J Neurology Neuromedicine
www.jneurology.com
Journal of Neurology & Neuromedicine

Mini Review

Open Access

# Enhancing Intracranial Aneurysm Detection with Artificial Intelligence in Radiology

Ilya Adamchic

Department of Radiology, Vivantes Hospital im Friedrichshain, Berlin, Germany

**Article Info**

**Article Notes**
Received: January 15, 2025
Accepted: February 27, 2025

***Correspondence:**
*Dr. Ilya Adamchic, Department of Radiology, Vivantes Hospital im Friedrichshain, Berlin, Germany;
Email: i.adamchic@gmail.com



**Keywords**
Intracranial Aneurysm Detection
Artificial Intelligence
Deep Learning
Convolutional Neural Networks
Diagnostic Accuracy
Medical Imaging Advancements
AI Integration in Clinical Workflows

## ABSTRACT

Intracranial aneurysms (IAs) pose a significant public health challenge due to their potential for rupture and associated morbidity and mortality. Despite advancements in imaging technologies such as magnetic resonance angiography (MRA) and computed tomography angiography (CTA), detecting small, incidental IAs remains challenging, particularly amid increasing global imaging volumes and resource constraints. Artificial intelligence (AI) has emerged as a transformative tool in medical imaging, demonstrating potential to enhance diagnostic accuracy and efficiency. Deep learning models, particularly convolutional neural networks (CNNs), have shown near-expert accuracy in detecting subtle aneurysmal features, enabling early diagnosis and improving clinical workflows. AI-driven approaches extend beyond detection to include rupture risk assessment, predictive diagnostics, and treatment planning, thereby improving patient-specific care and reducing unnecessary interventions.

However, challenges such as false-positive rates, ethical considerations, and the need for robust validation studies hinder AI adoption in clinical practice. This review contextualizes recent advancements and the findings of Adamchic et al. (2024), within the broader landscape of AI applications in IA diagnostics. It discusses AI's role in addressing diagnostic variability, mitigating radiologist workloads, and enhancing reproducibility, particularly for junior clinicians. The article also explores barriers to widespread implementation, including data safety, algorithm transparency, and financial constraints, while emphasizing the need for collaborative efforts to refine AI models and integrate them seamlessly into radiology workflows. By addressing these challenges, AI has the potential to revolutionize intracranial aneurysm management, improving patient outcomes and transforming modern radiology practices.

## Introduction

IAs pose a significant public health challenge, with a prevalence of 3–7% in the general population, varying based on demographics and comorbidities[1,2]. These cerebrovascular anomalies, if undetected, carry risks of rupture leading to subarachnoid hemorrhage, which leads to considerable morbidity and mortality[3,4]. Proactive treatment of high-risk unruptured intracranial aneurysms and advancements in endovascular techniques have contributed to a significant decline in aneurysmal SAH rates resulting in reduced rupture-related mortality and reduced associated economic burden[5]. Despite advances in imaging technologies such as MRA and CTA, detecting small intracranial aneurysms (<5 mm), especially when they are incidental findings on imaging performed for unrelated pathologies, remains a significant challenge[6,7]. This difficulty is compounded by the increasing volume of imaging studies performed globally, which strains radiology resources and contributes to diagnostic variability[6,7,8,9].

AI has emerged as a transformative tool in medical imaging, demonstrating the ability to augment diagnostic accuracy and reduce radiologist workload[7,9,10,11]. Specifically, deep learning models, a subset of AI, have shown potential in automating the detection and characterization of IAs with sensitivity levels comparable to expert neuroradiologists[9,12,13]. For example, CNNs have been employed to identify complex aneurysmal features, enabling near-real-time diagnostics and potentially improving clinical workflows[10,14]. Notably, combined AI-radiologist interpretations have consistently outperformed standalone readings, underscoring the symbiotic potential of this technology[9,12,13].

