

PRISMA AI reporting guidelines for systematic reviews and meta-analyses on AI in healthcare



Systematic reviews and meta-analyses play an essential part in guiding clinical practice at the point of care, as well as in the formulation of clinical practice guidelines and health policy^{1,2}. There are three essential components to an impactful systematic review. First, the design of a study should be based upon a robust research question and search strategy. Second, minimization of bias should be enhanced by using quality-assessment tools and study-design-specific eligibility criteria. Third, reporting of results should be conducted transparently through adherence to expert-derived reporting items. Thousands of systematic reviews, including meta-analyses, are produced annually, with an increasing proportion reporting on artificial intelligence (AI) interventions in health care. With this rapid expansion, there is a need for reporting guidelines tailored to AI^{3–7} that will support high-quality, reproducible, and clinically relevant systematic reviews.

AI is being integrated rapidly into society and in medicine. A literature search of studies referencing AI in health care over the past 20 years returned more than 70,000 published articles. Given that interest in AI is reaching an all-time high, there arise new concerns regarding the quality of these studies, including a lack of: clear explainability of how AI algorithms function; strong evidence of effectiveness in clinical settings; and standardized reporting within primary studies. Efforts have been made to improve understanding of this technology to allow for critical appraisal of AI interventions and to reduce inconsistencies in how studies are structured, as well as reporting of data, methods and results^{3,5,7}. As systematic reviews on AI interventions increase, so does the importance of the transparency and reproducibility of reported data.

The most accepted guideline for reporting systematic reviews and meta-analyses is the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) statement. This evidence-based guideline was first published in 2009 (ref.²) and served as a set of minimum reporting items that should be addressed when describing a systematic

Table 1 | Process for development of PRISMA-AI

Step	Process	Goal(s)
1. Literature review	An umbrella review (ongoing) is conducted to examine the quality of reporting in systematic reviews with/without meta-analysis, scoping reviews, diagnostic test accuracy (DTA) meta-analysis, protocols	a) Identification of variability in assessment and reporting b) Identification of list-editable and additional items (first set)
2. Delphi survey	Delphi survey among multi-specialty experts (in each medical specialty) who have already published about AI applications in leading medical journals and the lead authors of PRISMA, STARD-AI, CONSORT-AI, SPIRIT-AI, TRIPOD-AI, PROBAST-AI, CLAIM-AI and DECIDE-AI, to ensure that the criteria have global applicability in all disciplines and for each type of study that involve AI	c) Identification of editable and adjunctive items (second set)
3. Consensus meeting	Establishment of consensus for approval of PRISMA-AI implementations	d) Creation of the PRISMA-AI Implementation Criteria Checklist
4. Piloting	Piloting of PRISMA-AI implementation in a broad range of users	
5. Checklist and statement document	Publication of the PRISMA-AI Implementations Criteria Checklist and the explanation and elaboration document	
6. Dissemination	Dissemination of PRISMA-AI Implementation through media campaigns and implementation of the PRISMA-AI Checklist on the PRISMA website	

review or meta-analysis. In 2021, updated PRISMA guidelines were published to reflect new evidence and mandates emerging in the years between PRISMA 2009 and its recent update¹. PRISMA and its extensions are widely accepted by journals and guideline panels. Their direct applicability to particular topics, such as AI interventions, may benefit from inclusion of specific requirements that capture all of the nuances particular to these studies.

An ongoing umbrella review (a review of reviews) has found that nearly 7,000 reviews (systematic and non-systematic) have been published on AI in the category ‘medicine’. This number is destined to grow: a search in PROSPERO shows that the number of ongoing systematic reviews on AI is about 1,300. Since 2013, there has been an increasing trend in review articles on AI over time, with an annual average increase of 52%. However, only 20% specified in the title or abstract that they were ‘systematic’ or reported the term

‘PRISMA’ in the abstract. Despite widespread acceptance of PRISMA guidelines¹, they seem to be underused for AI-based intervention reviews. Nevertheless, the review articles that include ‘systematic’ or ‘PRISMA’ in their title or abstract have been cited more frequently than the reviews that do not. However, the most cited review article (more than 6,000 citations in 5 years) does not cite any reporting guidelines, emphasizing the need for more-stringent reporting protocols.











