

Drugs **Health Technologies** Health Systems

# **Health Technology Review**

# **Supporting Information for RapidAI Review**

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# <span id="page-4-0"></span>**Abbreviations**

- **AI** artificial intelligence
- **ICH** intracranial hemorrhage
- **LVO** large vessel occlusion
- **QUADAS-2** Quality Assessment of Diagnostic Accuracy Studies 2
- **ROBINS-I** Risk Of Bias In Nonrandomized Studies of Interventions

# <span id="page-5-0"></span>**Selection of Included Studies**

## <span id="page-5-1"></span>**Figure 1: Selection of Included Studies**



# <span id="page-6-0"></span>**List of Included Publications**

The citations provided in this list are the publications that were included in this rapid review (in reverse chronological and alphabetical order).

Delora A, Hadjialiakbari C, Percenti E, Torres J, Alderazi YJ, Ezzeldin R, Hassan AE, Ezzeldin M. Viz LVO versus Rapid LVO in detection of large vessel occlusion on CT angiography for acute stroke. J Neurointerv Surg. 2024 May 21;16(6):599 to 602. doi: 10.1136/jnis-2023-020445. PMID: 37355255.

Slater LA, Ravintharan N, Goergen S, et al. RapidAI compared with Human Readers of Acute Stroke Imaging for Detection of Intracranial Vessel Occlusion. Stroke: Vascular and Interventional Neurology. 2024;4:e001145

Chan N, Sibtain N, Booth T, de Souza P, Bibby S, Mah YH, Teo J, U-King-Im JM. Machine-learning algorithm in acute stroke: real-world experience. Clin Radiol. 2023 Feb;78(2):e45-e51. doi: 10.1016/j. crad.2022.10.007. Epub 2022 Nov 18. PMID: 36411087.

Soun JE, Zolyan A, McLouth J, et al. Impact of an automated large vessel occlusion detection tool on clinical workflow and patient outcomes. Frontiers in neurology [electronic resource]. 2023; 14():1179250. PubMed: 37305764

Yedavalli V, Heit JJ, Dehkharghani S, et al. Performance of RAPID noncontrast CT stroke platform in large vessel occlusion and intracranial hemorrhage detection. Front Neurol. 2023; 14():. PubMed:

Mallon DH, Taylor EJR, Vittay OI, Sheeka A, Doig D, Lobotesis K. Comparison of automated ASPECTS, large vessel occlusion detection and CTP analysis provided by Brainomix and RapidAI in patients with suspected ischemic stroke. J Stroke Cerebrovasc Dis. Oct 2022; 31(10):106702. PubMed: 35994882

Eldaya RW, Kansagra AP, Zei M, et al. Performance of Automated RAPID Intracranial Hemorrhage Detection in Real-World Practice: A Single-Institution Experience. J Comput Assisted Tomogr. Sep-Oct 01 2022; 46(5):770 to 774. PubMed: 35617649

Schlossman J, Ro D, Salehi S, Chow D, Yu W, Chang PD, Soun JE. Head-to-head comparison of commercial artificial intelligence solutions for detection of large vessel occlusion at a comprehensive stroke centre. Front Neurol. 2022 Oct 10;13:1026609. doi: 10.3389/fneur.2022.1026609. PMID: 36299266; PMCID: PMC9588973.

Adhya J, Li C, Eisenmenger L, Cerejo R, Tayal A, Goldberg M, Chang W. Positive predictive value and stroke workflow outcomes using automated vessel density (RAPID-CTA) in stroke patients: One year experience. Neuroradiol J. 2021 Oct;34(5):476 to 481. doi: 10.1177/19714009211012353. Epub 2021 Apr 28. PMID: 33906499; PMCID: PMC8559016.

Dehkharghani S, Lansberg M, Venkatsubramanian C, Cereda C, Lima F, Coelho H, Rocha F, Qureshi A, Haerian H, Mont'Alverne F, Copeland K, Heit J. High-Performance Automated Anterior Circulation CT Angiographic Clot Detection in Acute Stroke: A Multireader Comparison. Radiology. 2021 Mar;298(3):665 to 670. doi: 10.1148/radiol.2021202734. Epub 2021 Jan 12. PMID: 33434110.

<span id="page-7-0"></span>Amukotuwa SA, Straka M, Smith H, Chandra RV, Dehkharghani S, Fischbein NJ, Bammer R. Automated Detection of Intracranial Large Vessel Occlusions on CT Angiography: A Single Center Experience. Stroke. 2019 Oct;50(10):2790 to 2798. doi: 10.1161/STROKEAHA.119.026259. Epub 2019 Sep 9. PMID: 31495328.

# **List of Excluded Publications and Reasons for Exclusion**

The citations provided in this list are studies that were excluded after full-text review as part of the rapid review (in reverse chronological and alphabetical order).

#### **Ineligible Population (n = 15)**

Alwood BT, Meyer DM, Ionita C, et al. Multicenter comparison using 2 AI stroke CT perfusion software packages for determining thrombectomy eligibility. J Stroke Cerebrovasc Dis. 2024 Jul;33(7):107750. Epub 2024 May 2. PubMed: 38703875.

Pisani L, Haussen DC, Mohammaden M, et al. Comparison of CT Perfusion Software Packages for Thrombectomy Eligibility. Ann Neurol. 11 2023; 94(5):848 to 855. PubMed: 37584452

Yedavalli V, Hamam O, Mohseni A, et al. Pretreatment brain CT perfusion thresholds for predicting final infarct volume in distal medium vessel occlusions. J Neuroimaging. Nov-Dec 2023; 33(6):968 to 975. PubMed: 37357133

Xiong Y, Luo Y, Wang M, et al. Evaluation of Diffusion-Perfusion Mismatch in Acute Ischemic Stroke with a New Automated Perfusion-Weighted Imaging Software: A Retrospective Study. Neurol. Dec 2022; 11(4):1777 to 1788. PubMed: 36201112

Wouters A, Robben D, Christensen S, et al. Prediction of Stroke Infarct Growth Rates by Baseline Perfusion Imaging. Stroke. 02 2022; 53(2):569 to 577. PubMed: 34587794

Bouslama M, Ravindran K, Harston G, et al. Noncontrast CT e-Stroke Infarct Volume Is Similar to RAPID CT Perfusion in Estimating Postreperfusion Infarct Volumes. Stroke. 01 2021; 52(2):634 to 641. PubMed: 33430633