The integration of AI in IA management extends beyond detection to encompass rupture risk assessment, treatment response prediction, and patient-specific care optimization[15,16]. Early detection and accurate risk stratification of IAs are pivotal, as interventions such as surgical clipping or endovascular embolization entail inherent risks and must be judiciously balanced against the natural history of the aneurysm[17]. In this context, AI offers opportunities to standardize measurements, mitigate interobserver variability, and enhance the reproducibility of diagnostic outcomes, particularly for junior clinicians.

Despite its promise, the adoption of AI in clinical settings faces hurdles. Relatively high false-positive rates, limited generalizability of models, and challenges in clinical validation hinder widespread acceptance[2,18,19]. Furthermore, ethical considerations and the need for robust, multicenter validation studies are critical to ensuring AI's reliability and applicability[20,21]. As research progresses, efforts to seamlessly integrate AI into routine radiology practice have the potential to revolutionize the detection, characterization, and management of IAs, ultimately improving patient outcomes.

A recently published study by Adamchic et al. (2024) evaluated the diagnostic performance of AI in detecting incidental intracranial aneurysms using time-of-flight magnetic resonance angiography (TOF-MRA). The analysis of 500 brain MRI scans compared AI-based detection with expert neuroradiologist readings. AI identified 72.6% of aneurysms, while the neuroradiologist had a higher sensitivity of 92.5%. However, combining AI with expert assessment improved detection reliability and reduced reading time by 23% (19 seconds per case). AI demonstrated better detection of smaller aneurysms but missed some larger ones, whereas the neuroradiologist primarily missed small aneurysms (<3 mm). An example of an AI-identified aneurysm missed by the radiologist is shown in Figure 1. These findings highlight AI's potential to enhance efficiency in aneurysm detection while underscoring the need for further refinements to improve sensitivity and specificity in clinical practice. Although AI supports neuroradiologists, it cannot replace expert interpretation. The best diagnostic accuracy is achieved by combining AI with human expertise, optimizing the reporting process and workflow. This review aims to contextualize the findings of Adamchic et al. (2024) within the broader landscape of AI applications in IA diagnostics, highlighting advancements, challenges, and future directions.

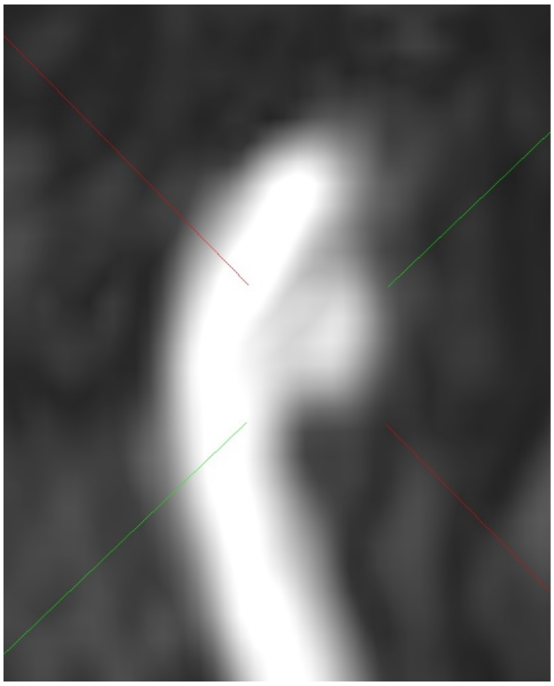

**Figure 1:** AI-detected intracranial aneurysm in the petrous segment of the internal carotid artery, missed on initial radiologist interpretation. The aneurysm is highlighted on the TOF-MRA image, demonstrating the potential of AI-assisted detection in routine brain MRI analysis.

## Advancements in Artificial Intelligence for Intracranial Aneurysm Detection

AI has revolutionized the approach to IA detection, significantly enhancing diagnostic capabilities. The advent of CNNs, particularly in medical imaging, has facilitated improved sensitivity and specificity in identifying aneurysms. Advanced imaging techniques like MRA and CTA have been augmented by AI, enabling more precise and consistent interpretations[2,4,5].

