
AI Triage for Stroke Imaging: Promise vs Risk of Deskilling Radiology Trainees

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Dear Editor,

Artificial intelligence (AI) has rapidly entered acute stroke care. Commercial platforms now detect large-vessel occlusion (LVO) on CT angiography and immediately notify stroke teams. Randomized and real-world data confirm that these tools reduce notification and thrombectomy initiation times, resulting in improved functional outcomes for patients (1,2). In spoke-and-hub networks, AI-assisted notification particularly strengthens equity of care by expediting transfers during nights and weekends (2).

Alongside these benefits, one underrecognized concern is the potential deskilling of radiology trainees. Overreliance on automated alerts risks diminishing the very competencies that training should cultivate, which include visual pattern recognition, logical reasoning, and confident communication with clinicians. Survey-based studies suggest that while trainees appreciate AI's efficiency, many are concerned about the erosion of independent judgment (3).

A second challenge is algorithmic variability. The reported sensitivity and specificity for LVO detection range widely, from 85–95% for the anterior circulation to lower performance in posterior circulation or artifact-heavy studies (4,5). Such blind spots create a paradox: AI accelerates decisions in straightforward cases but risks missing diagnoses in the more complex ones, the very instances in which human expertise is indispensable.

The solution is not to resist AI but to integrate it deliberately into radiology education. With thoughtful design, AI can both streamline workflow and strengthen training. We propose three practical steps:

1. AI-enhanced teaching modules: Residency curricula should include structured sessions on AI fundamentals, limitations, and critical appraisal. For instance, case-based teaching where 20% of cases are AI-flagged and 80% require independent interpretation can balance efficiency with skill-building.
2. Dual-read policy during rollout: For the first 12–18 months post-implementation, trainees should interpret CT angiography independently before reviewing AI output. Discrepancies should be logged to track both trainee learning curves and AI reliability.

3. Continuous audit and feedback: Institutions should perform monthly audits comparing AI performance with ground-truth adjudication. Cases of false negatives or false positives can be integrated into morbidity and mortality or case conferences to reinforce learning.

Such an approach acknowledges both the transformative benefits of AI in stroke triage and its risks to training. By embedding AI into structured teaching and feedback loops, future radiologists can remain technologically adept while preserving diagnostic rigor.

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REFERENCES

1. Martinez-Gutierrez, J. C., Kim, Y., Salazar-Marioni, S., Tariq, M. B., Abdelkhaleq, R., Niktabe, A., Ballekere, A. N., Iyyangar, A. S., Le, M., Azeem, H., Miller, C. C., Tyson, J. E., Shaw, S., Smith, P., Cowan, M., Gonzales, I., McCullough, L. D., Barreto, A. D., Giancardo, L., & Sheth, S. A. (2023). Automated Large Vessel Occlusion Detection Software and Thrombectomy Treatment Times: A Cluster Randomized Clinical Trial. *JAMA Neurology*, 80(11), 1182–1190. <https://doi.org/10.1001/jamaneurol.2023.3206>
2. Soun, J. E., Zolyan, A., McLouth, J., Elstrott, S., Nagamine, M., Liang, C., Dehkordi-Vakil, F. H., Chu, E., Florioli, D., Kuoy, E., Joseph, J., Abi-Jaoudeh, N., Chang, P. D., Yu, W., & Chow, D. S. (2023). Impact of an automated large vessel occlusion detection tool on clinical workflow and patient outcomes. *Frontiers in neurology*, 14, 1179250. <https://doi.org/10.3389/fneur.2023.1179250>
3. Tejani, A. S., Elhalawani, H., Moy, L., Kohli, M., & Kahn, C. E., Jr (2022). Artificial Intelligence and Radiology Education. *Radiology. Artificial intelligence*, 5(1), e220084. <https://doi.org/10.1148/ryai.220084>
4. Luijten, S. P. R., Wolff, L., Duvekot, M. H. C., van Doormaal, P. J., Moudrous, W., Kerkhoff, H., Lycklama A Nijeholt, G. J., Bokkers, R. P. H., Yo, L. S. F., Hofmeijer, J., van Zwam, W. H., van Es, A. C. G. M., Dippel, D. W. J., Roozenbeek, B., van der Lugt, A., & MR CLEAN Registry and PRESTO investigators (2022). Diagnostic performance of an algorithm for automated large vessel occlusion detection on CT angiography. *Journal of neurointerventional surgery*, 14(8), 794–798. <https://doi.org/10.1136/neurintsurg-2021-017842>
5. Amukotuwa, S. A., Straka, M., Smith, H., Chandra, R. V., Dehkharghani, S., Fischbein, N. J., & Bammer, R. (2019). Automated Detection of Intracranial Large Vessel Occlusions on Computed Tomography Angiography: A Single Center Experience. *Stroke*, 50(10), 2790–2798. <https://doi.org/10.1161/STROKEAHA.119.026259>