Maegerlein C, Fischer J, Monch S, et al. Automated Calculation of the Alberta Stroke Program Early CT Score: Feasibility and Reliability. Radiology. 04 2019; 291(1):141 to 148. PubMed: 30720400

Demeestere J, Scheldeman L, Cornelissen SA, et al. Alberta Stroke Program Early CT Score Versus Computed Tomographic Perfusion to Predict Functional Outcome After Successful Reperfusion in Acute Ischemic Stroke. Stroke. 10 2018; 49(10):2361 to 2367. PubMed: 30355098

Automated CT perfusion imaging to aid in the selection of patients with acute ischemic stroke for mechanical thrombectomy: A health technology assessment. Ont Health Technol Assess Ser. 2020; 20(13)():1 to 87. PubMed: 2005424949

Lakatos L, Bolognese M, Müller M, Österreich M, von Hessling A. Automated Supra- and Infratentorial Brain Infarct Volume Estimation on Diffusion Weighted Imaging Using the RAPID Software. Front Neurol. 2022; 13():. PubMed:

Kurmann CC, Kaesmacher J, Cooke DL, et al. Evaluation of time-resolved whole brain flat panel detector perfusion imaging using RAPID ANGIO in patients with acute stroke: Comparison with CT perfusion imaging. J Neurointerv Surg. 2023; 15(4):387 to 392. PubMed:

Pistocchi S, Strambo D, Bartolini B, et al. MRI software for diffusion-perfusion mismatch analysis may impact on patients' selection and clinical outcome. Eur Radiol. 2022; 32(2):1144 to 1153. PubMed:

Amukotuwa SA, Straka M, Dehkharghani S, Bammer R. Fast Automatic Detection of Large Vessel Occlusions on CT Angiography. Stroke. 2019 Dec;50(12):3431 to 3438. doi: 10.1161/ STROKEAHA.119.027076. Epub 2019 Nov 4. PMID: 31679501; PMCID: PMC6878187.

Albers GW, Wald MJ, Mlynash M, Endres J, Bammer R, Straka M, Maier A, Hinson HE, Sheth KN, Taylor Kimberly W, Molyneaux BJ. Automated Calculation of Alberta Stroke Program Early CT Score: Validation in Patients With Large Hemispheric Infarct. Stroke. 2019 Nov;50(11):3277 to 3279. doi: 10.1161/ STROKEAHA.119.026430. Epub 2019 Sep 10. PMID: 31500555.

Siegler JE, Olsen A, Pulst-Korenberg J, Cristancho D, Rosenberg J, Raab L, Cucchiara B, Messé SR. Multicenter Volumetric Assessment of Artifactual Hypoperfusion Patterns using Automated CT Perfusion Imaging. J Neuroimaging. 2019 Sep;29(5):573 to 579. doi: 10.1111/jon.12641. Epub 2019 Jun 14. PMID: 31199025; PMCID: PMC6731139.

#### **Ineligible Intervention (n = 13)**

Westwood M, Ramaekers B, Grimm S, Armstrong N, Wijnen B, Ahmadu C, de Kock S, Noake C, Joore M. Software with artificial intelligence-derived algorithms for analysing CT brain scans in people with a suspected acute stroke: a systematic review and cost-effectiveness analysis. Health Technol Assess. 2024 Mar;28(11):1 to 204. doi: 10.3310/RDPA1487. PMID: 38512017; PMCID: PMC11017149.

Yedavalli V, Kihira S, Shahrouki P, Hamam O, Tavakkol E, McArthur M, Qiao J, Johanna F, Doshi A, Vagal A, Khatri P, Srinivasan A, Chaudhary N, Bahr-Hosseini M, Colby GP, Nour M, Jahan R, Duckwiler G, Arnold C, Saver JL, Mocco J, Liebeskind DS, Nael K. CTP-based estimated ischemic core: A comparative multicenter study between Olea and RAPID software. J Stroke Cerebrovasc Dis. 2023 Nov;32(11):107297. doi: 10.1016/j.jstrokecerebrovasdis.2023.107297. Epub 2023 Sep 20. PMID: 37738915.

Werdiger F, Gotla S, Visser M, et al. Automated occlusion detection for the diagnosis of acute ischemic stroke: A detailed performance review. Eur J Radiol. Jul 2023; 164():110845. PubMed: 37148842

Lee KY, Liu CC, Chen DY, Weng CL, Chiu HW, Chiang CH. Automatic detection and vascular territory classification of hyperacute staged ischemic stroke on diffusion weighted image using convolutional neural networks. Sci Rep. 01 09 2023; 13(1):404. PubMed: 36624122

Al-Kawaz M, Primiani C, Urrutia V, Hui F. Impact of RapidAI mobile application on treatment times in patients with large vessel occlusion. J Neurointerv Surg. Mar 2022; 14(3):233 to 236. PubMed: 33795483

Sreekrishnan, Anirudh and Giurgiutiu, Dan-Victor and Kitamura, Felipe and Martinelli, Carlos and Abdala, Nitamar and Haerian, Hafez and Dehkharghani, Seena and Kwok, Keith and Yedavalli, Vivek and Heit, Jeremy. (2023). Decreasing false-positive detection of intracranial hemorrhage (ICH) using RAPID ICH 3. Journal of stroke and cerebrovascular diseases: the official journal of National Stroke Association. 32. 107396. 10.1016/j.jstrokecerebrovasdis.2023.107396.

Heit JJ, Coelho H, Lima FO, Granja M, Aghaebrahim A, Hanel R, Kwok K, Haerian H, Cereda CW, Venkatasubramanian C, Dehkharghani S, Carbonera LA, Wiener J, Copeland K, Mont'Alverne F. Automated Cerebral Hemorrhage Detection Using RAPID. AJNR Am J Neuroradiol. 2021 Jan;42(2):273 to 278. doi: 10.3174/ajnr.A6926. Epub 2020 Dec 24. PMID: 33361378; PMCID: PMC7872180.