CNNs have demonstrated exceptional capability in localizing and characterizing intracranial aneurysms (IAs), with studies showing near-human or even superior performance in detecting these abnormalities. In particular, the DeepMedic CNN has achieved high diagnostic accuracy across diverse datasets, proving especially effective in identifying small aneurysms (<5 mm) that are often missed during manual reviews[22,23]. DeepMedic achieved a Dice Similarity Coefficient of 0.868 and a Connectivity-

Area-Length of 0.971, indicating strong agreement with the ground truth vessel structures (DSA). Notably, it successfully detected all IAs with less than 10% error in key morphometric measurements, whereas expert radiologists missed 34.7% of IAs, particularly those in the cavernous carotid region, and showed significantly greater variability in aneurysm size and shape assessment. These findings highlight the potential of AI to improve both detection accuracy and consistency, especially in anatomically challenging locations. Furthermore, another study demonstrated that AI integration into imaging workflows reduces variability in human interpretation, particularly among less experienced radiologists, resulting in more reliable and standardized diagnostic outcomes[24]. These results emphasize the transformative role AI can play in neuroradiology, not only enhancing detection but also supporting clinical decision-making through improved precision and reproducibility.

The utility of AI extends beyond detection. Radiomics-based models that combine imaging data with clinical parameters have shown promise in assessing rupture risks and predicting aneurysm growth[25,26]. These predictive models rely on high-dimensional imaging features, such as texture and shape, to identify patterns associated with aneurysm behavior. Liu et al. (2019) assessed the predictive performance of machine learning models for aneurysm using the area under the curve. Among the models tested, the glm_lasso model achieved the highest area under the curve of 0.853 (95% CI, 0.767–0.940), demonstrating strong predictive capability when incorporating both morphological and clinical features. Such tools enable clinicians to make more informed decisions about intervention timing and treatment strategies, reducing the risk of unnecessary procedures and improving patient outcomes.

## Challenges in False Positives and Their Clinical Implications

Despite its potential, AI in IA detection faces notable challenges, with false positives being a concern. High false-positive rates can offset the benefits of automated systems by increasing radiologists' workloads[8]. The paper reports sensitivity, false-positive rate, and area under the receiver operating characteristic curve (ROC-AUC) for AI in aneurysm detection. Standalone AI had 91.2% sensitivity, 16.5% false-positive rate, and 0.936 ROC-AUC, while AI-assisted readers had 90.3% sensitivity, 7.9% false-positive rate, and 0.910 ROC-AUC. Each flagged finding must be carefully reviewed to determine its clinical relevance, potentially consuming additional time and resources. The consequences of false positives are multifaceted. For patients, unnecessary follow-up imaging and invasive procedures not only increase healthcare costs but also introduce emotional stress and potential medical complications. For clinicians, the time spent investigating false positives can detract from other critical tasks, thereby limiting the efficiency gains promised by AI. Addressing these issues requires improvements in algorithm design and post-processing techniques to refine detection accuracy[27].

Moreover, false positives may erode trust in AI among clinicians. Radiologists may become skeptical of AI-generated results if the technology consistently flags irrelevant findings, leading to underutilization of these tools in practice. Strategies to mitigate this include better calibration of algorithms to prioritize specificity in clinical settings without significantly compromising sensitivity. Comparative studies evaluating the balance between sensitivity and specificity in different AI models could guide their optimization for clinical application.

## Assessing the Impact on Radiologists' Workload

The integration of AI into clinical workflow has profound implications for radiologists' workload. On one hand, AI has the potential to streamline the review of routine cases, allowing radiologists to allocate more time to complex diagnostics. On the other hand, false-positives could inadvertently increase workload by necessitating additional reviews of flagged cases[8,9,27]. Quantitative assessments of AI's impact on workload remain limited, highlighting a significant gap in current research. Initial studies suggest that while AI reduces the time required for certain tasks, such as aneurysm segmentation and measurement, the overall net effect on workload may vary depending on the model and clinical context[4,6]. Future studies should focus on measuring time savings versus additional efforts in real-world settings to better quantify AI's practical benefits.

Training radiologists to interpret AI-generated data effectively is another critical factor influencing workload. Familiarity with AI outputs, including understanding algorithmic limitations and potential biases, is essential for ensuring efficient use of these tools. Integrating AI training into radiology education could help bridge this gap, fostering a collaborative environment where AI complements human expertise.