Several reporting guidelines have been updated thanks to pioneering efforts made by the SPIRIT-AI⁷ and CONSORT-AI³ extensions committees to ensure applicability to clinical studies and reporting involving AI. These efforts are relevant because of the number of active clinical studies involving AI listed on clinicaltrials.gov. In 2020, a search of studies that included ‘artificial intelligence’, ‘machine learning’, or ‘deep learning’ found around 300 active studies⁸. A search today returns a 7-fold increase, with more than 2,100 active studies

on 1 October 2022. The SPIRIT and CONSORT working groups received expert consultation and underwent a Delphi process to provide a consensus-based guideline. These efforts resulted in the CONSORT-AI³ and SPIRIT-AI⁷ extensions, which identify additional reporting items that were deemed essential for clinical studies involving AI. Other AI extensions of existing reporting guidelines, de novo guidelines, or bias reporting tools include: prediction model risk of bias assessment tool (PROBAST-AI), quality-assessment tool for artificial-intelligence-centered diagnostic test accuracy studies (QUADAS-AI)⁹, checklist for artificial intelligence in medical imaging (CLAIM)⁴, and early-stage clinical evaluation of decision support systems driven by artificial intelligence (DECIDE-AI)⁶. Guidance including standards for reporting of diagnostic accuracy studies (STARD-AI)⁵ and transparent reporting of a multivariable prediction model of individual prognosis or diagnosis (TRIPOD-AI) will shortly be available to cover study designs for diagnostic accuracy studies and clinical prediction model studies, respectively. These efforts highlight the importance of extended frameworks for systematic reviews that are reporting on AI in healthcare.

The PRISMA-AI Steering Committee has begun the process of creating an AI implementation of PRISMA guidelines and extensions¹ for studies addressing AI-based interventions (Table 1). Our efforts include registering our extension with clinicaltrials.gov (NCT05382455) and the EQUATOR (enhancing the quality and transparency of health research) network as a guideline under development. Clinicians, researchers, statisticians, computer scientists, engineers, methodologists designing clinical trials, systematic reviewers, patients, journal editors, published AI-extensions contributors, and trialists with an interest in AI related to health care are being recruited to establish a community collaboration that will create reporting guidelines for systematic reviews and meta-analyses that include AI. The EQUATOR network's development guidance¹⁰ will be used by the PRISMA-AI team to establish a consensus for the framework of reporting guidelines on AI in systematic reviews and meta-analyses.

The PRISMA-AI implementations will reflect the most pertinent technical details needed for reproducibility, focusing on requirements to critically follow and authenticate the methods used in systematic reviews and meta-analyses relating to outcomes, risk of bias, and applicability. The PRISMA-AI implementations will assist stakeholders interested

in using AI-related information in systematic reviews by creating a framework for reviewers that evaluates the quality of the data reported in publications, delivers a tool for training researchers in AI methodology, and supports end-users of systematic reviews such as clinicians, researchers, patients, and policymakers to better estimate the validity and applicability of findings from systematic reviews in their decision-making processes.

Giovanni E. Cacciamani ^{1,2,3,4,5}✉, **Timothy N. Chu**^{1,2,3}, **Daniel I. Sanford**^{1,2,3}, **Andre Abreu**^{1,2,3,4,5}, **Vinay Duddalwar** ^{3,6}, **Assad Oberai**^{7,8}, **C.-C. Jay Kuo**⁹, **Xiaoxuan Liu**^{10,11,12}, **Alastair K. Denniston** ^{10,11,12,13,14}, **Baptiste Vasey**^{15,16}, **Peter McCulloch** ¹⁵, **Robert F. Wolff**¹⁷, **Sue Mallett** ¹⁸, **John Mongan**^{19,20}, **Charles E. Kahn Jr** ²¹, **Viknesh Sounderajah**²², **Ara Darzi** ²², **Philipp Dahm**²³, **Karel G. M. Moons**²⁴, **Eric Topol** ²⁵, **Gary S. Collins** ²⁶, **David Moher** ²⁷, **Inderbir S. Gill**^{1,2,3,4,5} & **Andrew J. Hung**^{1,2,5}