Hokkinen L, Makela T, Savolainen S, Kangasniemi M. CT angiography-based deep learning method for treatment selection and infarct volume prediction in anterior cerebral circulation large vessel occlusion. Acta Radiol Open. Nov 2021; 10(11):20584601211060347. PubMed: 34868662

Hokkinen L, Makela T, Savolainen S, Kangasniemi M. Evaluation of a CTA-based convolutional neural network for infarct volume prediction in anterior cerebral circulation ischemic stroke. Eur Radiol Exp. 06 24 2021; 5(1):25. PubMed: 34164743

Kim YC, Lee JE, Yu I, et al. Evaluation of Diffusion Lesion Volume Measurements in Acute Ischemic Stroke Using Encoder-Decoder Convolutional Network. Stroke. 06 2019; 50(6):1444 to 1451. PubMed: 31092169

Deshpande A, Elliott J, Jiang B, et al. End to end stroke triage using cerebrovascular morphology and machine learning. Front Neurol. 2023; 14(no pagination)():. PubMed: 2026464700

Rajendra Acharya U, Meiburger KM, Faust O, et al. Automatic detection of ischemic stroke using higher order spectra features in brain MRI images. Cogn Syst Res. December 2019; 58():134 to 142. PubMed: 2002100357

Xiong Y, Huang CC, Fisher M, Hackney DB, Bhadelia RA, Selim MH. Comparison of Automated CT Perfusion Softwares in Evaluation of Acute Ischemic Stroke. J Stroke Cerebrovasc Dis. 2019 Dec;28(12):104392. doi: 10.1016/j.jstrokecerebrovasdis.2019.104392. Epub 2019 Sep 25. PMID: 31562038.

#### **Ineligible Comparator (n = 7)**

Siegler JE, Rosenberg J, Cristancho D, et al. CT perfusion in stroke mimics. Int J Stroke. 04 2020; 15(3):299 to 307. PubMed: 31409213

Kauw F, Heit JJ, Martin BW, van Ommen F, Kappelle LJ, Velthuis BK, de Jong HWAM, Dankbaar JW, Wintermark M. CT Perfusion Data for Acute Ischemic Stroke Evaluation Using Rapid Software: Pitfalls of Automated Postprocessing. J Comput Assist Tomogr. 2020 Jan/Feb;44(1):75 to 77. doi: 10.1097/ RCT.0000000000000946. PMID: 31804241.

Bulwa Z, Dasenbrock H, Osteraas N, Cherian L, Crowley RW, Chen M. Incidence of Unreliable Automated CT Perfusion Maps. J Stroke Cerebrovasc Dis. Dec 2019; 28(12):104471. PubMed: 31680033

Campbell BC, Yassi N, Ma H, et al. Imaging selection in ischemic stroke: feasibility of automated CTperfusion analysis. Int J Stroke. Jan 2015; 10(1):51 to 4. PubMed: 25319251

Hoving JW, Marquering HA, Majoie CBLM, et al. Volumetric and spatial accuracy of CT perfusion estimated ischemic core volume in patients with acute ischemic stroke. Stroke. 2018; 49(10)():2368 to 2375. PubMed: 627080929

Campbell BCV, Yassi N, Ma H, et al. Imaging selection in ischemic stroke trials - Feasibility of automated CT perfusion analysis. Cerebrovasc Dis. May 2014; 37(Supplement 1)():81. PubMed: 614324511

John S, Hussain SI, Piechowski B, Dogar MA. Discrepancy in core infarct between non-contrast CT and CT perfusion when selecting for mechanical thrombectomy. J Cerebrovasc Endovasc Neurosurg. 2020; 22(1):8 to 14. PubMed:

#### **Ineligible Study Design (n = 3)**

Gilotra K, Swarna S, Mani R, Basem J, Dashti R. Role of artificial intelligence and machine learning in the diagnosis of cerebrovascular disease. Front Hum Neurosci. 2023; 17():1254417. PubMed: 37746051

Morelli N, Colombi D, Michieletti E. Ischemic Core Estimation by CT Perfusion: A Matter of (rCBF) Numbers. *Am J Roentgenol*. 2023;221(2):284. <https://www.ncbi.nlm.nih.gov/pmc/articles/37134207>

Byrne D, Walsh JP, MacMahon PJ. An acute stroke CT imaging algorithm incorporating automated perfusion analysis. Emerg. Jun 2019; 26(3):319 to 329. PubMed: 30706257

#### **Not Published in English (n = 3)**

Cirio JJ, Diluca P, Ciardi C, et al. [Impact of artificial intelligence on therapeutic metrics of cerebrovascular attack during the COVID-19 pandemic]. Medicina (B Aires). 2023; 83(5):705 to 718. PubMed: 37870328

Cirio JJ, Diluca P, Ciardi C, et al. Impact of artificial intelligence on therapeutic metrics of cerebrovascular attack during the COVID-19 pandemic. Medicina (Argentina). 2023; 83(5):705 to 718

Cirio JJ, Ciardi C, Buezas M, et al. Implementation of artificial intelligence in hyperacute arterial reperfusion treatment in a comprehensive stroke centre. Neurologia Argentina. 01 Oct 2021; 13(4)():212 to 220.

#### **Published in an Ineligible Format (n = 34)**

Granja MF, Ramirez K, Espinel L, et al. Performance of Rapidai NCCT Stroke Software in Colombia's Early Stroke System: Preliminary Results. *Stroke Conference: American Stroke Association's.* 2024;55(Supplement 1).

Kashyap B, Herrmann AA, Droegemueller CJ, et al. Application of a Horizontal Communication Process in Combination With Artificial Intelligence (AI) to Improve Stroke Care in Patients With Large Vessel Occlusion (LVO). *Stroke Conference: American Stroke Association's.* 2024;55(Supplement 1).

Lavados P, Gonzalez P, Olavarria V, Albers GW. Improved Outcomes for Acute Ischemic Stroke Patients After Implementation of the RapidAI Platform in a Comprehensive Stroke Center in Santiago, Chile. *Stroke Conference: American Stroke Association's.* 2024;55(Supplement 1).

Mahdi Sowlat M, Zamarud A, Albers GW, Campbell B, Heit JJ, Spiotta AM. Detecting Medium Vessel Occlusions and Collateral Assessment With Multimodality AI Approach. *Stroke Conference: American Stroke Association's.* 2024;55(Supplement 1).

Malisch TW, Asif K, Geraghty S, Olges M, Copeland K, Albers G. Improved Stroke Outcomes Following Implementation of RapidAI Platform at Ascension-Illinois. *Stroke Conference: American Stroke Association's.* 2024;55(Supplement 1).