## Data Safety and Ethical Considerations

AI's reliance on large datasets raises important questions about data safety and privacy. Intracranial aneurysm detection often requires the analysis of sensitive imaging and clinical data, necessitating robust safeguards to prevent unauthorized access and ensure compliance with regulations like the General Data Protection Regulation (GDPR)[28]. Secure data storage, encryption, and anonymization are critical components of AI implementation, particularly in multicenter studies involving diverse patient populations.

Ethical considerations surrounding AI also merit attention. Questions of accountability arise when AI tools influence clinical decisions, especially in cases of misdiagnosis or treatment delays. Establishing clear guidelines for AI usage, including delineating responsibilities between clinicians and AI systems, is crucial for maintaining ethical standards in practice[29].

Transparency in AI algorithms, or explainability, is essential for fostering trust and usability among clinicians. The INTRPRT guideline underscores that transparency is not an inherent property of the algorithm but a user-centric affordance. Designing explainable AI for medical applications requires a human-centered approach, where understanding user needs and contextual constraints is foundational. This includes iterative prototyping and empirical validation with end-users to ensure the algorithms align with clinical practices and user expectations. Such methodologies not only enhance trust but also mitigate the risks of developing systems that may be computationally sophisticated but clinically irrelevant[30].

## Financial Implications and Reimbursement Models

Implementing AI in radiology poses financial challenges, especially regarding reimbursement models. Traditional fee-for-service frameworks often overlook the value of AI tools that enhance diagnostic accuracy and streamline workflows. Innovative reimbursement mechanisms, such as the New Technology Add-On Payment (NTAP) in the U.S. and similar policies in the U.K. and Japan, are crucial for incentivizing adoption. Reimbursement should prioritize AI applications that improve diagnostic performance or offer transformational insights supported by robust clinical evidence[31,32]. To address financial challenges in AI adoption, healthcare providers should explore alternative reimbursement strategies, such as bundled payments or performance-based incentives that reward improved efficiency and accuracy. For example, insurers could offer reimbursement bonuses for AI tools that demonstrably reduce misdiagnoses and unnecessary follow-up imaging. Cost-effectiveness studies should be structured to include real-world economic benefits, such as shorter hospital stays, reduced radiologist workload, and fewer unnecessary procedures. A practical example is using AI-assisted stroke detection, which can accelerate treatment decisions by directly contacting the neurointerventional team after automatic analysis of the stroke protocol images, reduce disability rates, and lower long-term rehabilitation costs. To mitigate high initial and operational costs, hospitals can adopt shared AI platforms or cloud-based subscription models, similar to how radiology groups pool resources for PACS. In low-resource settings, public-private partnerships could help subsidize AI integration, ensuring equitable access to AI-driven diagnostics without overburdening healthcare budgets.

## Applicability in Daily Practice

The integration of AI into clinical radiology requires alignment with workflows and infrastructure[33,34]. Seamless integration into radiology platforms, enhanced by features like natural language processing, improves user experience and minimizes disruptions. Standardized data exchange, such as DICOM metadata optimization, is critical for workflow consistency. Multicenter trials are essential to validate AI's performance across varied settings, ensuring reliability and generalizability. Healthcare infrastructure variability poses challenges, as high-resource settings adopt AI more readily than resource-limited regions. Cloud-based AI systems and telemedicine offer viable solutions for equitable access. Collaboration between radiologists and developers is vital. Feedback informs iterative algorithm refinement, ensuring clinical relevance and responsiveness to dynamic needs. Non-interpretive AI tools, such as automated protocol optimization and image quality control, reduce administrative burdens while enhancing diagnostic efficiency. These strategies collectively promote equitable, efficient, and sustainable AI integration into radiology practice.

