing limitations to harness its full benefits and ensure patient-centered, effective, and ethical integration into medical practices.

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