Yedavalli V, Heit JJ, Dehkharghani S, et al. Performance of RAPID noncontrast CT stroke platform in large vessel occlusion and intracranial hemorrhage detection. medRxiv. 2023; 16():. PubMed: 2026945999

Deshpande A, Elliott J, Jiang B, et al. End to end stroke triage using cerebrovascular morphology and machine learning. medRxiv. 2023; 01():. PubMed: 2023736914

Kroon L, Schutte C. Bridging the Gap: Telestroke's Impact on Access to Stroke Care in South Africa. Int J Stroke. October 2023; 18(3 Supplement)():453. PubMed: 642828378

Almajidi M, Omairi M, Ajamaya B, Jevtic I, Antulov R. IMPLEMENTATION of AUTOMATED QUANTIFIED CTP in PATIENTS with NIHSS = 6-A SINGLECENTER EXPERIENCE. Neuroradiology. September 2023; 65(Supplement 1)():S98-S99. PubMed: 642678904

Biswas V, Sitaram A, Pollard C, Izzath MWK, Muir K. Variable penumbra but not core volume by occlusion site in large vessel occlusion. Eur Stroke J. May 2023; 8(2 Supplement)():527 to 528. PubMed: 641735590

Kihira S, Shahrouki P, Tavakol E, et al. CTP-based estimated Ischemic Core: A Comparative Multicenter Study between Olea and RAPID software. Eur Stroke J. May 2023; 8(2 Supplement)():525 to 526. PubMed: 641735460

Miao K, Miao J. Diagnosis and Prognosis of Stroke Using Artificial Intelligence and Imaging. Neurology Conference: American Academy Of Neurology Annual Meeting, AAN. 2023; 100(17 Supplement 2):. PubMed: 641672041

Affeldt ZS, Sabayan B, Droegemueller CJ, et al. Use of an Integrated Communication Tool Improves Stroke Care for Patients With Large Vessel Occlusion. Acad Emerg Med. May 2023; 30(Supplement 1)():94. PubMed: 641605611

Marigold R. Benefits of a regional CT artificial intelligence work steam in identifying patients for transfer to a comprehensive stroke centre (CSC) for mechanical thrombectomy. Int J Stroke. January 2023; 18(1 Supplement)():26. PubMed: 640506051

Leer M, McParland S, Wiggam I. How useful is artificial intelligence to support interpretation of CTA in hyperacute stroke?. Int J Stroke. January 2023; 18(1 Supplement)():68 to 69. PubMed: 640505744

Degan D, Turinese E, Iannucci G, et al. Rapid Software Effectiveness in Selecting Patients with Acute Ischemic Stroke Eligible for Endovascular Mechanical Thrombectomy. Neurol Sci. December 2022; 43(Supplement 1)():S359. PubMed: 639930188

Lambert J, Dewachter B, Demeestere J, Demaerel P, Lemmens R. Automated Aspects Software to Assist in Clinical Decisioning for Mechanical Thrombectomy. Neuroradiology. September 2022; 64(Supplement 1) ():S31. PubMed: 639201234

Fouarge E, Ciobanu C, Cornet O, et al. Evaluation of Perfusion Imaging in Late Window Thrombectomy in Everyday Clinical Practice: Results of a Prospective Registry from a Network of Belgian Hospitals. Eur Stroke J. May 2022; 7(1 SUPPL)():262. PubMed: 638375599

Chang W, Eisenmenger L, Cerejo R, Li C, Goldberg MF. Artificial intelligence for automated detection of intracranial hemorrhage (rapid ICH): Initial clinical experience. Stroke Conference. 2022; 53(SUPPL 1):. PubMed: 637367335

Catapano J, Lee K, Desai S, Ducruet AF, Albuquerque FC, Jadhav AP. Number-needed-to-review: A novel metric to assess triage efficiency of large vessel occlusion detection systems. Stroke Conference. 2022; 53(SUPPL 1):. PubMed: 637365693

Vargas J, Moorhead S, Chaudry M, Turner R, Turk A. A comparison of 2 automated CTP algorithms for estimation of core infarct. J Neurointerv Surg. August 2021; 13(SUPPL 1)():A72. PubMed: 635846865

Dehkharghani S, Lansberg MG, Venkatsubramanian C, et al. Rapid-lvo for automated detection of intracranial large vessel occlusion in ct angiography of the brain. Stroke Conference: American Stroke Association International Stroke Conference, ISC. 2021; 52(SUPPL 1):. PubMed: 634989714

Miao KH, Miao JH. Enhancing Pain Management and Rehabilitation Outcomes in Stroke Patients with Artificial Intelligence and Medical Imaging. *J Investig Med*. 2021 April;69(4):935. PubMed: PM641217957

Pisani L, Mohammaden M, Bouslama M, et al. Comparison of 3 automated ct perfusion software packages for thrombectomy eligibility and final infarct volume prediction. Stroke Conference: American Stroke Association International Stroke Conference, ISC. 2021; 52(SUPPL 1):. PubMed: 634989474

Seo K, Kim GS, Yun PH, Suh SH. An introduction of the rapid software increased the number of mechanical thrombectomy with favourable outcome in stroke patients. Neuroradiology. 2019; 61(1)():S106. PubMed: 631878630

Mehta S, Panezai S, Strauss S, et al. RAPIDTM based treatment algorithms lead to faster activation of neurointervention team and reduce recanalization times. Neurology Conference: 71st Annual Meeting of the American Academy of Neurology, AAN. 2019; 92(15 Supplement 1):. PubMed: 629239448

Bouslama M, Rodrigues G, Ravindran K, Haussen D, Frankel M, Nogueira R. Ct perfusion and e-aspects automated noncontract CT ischemic core volumes: Correlations and clinical outcome prediction. Eur Stroke J. May 2019; 4(Supplement 1)():405. PubMed: 628560803

Chen L, Hallett C, Fernandes C, et al. Automated multi-feature quantification of plain CT in acute stroke. Eur Stroke J. May 2019; 4(Supplement 1)():432. PubMed: 628561132

Austein F, Jurgensen N, Lindner T, Jansen O. Impact of diferent reconstruction algorithms and diferent slice thickness on automated stroke software tool to detect early ischemic changes. Clin Neuroradiol. September 2018; 28(Supplement 1)():S88. PubMed: 624304752

Demeestere J, Scheldeman L, Cornelissen S, et al. Conventional and Automated Aspects versus Ct perfusion core volume to predict functional outcome in reperfused acute ischemic stroke patients undergoing endovascular therapy. Stroke Conference: American Heart Association/American Stroke Association. 2018; 49(Supplement 1):. PubMed: 621004873