## Conclusion

Artificial intelligence is transforming the detection and management of intracranial aneurysms, addressing critical challenges such as diagnostic variability, resource constraints, and the identification of subtle abnormalities. Deep learning models, particularly CNNs, have demonstrated near-expert accuracy in detecting small aneurysms (<5 mm) often missed during routine reviews. Furthermore, the integration of radiomics-based AI tools into clinical workflows enables predictive diagnostics, such as rupture risk assessment and treatment planning, improving patient outcomes and reducing unnecessary interventions. These advancements not only enhance diagnostic precision but also mitigate interobserver variability, particularly benefiting less experienced radiologists.

However, AI adoption faces persistent challenges. Relatively high false-positive rates, which may lead to an increased workload for radiologists and necessitate careful clinical review, could offset some of AI's efficiency gains. False positives also introduce patient anxiety and additional healthcare costs, underlining the need for refined algorithms and better specificity without compromising sensitivity. Effective radiologist training and AI-radiologist collaborations are critical for overcoming these limitations and fostering trust in AI systems. Quantitative studies assessing the net impact of AI on workload, particularly in high-volume settings, remain essential, incorporating metrics such as true positive and false negative rates as part of the broader evaluation of diagnostic performance and efficiency.

| Component | Pros | Cons |
|---|---|---|
| Diagnostic Accuracy | ✔ Enhanced sensitivity & standardization | ✖ False positives & generalizability issues |
| Workflow Integration | ✔ Automation & efficiency | ✖ Requires robust IT infrastructure |
| Radiologist Workload | ✔ Reduces reading time | ✖ Possible increase in verification workload |
| Billing & Reimbursement | ✔ Potential cost savings | ✖ Unclear reimbursement models |
| Privacy & Data Security | ✔ Improved patient data management | ✖ Regulatory & ethical challenges |

**Figure 2:** AI Integration in radiology: Key Challenges, Benefits, and Considerations

AI implementation also raises ethical and practical concerns, including data safety, privacy compliance, and the need for transparent algorithms to foster trust among clinicians and patients. Addressing accountability in diagnostic errors is crucial for safe AI integration into clinical practice. Economic challenges, such as high initial costs and limited reimbursement models, further complicate adoption, especially in resource-limited settings. Outcome-based reimbursement frameworks and cost-effectiveness studies can provide financial justification for AI investments. Scalable, cloud-based solutions may ensure equitable access to AI's benefits globally.

Seamless integration into radiology workflows is vital for AI's practical applicability. User-friendly interfaces, interoperability with radiology systems, and multicenter trials to validate generalizability are essential steps forward. Collaboration between radiologists and developers remains pivotal, as iterative feedback ensures that AI systems address clinical needs effectively and remain relevant in dynamic healthcare environments.

Future advancements may include real-time diagnostic tools and patient-specific AI models for rupture risk prediction, further solidifying AI's role in modern radiology. By addressing existing challenges through research, collaboration, and ethical considerations, AI can become a cornerstone of intracranial aneurysm diagnostic and management recommendations, enhancing patient care and clinical outcomes while ensuring its limitations are minimized. Figure 2, "AI Integration in radiology: Key Challenges, Benefits, and Considerations" provides a visual summary of the major components involved in AI implementation, highlighting its advantages and potential challenges across different aspects of radiology practice.

## Conflicts of Interest

The author declares that there are no conflicts of interest regarding the publication of this article.

## References

1. Vlak MH, Algra A, Brandenburg R, et al. Prevalence of unruptured intracranial aneurysms, with emphasis on sex, age, comorbidity, country, and time period: a systematic review and meta-analysis. Lancet Neurol. 2011; 10(7): 626-636. https://doi.org/10.1016/S1474-4422(11)70109-0

2. Marasini A, Shrestha A, Phuyal S, et al. Role of Artificial Intelligence in Unruptured Intracranial Aneurysm: An Overview. Front Neurol. 2022; 13: 784326. doi: 10.3389/fneur.2022.784326

3. van Gijn J, Kerr RS, Rinkel GJ, Subarachnoid haemorrhage. Lancet. 2007; 369(9558): 306-18. https://doi.org/10.1016/ S0140-6736(07)60153-6