¹USC Institute of Urology and Catherine and Joseph Aresty Department of Urology, Keck School of Medicine, University of Southern California, Los Angeles, CA, USA. ²AI Center at USC Urology, USC Institute of Urology, University of Southern California, Los Angeles, CA, USA. ³Department of Radiology, University of Southern California, Los Angeles, CA, USA. ⁴Center for Image-Guided and Focal Therapy for Prostate Cancer, Institute of Urology and Catherine and Joseph Aresty Department of Urology, Keck School of Medicine, University of Southern California, Los Angeles, CA, USA. ⁵Norris Comprehensive Cancer Center, Institute of Urology, Keck School of Medicine of the University of Southern California, Los Angeles, CA, USA. ⁶USC Radiomics Laboratory, Keck School of Medicine, Department of Radiology, University of Southern California, Los Angeles, CA, USA. ⁷Department of Aerospace and Mechanical Engineering, Viterbi School of Engineering, University of Southern California, Los Angeles, CA, USA. ⁸Department of Biomedical Engineering, Viterbi School of Engineering, University of Southern California, Los Angeles, CA, USA. ⁹Ming Hsieh Department of Electrical and Computer Engineering, University of Southern California, Los Angeles, CA, USA. ¹⁰University Hospitals Birmingham NHS Foundation Trust, Birmingham, UK. ¹¹Institute of Inflammation and Ageing, College of Medical and Dental Sciences, University of

Birmingham, Birmingham, UK. ¹²Birmingham Health Partners Centre for Regulatory Science and Innovation, University of Birmingham, Birmingham, UK. ¹³NIHR Birmingham Biomedical Research Centre, University of Birmingham, Birmingham, UK. ¹⁴Health Data Research, London, UK. ¹⁵Nuffield Department of Surgical Sciences, University of Oxford, Oxford, UK. ¹⁶Department of Surgery, Geneva University Hospital, Geneva, Switzerland. ¹⁷Kleijnen Systematic Reviews Ltd, Escrick, York, UK. ¹⁸Centre for Medical Imaging, University College London, London, UK. ¹⁹Department of Radiology and Biomedical Imaging, University of California San Francisco, San Francisco, CA, USA. ²⁰Center for Intelligent Imaging, University of California San Francisco, San Francisco, CA, USA. ²¹Department of Radiology and Institute for Biomedical Informatics, University of Pennsylvania, Philadelphia, PA, USA. ²²Institute of Global Health Innovation, Imperial College London, London, UK. ²³Minneapolis VAMC, Urology Section and University of Minnesota, Department of Urology, Minneapolis, MN, USA. ²⁴Julius Center for Health Sciences and Primary Care, UMC Utrecht, Utrecht University, Utrecht, The Netherlands. ²⁵Scripps Research Translational Institute, Scripps Research, La Jolla, CA, USA. ²⁶Centre for Statistics in Medicine, Nuffield Department of Orthopaedics, Rheumatology & Musculoskeletal Sciences, University of Oxford, Oxford, UK. ²⁷Centre for Journalism, Clinical Epidemiology Program, Ottawa Hospital Research Institute, Ottawa, Canada. ✉e-mail: Giovanni.cacciamani@med.usc.edu

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Competing interests

P.D. serves as coordinating editor of *Cochrane Urology*. G.S.C. is the director of the UK EQUATOR Centre. D.M. is the director of the Canadian EQUATOR Centre. X.L. is an industry fellow (observer) with Hardian Health. A.J.H. is a consultant for Intuitive. I.S.G. is a consultant for STEBA. J.M. is a consultant for Siemens. C.E.K. receives salary support as editor of *Radiology: Artificial Intelligence*. V.D. is a consultant for Radmetrix Inc. and Westat Inc., and is an advisory board member to DeepTek Inc. A.K.D. is chair of the Health Security initiative at Flagship Pioneering UK Ltd. The other authors declare no competing interests.