Karamchandani RR, Singh SJ, Rhoten JB, et al. CT perfusion core infarct measurement compared to diffusion-weighted MRI in patients with revascularization of anterior circulation, large artery occlusions. Stroke Conference: American Heart Association/American Stroke Association. 2018; 49(Supplement 1):. PubMed: 621004425

Paz D, Yagoda D, Wein T. Single Site performance of AI software for stroke detection and Triage. medRxiv. 2021; ():2021.04.02.21253083. PubMed:

Pourmussa B, Gorovoy D. A retrospective analysis of the diagnostic performance of an FDA approved software for the detection of intracranial hemorrhage. medRxiv. 2023; ():2023.11.02.23297974. PubMed:

Kamal H, Abdelhamid N, Zhu L, Sarraj A. Does RAPID reduce groin puncture times in acute, ischemic stroke? Presented at International Stroke Conference; 21 to 24 February 2017; Houston (TX). Stroke 2017;48(Suppl. 1):TP296.

#### **Duplicate Publications (n = 1)**

Hoving JW, Marquering HA, Majoie C, et al. Volumetric and Spatial Accuracy of CT Perfusion Estimated Ischemic Core Volume in Patients With Acute Ischemic Stroke. Stroke. 2018 10;49(10):2368 to 2375. PubMed: PM30355095

# <span id="page-14-0"></span>**Characteristics of Included Publications**

# <span id="page-14-1"></span>**Table 1: Characteristics of Included Cohort Studies**





CTA = CT angiography; ICA = internal carotid artery; ICH = intracranial hemorrhage; IQR = interquartile range; LVO = large vessel occlusion; MCA = middle cerebral artery; mRS = modified Rankin Scale; NIHSS = US National Institutes of Health Stroke Scale; NR = not reported; SES = socioeconomic status; TICI = Thrombolysis in Cerebral Infarction; tPA = tissue plasminogen activator.

a Intervention group vs. comparator group, respectively.

<sup>ь</sup>Baseline demographics were reported for patients who received acute therapies (i.e., tPA, thrombectomy, or both) and not the entire study population (n = 43 for post-Rapid LVO group; n = 62 for pre-Rapid LVO).

c Unclear which types of LVO were considered eligible. The study population included patients with occlusions of the ICA, carotid terminus, M1 MCA segment, or M2 MCA segment.

# <span id="page-15-0"></span>**Table 2: Characteristics of Included Diagnostic Accuracy Studies**











<span id="page-20-0"></span>

AUC = area under the receiver operating characteristic curve; CT = CT; CTA = CT angiography; CTP = CT perfusion; FN = false negatives; FP = false positives; ICA = internal carotid artery; MCA = middle cerebral artery; NCCT = non-contrast CT; NPV = negative predictive value; NR = not reported; PPV = positive predictive value; SES = socioeconomic status; TN = true negatives; TP = true positives; tPA = tissue plasminogen activator.

ªUnclear which types of LVO were considered eligible. In Delora et al. (2024),∛ the study population included patients with occlusions of the ICA, M1 MCA segment, and M2 MCA segment. The study population from Adhya et al. (2021) included patients with occlusions of the ICA, carotid terminus, M1 MCA segment, and M2 MCA segment. b Baseline demographics were reported for patients who received acute therapies (i.e., tPA, thrombectomy, or both; n = 48) and not the entire study population. c Baseline demographics were reported for patients with LVO according to the reference standard (n = 62) and not the entire study population.

# **Critical Appraisal of Included Studies**

# **ROBINS-I Detailed Assessments**

## <span id="page-20-1"></span>**Table 3: Risk of Bias Assessment of Time to Intervention Outcomes Reported by Soun et al. (2023)[1](#page-60-1) – ROBINS-I**



NI = no information; ROBINS-I = Risk Of Bias In Nonrandomized Studies – of Interventions.

# <span id="page-21-0"></span>**Table 4: Risk of Bias Assessment of Functional Status Outcomes Reported by Soun et al. (2023)[1](#page-60-1) – ROBINS-I**



NIHSS = US National Institutes of Health Stroke Scale; ROBINS-I = Risk Of Bias In Nonrandomized Studies – of Interventions.

# <span id="page-22-0"></span>**Table 5: Risk of Bias Assessment of Response to Therapy Outcomes Reported by Soun et al. (2023)[1](#page-60-1) – ROBINS-I**



ROBINS-I = Risk Of Bias In Nonrandomized Studies – of Interventions.

# <span id="page-23-0"></span>**Table 6: Risk of Bias Assessment of Time to Intervention Outcomes Reported by Adhya et al. (2021)[2](#page-60-2) – ROBINS-I**



NI = no information; ROBINS-I = Risk Of Bias In Nonrandomized Studies – of Interventions.

# <span id="page-24-1"></span><span id="page-24-0"></span>**Table 7: Risk of Bias Assessment of Functional Status Outcomes Reported by Adhya et al. (2021)[2](#page-60-2) – ROBINS-I**



ROBINS-I = Risk Of Bias In Nonrandomized Studies – of Interventions.

# **QUADAS-2 Detailed Assessments**

#### <span id="page-24-2"></span>**Table 8: Risk of Bias Assessment of Delora et al. (2024[\)3](#page-60-3) – QUADAS-2**







## <span id="page-26-0"></span>**Table 9: Risk of Bias Assessment of Slater et al. (2024[\)4](#page-60-4) – QUADAS-2**







# <span id="page-28-0"></span>**Table 10: Risk of Bias Assessment of Chan et al. (2023[\)5](#page-60-5) – QUADAS-2**





# <span id="page-29-0"></span>**Table 11: Risk of Bias Assessment of Soun et al. (2023)[1](#page-60-1) – QUADAS-2**







## <span id="page-31-0"></span>**Table 12: Risk of Bias Assessment of Yedavalli et al. (2023)[6](#page-60-6) – QUADAS-2**







<span id="page-33-0"></span>CT = CT; CTA = CT angiography; FN = false negative; FP = false positive; ICH = intracranial hemorrhage; LVO = large vessel occlusion; NA = not applicable; QUADAS-2 = Quality Assessment of Diagnostic Accuracy Studies 2; TN = true negative; TP = true positive.

# **Table 13: Risk of Bias Assessment of Eldaya et al. (2022[\)11](#page-60-11) – QUADAS-2**







CT = CT; CTA = CT angiography; ICH = intracranial hemorrhage; LVO = large vessel occlusion; NA = not applicable; NCCT = non-contrast CT; QUADAS-2 = Quality Assessment of Diagnostic Accuracy Studies 2.