4. Shi Z, Hu B, Schoepf UJ, et al. Artificial Intelligence in the Management of Intracranial Aneurysms: Current Status and Future Perspectives. AJNR Am J Neuroradiol. 2020; 41(3): 373-379. doi: 10.3174/ajnr.A6468

5. Salem MM, Maragkos GA, Gomez-Paz S, et al. Trends of Ruptured and Unruptured Aneurysms Treatment in the United States in Post-ISAT Era: A National Inpatient Sample Analysis. J Am Heart Assoc. 2021; 10(4): e016998. doi: 10.1161/JAHA.120.016998

6. Planinc A, Špegel N, Podobnik Z, et al. Assessing accuracy and consistency in intracranial aneurysm sizing: human expertise vs. artificial intelligence. Sci Rep. 2024; 14(1): 16080. doi: 10.1038/ s41598-024-65825-4.

7. Wen Z, Wang Y, Zhong Y, et al. Advances in research and application of artificial intelligence and radiomic predictive models based on intracranial aneurysm images. Front Neurol. 2024; 15: 1391382. doi: 10.3389/fneur.2024.1391382

8. Din M, Agarwal S, Grzeda M, et al. Detection of cerebral aneurysms using artificial intelligence: a systematic review and meta-analysis. J Neurointerv Surg. 2023; 15(3): 262-271. doi: 10.1136/jnis-2022-019456

9. Adamchic I, Kantelhardt SR, Wagner HJ, et al. Artificial intelligence can help detecting incidental intracranial aneurysm on routine brain MRI using TOF MRA data sets and improve the time required for analysis of these images. Neuroradiology. 2024; 66(12): 2195-2204. doi: 10.1007/s00234-024-03460-6

10. Stember JN, Chang P, Stember DM, et al. Convolutional Neural Networks for the Detection and Measurement of Cerebral Aneurysms on Magnetic Resonance Angiography. J Digit Imaging. 2019; 32(5): 808-815. doi: 10.1007/s10278-018-0162-z

11. Najjar R. Redefining Radiology: A Review of Artificial Intelligence Integration in Medical Imaging. Diagnostics (Basel). 2023; 13(17): 2760. doi: 10.3390/diagnostics13172760

12. Li Y, Zhang H, Sun Y, et al. Deep learning-based platform performs high detection sensitivity of intracranial aneurysms in 3D brain TOF-MRA: An external clinical validation study. Int J Med Inform. 2024; 188: 105487. doi: 10.1016/j.ijmedinf.2024.105487

13. Gu F, Wu X, Wu W, et al. Performance of deep learning in the detection of intracranial aneurysm: A systematic review and meta-analysis. Eur J Radiol. 2022; 155: 110457. doi: 10.1016/j.ejrad.2022.110457

14. Park A, Chute C, Rajpurkar P, et al. Deep Learning-Assisted Diagnosis of Cerebral Aneurysms Using the HeadXNet Model. JAMA Netw Open. 2019; 2(6): e195600. doi: 10.1001/jamanetworkopen.2019.5600

15. Cao H, Zeng H, Lv L, et al. Assessment of intracranial aneurysm rupture risk using a point cloud-based deep learning model. Front Physiol. 2024; 15: 1293380. doi: 10.3389/fphys.2024.1293380

16. Kim HC, Rhim JK, Ahn JH, et al. Machine Learning Application for Rupture Risk Assessment in Small-Sized Intracranial Aneurysm. J Clin Med. 2019; 8(5): 683. doi: 10.3390/jcm8050683

17. Deshmukh AS, Priola SM, Katsanos AH, et al. The Management of Intracranial Aneurysms: Current Trends and Future Directions. Neurol Int. 2024; 16(1): 74-94. doi: 10.3390/neurolint16010005

18. Yang J, Xie M, Hu C, et al. Deep Learning for Detecting Cerebral Aneurysms with CT Angiography. Radiology. 2021; 298(1): 155-163. doi: 10.1148/radiol.2020192154

19. Bo ZH, Qiao H, Tian C, et al. Toward human intervention-free clinical diagnosis of intracranial aneurysm via deep neural network. Patterns (NY). 2021; 2(2): 100197. doi: 10.1016/j.patter.2020.100197