## <span id="page-35-0"></span>**Table 14: Risk of Bias Assessment of Mallon et al. (2022[\)7](#page-60-7) – QUADAS-2**







ASPECTS = Alberta Stroke Program Early CT score; CT = CT; CTA = CT angiography; CTP = CT perfusion; LVO = large vessel occlusion; NA = not applicable; NCCT = non-contrast CT; QUADAS-2 = Quality Assessment of Diagnostic Accuracy Studies 2.

## <span id="page-37-0"></span>**Table 15: Risk of Bias Assessment of Schlossman et al. (2022[\)8](#page-60-8) – QUADAS-2**







## <span id="page-39-0"></span>**Table 16: Risk of Bias Assessment of Adhya et al. (2021)[2](#page-60-2) – QUADAS-2**







## <span id="page-41-0"></span>**Table 17: Risk of Bias Assessment of Dehkharghani et al. (2021[\)9](#page-60-9) – QUADAS-2**







## <span id="page-43-0"></span>**Table 18: Risk of Bias Assessment of Amukotuwa et al. (2019[\)10](#page-60-10) – QUADAS-2**





# <span id="page-45-0"></span>**Main Study Findings**

#### **Table 19: Study Results, by Outcome — Time to Intervention**



<span id="page-45-1"></span>C = comparator; CTA = CT angiography; I = intervention; IQR = interquartile range; LVO = large vessel occlusion; NR = not reported; SD = standard deviation; tPA = tissue plasminogen activator.

ªDefined as the time from when the CTA images are available for the radiologist to the earlier time of either the report being available or read-back verification was provided for the clinicians.

b The sample size for the analysis was not explicitly reported; as such, the amount of missing data are unknown.

c Statistically significant.

d Statistical test not reported (Student's t test or Mann–Whitney U test).

e Wilcoxon rank sum test.

<span id="page-46-0"></span>

#### **Table 20: Study Results, by Outcome — Functional Status**

C = comparator; CTA = CT angiography; I = intervention; IQR = interquartile range; LVO = large vessel occlusion; mRS = modified Rankin Scale; NIHSS = US National Institutes of Health Stroke Scale; NR = not reported; SD = standard deviation.

ªThe National Institutes of Health Stroke Scale is a 15-item neurologic examination stroke scale used for evaluating stroke-related neurologic deficit. Total scores range from 0 to 42, with higher scores indicating more s neurologic deficit.<sup>[12](#page-60-14)</sup>

°The sample size for the analysis was not explicitly reported; as such, the amount of missing data are unknown. The analyses for Thrombolysis in Cerebral Infarction scores and mRS scores included 62 and 46 participants in pre-RapidAI group and 46 and 34 participants in the post-RapidAI group, respectively, but it is unclear if these samples sizes are applicable to other clinical outcomes.

°Wilcoxon rank sum test. After adjusting for the effects of high cholesterol, heart disease, atrial fibrillation, therapies received, and NIHSS on admission via multivariate regression, the P value for the between-group d NIHSS score at discharge was < 0.01. The between-group difference for 36-hour post-treatment NIHSS score was not statistically significant when adjusted for the same variables (P value not reported). d Statistically significant.

°The modified Rankin Scale is a clinician-reported tool for measuring the degree of disability and dependence in daily activities in people who have experienced stroke. Scores range from 0 (no symptoms at all) to 6 (death higher score indicates greater disability. [13](#page-60-15)

f Considered 'significant morbidity/mortality'.

g Statistical test not reported (Student's t test or Mann–Whitney U test).

h Considered 'functionally independent'.

#### **Table 21: Study Results, by Outcome — Response to Therapy**



<span id="page-47-0"></span>C = comparator; CTA = CT angiography; I = intervention; IQR = interguartile range; LVO = large vessel occlusion; NR = not reported; TICI = Thrombolysis in Cerebral Infarction.

ªThe Thrombolysis in Cerebral Infarction (TICI) scale is a grading system used to evaluate the degree of perfusion obtained following recanalization of an arterial occlusion. The TICI scale ranges from 0 (no reperfusion) (complete reperfusion). [14](#page-60-16)

b Chi-square test.

#### **Table 22: Study Results, by Outcome — Diagnostic Accuracy for the Detection of M1 MCA and ICA LVO**

<span id="page-47-1"></span>







AUC = area under the receiver operating characteristic curve; CTA = CT angiography; FN = false negatives; FP = false positives; ICA = internal carotid artery; IT = index test; LVO = large vessel occlusion; MCA = middle cer artery; NCCT = non-contrast CT; NPV = negative predictive value; NR = not reported; PPV = positive predictive value; TN = true negatives; TP = true positives; RS = reference standard.

®Concordance refers to the overall rate of agreement between the index test and the reference standard. It measures how often the index test and the reference standard produced the same result (e.g., both positive or both negative) for the same set of cases, but does not assess the accuracy or correctness of either test relative to the absolute truth.

b Not reported in the publication. We calculated the value with Clopper-Pearson exact 95% confidence intervals from the available data via the EpiR package in R.[15](#page-60-22)

c Unlike other index tests included in this table, the Rapid NCCT Stroke platform detects LVO using NCCT images (rather than CTA images).

d Reported as 95% (89 to 98) in the publication, but was calculated as 95% (88 to 98) via the EpiR package in R. [15](#page-60-22)

e Patient selection methods were unclear.

f PPV and NPV values were not calculated for Dehkharghani et al. (2019) as it used a case-control selected cross-sectional design that artificially created a sample of equally divided LVO-positive and LVO-negative patients.

#### **Table 23: Study Results, by Outcome — Diagnostic Accuracy for the Detection of M1 and M2 MCA and ICA LVO**



<span id="page-50-0"></span>AUC = area under the receiver operating characteristic curve; FN = false negatives; FP = false positives; ICA = internal carotid artery; IT = index test; LVO = large vessel occlusion; MCA = middle cerebral artery; NPV = ne predictive value; NR = not reported; PPV = positive predictive value; TN = true negatives; TP = true positives; RS = reference standard.

®Concordance refers to the overall rate of agreement between the index test and the reference standard. It measures how often the index test and the reference standard produced the same result (e.g., both positive or both negative) for the same set of cases, but does not assess the accuracy or correctness of either test relative to the absolute truth.

b Not reported in the publication. We calculated the value with Clopper-Pearson exact 95% confidence intervals from the available data via the EpiR package in R.[15](#page-60-22)



#### **Table 24: Study Results, by Outcome — Diagnostic Accuracy for the Detection of M1 MCA LVO**

AUC = area under the receiver operating characteristic curve; FN = false negatives; FP = false positives; IT = index test; LVO = large vessel occlusion; MCA = middle cerebral artery; NPV = negative predictive value; NR = n reported; PPV = positive predictive value; TN = true negatives; TP = true positives; RS = reference standard.

<span id="page-51-0"></span>®Concordance refers to the overall rate of agreement between the index test and the reference standard. It measures how often the index test and the reference standard produced the same result (e.g., both positive or both negative) for the same set of cases, but does not assess the accuracy or correctness of either test relative to the absolute truth.

b Not reported in the publication. We calculated the value with Clopper-Pearson exact 95% confidence intervals from the available data via the EpiR package in R.[15](#page-60-22)

#### **Table 25: Study Results, by Outcome — Diagnostic Accuracy for the Detection of M2 MCA LVO**

<span id="page-51-1"></span>

AUC = area under the receiver operating characteristic curve; FN = false negatives; FP = false positives; IT = index test; LVO = large vessel occlusion; MCA = middle cerebral artery; NPV = negative predictive value; NR = n reported; PPV = positive predictive value; TN = true negatives; TP = true positives; RS = reference standard.

®Concordance refers to the overall rate of agreement between the index test and the reference standard. It measures how often the index test and the reference standard produced the same result (e.g., both positive or both negative) for the same set of cases, but does not assess the accuracy or correctness of either test relative to the absolute truth.

#### **Table 26: Study Results, by Outcome — Diagnostic Accuracy for the Detection of Other LVO**

<span id="page-52-0"></span>



AUC = area under the receiver operating characteristic curve; FN = false negatives; FP = false positives; ICA = internal carotid artery; IT = index test; LVO = large vessel occlusion; MCA = middle cerebral artery; NE = not estimable; NPV = negative predictive value; NR = not reported; PPV = positive predictive value; TN = true negatives; TP = true positives; RS = reference standard.

®Concordance refers to the overall rate of agreement between the index test and the reference standard. It measures how often the index test and the reference standard produced the same result (e.g., both positive or both negative) for the same set of cases, but does not assess the accuracy or correctness of either test relative to the absolute truth.

<sup>b</sup>Unclear which types of LVO were considered eligible. In Delora et al. (2024),<sup>[3](#page-60-24)</sup> the study population included patients with occlusions of the ICA, M1 MCA segment, and M2 MCA segment. The study population from Adhya et (2021) included patients with occlusions of the ICA, carotid terminus, M1 MCA segment, and M2 MCA segment.

c Not reported in the publication. We calculated the value with Clopper-Pearson exact 95% confidence intervals from the available data via the EpiR package in R.[15](#page-60-22)

 $\mathrm{^d}$ NPV was reported as 97% in the publication, but was calculated as 98% via the EpiR package in R. $^{15}$  $^{15}$  $^{15}$ 

°Patient eligibility was determined using the results of the index test (i.e., only patients who tested positive using the index test at a relative vessel density of 60% or less were included); as such, the values for sen specificity were not calculated as the sample was selected to exclude any true negatives and false negatives.

#### **Table 27: Study Results, by Outcome — Diagnostic Accuracy for the Detection of ICH**



AUC = area under the receiver operating characteristic curve; FN = false negatives; FP = false positives; ICH = intracranial hemorrhage; IT = index test; NPV = negative predictive value; NR = not reported; PPV = positive predictive value; TN = true negatives; TP = true positives; RS = reference standard.

<span id="page-53-0"></span>®Concordance refers to the overall rate of agreement between the index test and the reference standard. It measures how often the index test and the reference standard produced the same result (e.g., both positive or both negative) for the same set of cases, but does not assess the accuracy or correctness of either test relative to the absolute truth.

# <span id="page-54-0"></span>**Reasons for Certainty of Evidence Ratings**

#### <span id="page-54-1"></span>**Table 28: Certainty of Evidence Ratings for CTA With RapidAI Versus CTA Without RapidAI for People With Suspected Acute Stroke**



CI = confidence interval; CTA = CT angiography; mRS = modified Rankin Scale; NA = not applicable; NIHSS = US National Institutes of Health Stroke Scale; NR = not reported; NRS = nonrandomized study; TICI = Thrombolysis in Cerebral Infarction.

Source: Soun et al.  $(2023)^2$  $(2023)^2$  $(2023)^2$  and Adhya et al.  $(2021)^2$ 

## **Table 29: Certainty of Evidence Ratings for the Diagnostic Accuracy of RapidAI with Clinician Interpretation Relative to Clinician Interpretation (or Clinician Consensus) for Suspected Acute Stroke**

<span id="page-55-0"></span>

CI = confidence interval; ICH = intracranial hemorrhage; NR = not reported; QUADAS-2 = Quality Assessment of Diagnostic Accuracy Studies 2. Source: Eldaya et al. (2022). [11](#page-60-11)

# <span id="page-55-1"></span>**Table 30: Certainty of Evidence Ratings for the Diagnostic Accuracy of RapidAI Alone Relative to Clinician Interpretation (or Clinician Consensus) for Suspected Acute Stroke**





<span id="page-57-0"></span>

CI = confidence interval; CTA = CT angiography; ICA = internal carotid artery; LVO = large vessel occlusion; MCA = middle cerebral artery; NCCT = non-contrast CT; NR = not reported; QUADAS-2 = Quality Assessment of Diagnostic Accuracy Studies 2.

ªUnclear which types of LVO were considered eligible. In Delora et al. (2024), the study population included patients with occlusions of the ICA, M1 MCA segment, and M2 MCA segment. The study population from Adhya et al. (2021) included patients with occlusions of the ICA, carotid terminus, M1 MCA segment, and M2 MCA segment. Source: Delora et al. (2024),<sup>[3](#page-60-3)</sup> Slater et al. (202[4](#page-60-4)),<sup>4</sup> Chan et al. (2023),<sup>[5](#page-60-5)</sup> Soun et al. (2023),<sup>[1](#page-60-1)</sup> Yedavalli et al. (2023),<sup>[6](#page-60-6)</sup> Mallon et al. (2022),<sup>[7](#page-60-7)</sup> Schlossman et al. (2022),<sup>8</sup> Adhya et al. ([2](#page-60-2)021), $^2$  Dehkharghani et al. (2021), $^9$  $^9$  and Amukotuwa et al. (2019). $^{10}$  $^{10}$  $^{10}$ 

# **Patient Engagement**

## <span id="page-57-1"></span>**Table 31: Summary of Patient Engagement Using the Guidance for Reporting Involvement of Patients and the Public (version 2) Short Form Reporting Checklist[16](#page-60-27)**







AI = artificial intelligence; NA = not applicable.