20. Filippi CG, Stein JM, Wang Z, et al. Ethical Considerations and Fairness in the Use of Artificial Intelligence for Neuroradiology. AJNR Am J Neuroradiol. 2023; 44(11): 1242-1248. doi: 10.3174/ajnr.A7963

21. Shi Z, Hu B, Lu M, et al. China Aneurysm AI Project Group. Assessing the Impact of an Artificial Intelligence-Based Model for Intracranial Aneurysm Detection in CT Angiography on Patient Diagnosis and Outcomes (IDEAL Study)-a protocol for a multicenter, double-blinded randomized controlled trial. Trials. 2024; 25(1): 358. doi: 10.1186/s13063-024-08184-9

22. Patel TR, Patel A, Veeturi SS, et al. Evaluating a 3D deep learning pipeline for cerebral vessel and intracranial aneurysm segmentation from computed tomography angiography-digital subtraction angiography image pairs. Neurosurg Focus. 2023; 54(6): E13. doi: 10.3171/2023.3

23. Sichtermann T, Faron A, Sijben R, et al. Deep Learning-Based Detection of Intracranial Aneurysms in 3D TOF-MRA. AJNR Am J Neuroradiol. 2019; 40(1): 25-32. doi: 10.3174/ajnr.A5911

24. Alwalid O, Long X, Xie M, et al. Artificial Intelligence Applications in Intracranial Aneurysm: Achievements, Challenges and Opportunities. Acad Radiol. 2022; 29 (Suppl 3): S201-S214. doi: 10.1016/j.acra.2021.06.013

25. Liu Q, Jiang P, Jiang Y, et al. Prediction of Aneurysm Stability Using a Machine Learning Model Based on PyRadiomics-Derived Morphological Features. Stroke. 2019; 50(9): 2314-2321. doi: 10.1161/STROKEAHA.119.025777

26. Wen Z, Wang Y, Zhong Y, et al. Advances in research and application of artificial intelligence and radiomic predictive models based on intracranial aneurysm images. Front Neurol. 2024; 15: 1391382. doi: 10.3389/fneur.2024.1391382

27. Kuwabara M, Ikawa F, Sakamoto S, et al. Effectiveness of tuning an artificial intelligence algorithm for cerebral aneurysm diagnosis: a study of 10,000 consecutive cases. Sci Rep. 2023; 13(1): 16202. doi: 10.1038/s41598-023-43418-x

28. Shah C, Nachand D, Wald C, et al. Keeping Patient Data Secure in the Age of Radiology Artificial Intelligence: Cybersecurity Considerations and Future Directions. J Am Coll Radiol. 2023; 20(9): 828-835. doi: 10.1016/j.jacr.2023.06.023

29. Brady AP, Neri E. Artificial Intelligence in Radiology-Ethical Considerations. Diagnostics (Basel). 2020; 10(4): 231. doi: 10.3390/diagnostics10040231

30. Chen H, Gomez C, Huang CM, et al. Explainable medical imaging AI needs human-centered design: guidelines and evidence from a systematic review. npj Digit Med. 2022. https://doi.org/10.1038/s41746-022-00699-2

31. Kasireddy M, Lee RK. The Economics of Artificial Intelligence: Focusing on the Metrics. Appl Rad Oncol. 2022; (3): 13-15.

32. Lobig F, Subramanian D, Blankenburg M, et al. To pay or not to pay for artificial intelligence applications in radiology. npj Digit Med. 2023. https://doi.org/10.1038/s41746-023-00861-4

33. Pierre K, Haneberg AG, Kwak S, et al. Applications of Artificial Intelligence in the Radiology Roundtrip: Process Streamlining, Workflow Optimization, and Beyond. Semin Roentgenol. 2023; 58(2): 158-169. doi: 10.1053/j.ro.2023.02.003

34. Schmidt S. AI-based approaches in the daily practice of abdominal imaging. Eur Radiol. 2024; 34(1): 495-497. doi: 10.1007/s00330-023-10116-1