# <span id="page-60-25"></span><span id="page-60-24"></span><span id="page-60-23"></span><span id="page-60-18"></span><span id="page-60-17"></span><span id="page-60-13"></span><span id="page-60-12"></span><span id="page-60-0"></span>**References**

- <span id="page-60-1"></span>1. Soun JE, Zolyan A, McLouth J, et al. Impact of an automated large vessel occlusion detection tool on clinical workflow and patient outcomes. *Front Neurol.* 2023;14:1179250. [PubMed](https://pubmed.ncbi.nlm.nih.gov/37305764)
- <span id="page-60-19"></span><span id="page-60-2"></span>2. Adhya J, Li C, Eisenmenger L, et al. Positive predictive value and stroke workflow outcomes using automated vessel density (RAPID-CTA) in stroke patients: One year experience. *Neuroradiol J.* 2021;34(5):476-481. [PubMed](https://pubmed.ncbi.nlm.nih.gov/33906499)
- <span id="page-60-20"></span><span id="page-60-3"></span> 3. Delora A, Hadjialiakbari C, Percenti E, et al. Viz LVO versus Rapid LVO in detection of large vessel occlusion on CT angiography for acute stroke. *J Neurointerv Surg.* 2024;16(6):599-602. [PubMed](https://pubmed.ncbi.nlm.nih.gov/37355255)
- <span id="page-60-21"></span><span id="page-60-4"></span> 4. Slater LA, Ravintharan N, Goergen S, et al. *RapidAI* Compared With Human Readers of Acute Stroke Imaging for Detection of Intracranial Vessel Occlusion. *Stroke: Vascular and Interventional Neurology.* 2024;4(2):e001145.
- <span id="page-60-26"></span><span id="page-60-5"></span> 5. Chan N, Sibtain N, Booth T, et al. Machine-learning algorithm in acute stroke: real-world experience. *Clin Radiol.* 2023;78(2):e45-e51. [PubMed](https://pubmed.ncbi.nlm.nih.gov/36411087)
- <span id="page-60-14"></span><span id="page-60-6"></span> 6. Yedavalli V, Heit JJ, Dehkharghani S, et al. Performance of RAPID noncontrast CT stroke platform in large vessel occlusion and intracranial hemorrhage detection. *Front Neurol.* 2023;14:1324088. [PubMed](https://pubmed.ncbi.nlm.nih.gov/38156093)
- <span id="page-60-15"></span><span id="page-60-7"></span> 7. Mallon DH, Taylor EJR, Vittay OI, Sheeka A, Doig D, Lobotesis K. Comparison of automated ASPECTS, large vessel occlusion detection and CTP analysis provided by Brainomix and RapidAI in patients with suspected ischaemic stroke. *J Stroke Cerebrovasc Dis.* 2022;31(10):106702. [PubMed](https://pubmed.ncbi.nlm.nih.gov/35994882)
- <span id="page-60-22"></span><span id="page-60-16"></span><span id="page-60-8"></span>8. Schlossman J, Ro D, Salehi S, et al. Head-to-head comparison of commercial artificial intelligence solutions for detection of large vessel occlusion at a comprehensive stroke center. *Front Neurol.* 2022;13:1026609. [PubMed](https://pubmed.ncbi.nlm.nih.gov/36299266)
- <span id="page-60-9"></span> 9. Dehkharghani S, Lansberg M, Venkatsubramanian C, et al. High-Performance Automated Anterior Circulation CT Angiographic Clot Detection in Acute Stroke: A Multireader Comparison. *Radiology.* 2021;298(3):665-670. [PubMed](https://pubmed.ncbi.nlm.nih.gov/33434110)
- <span id="page-60-10"></span>10. Amukotuwa SA, Straka M, Smith H, et al. Automated Detection of Intracranial Large Vessel Occlusions on Computed Tomography Angiography: A Single Center Experience. *Stroke.* 2019;50(10):2790-2798. [PubMed](https://pubmed.ncbi.nlm.nih.gov/31495328)
- <span id="page-60-11"></span>11. Eldaya RW, Kansagra AP, Zei M, et al. Performance of Automated RAPID Intracranial Hemorrhage Detection in Real-World Practice: A Single-Institution Experience. *J Comput Assist Tomogr.* 2022;46(5):770-774. [PubMed](https://pubmed.ncbi.nlm.nih.gov/35617649)
- 12. Brott T, Adams HP, Olinger CP, et al. Measurements of acute cerebral infarction: a clinical examination scale. *Stroke.* 1989;20(7):864-870. [PubMed](https://pubmed.ncbi.nlm.nih.gov/2749846)
- 13.Banks JL, Marotta CA. Outcomes Validity and Reliability of the Modified Rankin Scale: Implications for Stroke Clinical Trials. *Stroke.* 2007;38(3):1091-1096. [PubMed](https://pubmed.ncbi.nlm.nih.gov/17272767)
- 14. Goyal M, Fargen KM, Turk AS, et al. 2C or not 2C: defining an improved revascularization grading scale and the need for standardization of angiography outcomes in stroke trials. *J Neurointerv Surg.* 2014;6(2):83-86. [PubMed](https://pubmed.ncbi.nlm.nih.gov/23390038)
- 15. Stevenson M, Sergeant E. epiR: Tools for the Analysis of Epidemiological Data. R package version 2.0.74. 2024; [https://CRAN.R](https://CRAN.R-project.org/package=epiR) [-project.org/package=epiR.](https://CRAN.R-project.org/package=epiR) Accessed 2024 Jun 5.
- <span id="page-60-27"></span>16. Staniszewska S, Brett J, Simera I, et al. GRIPP2 reporting checklists: tools to improve reporting of patient and public involvement in research. *BMJ.* 2017;358:j3453. [PubMed](https://pubmed.ncbi.nlm.nih.gov/28768629)



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