Diagn Interv Radiol 2026; DOI: 10.4274/dir.2026.264308

ARTIFICIAL INTELLIGENCE AND INFORMATICS

INVITED REVIEW

©Copyright 2026 Author(s) - Available online at dirjournal.org.
Content of this journal is licensed under a Creative Commons Attribution-NonCommercial 4.0 International License.

Artificial intelligence-powered solutions for environmental sustainability in medical imaging: a scoping review

Nikolaos Stogiannos[1-3]
Kleanthis Konstantinidis[4,5]
Stephan Ursprung[6]
Saif Afat[6]
Selmina Kalari[7,8]
Efstratios Karavasilis[8]
Judith Herrmann[6]
Konstantin Nikolaou[6,9]
Susan Cheng Shelmerdine[1,10,11]
Andrea Rockall[12]
Thomas Küstner[13,14]
Christina Malamateniou[1,3,15]

[1]CRRAG Research Group, Division of Radiography, Department of Allied Health, School of Health and Medical Sciences, City St George's, University of London, United Kingdom

[2]Magnitiki Tomografia Kerkiras, Corfu, Greece

[3]Imaging Informatics Working Group, European Federation of Radiographer Societies, Cumieira, Portugal

[4]General Hospital of Attica KAT, Advanced Imaging Modalities Department, Athens, Greece

[5]National and Kapodistrian University of Athens, School of Medicine, Athens, Greece

[6]University Hospital of Tübingen, Department of Diagnostic and Interventional Radiology, Tübingen, Germany

[7]St Savvas Oncological Hospital of Attica, Department of Radiotherapy, Athens, Greece

[8]Democritus University of Thrace, School of Medicine, Medical Physics Laboratory, Alexandroupolis, Greece

[9]University of Tübingen Faculty of Medicine, Tübingen, Germany

[10]Great Ormond Street Hospital for Children NHS Foundation Trust, Department of Clinical Radiology, London, United Kingdom

[11]University College London Great Ormond Street Institute of Child Health, London, United Kingdom

[12]Imperial College London Faculty of Medicine, London, United Kingdom

[13]University Hospital of Tübingen, Medical Image and Data Analysis (MIDAS.lab), Department of Diagnostic and Interventional Radiology, Tübingen, Germany

[14]University Hospital of Tübingen, Institute for Bioinformatics and Medical Informatics (IBMI), Tübingen, Germany

[15]European Society of Medical Imaging Informatics, Vienna, Austria

PURPOSE

Growing evidence shows that medical imaging has a substantial environmental impact. With the increasing adoption of artificial intelligence (AI) in clinical settings, it is important to explore how this technology may support environmental sustainability.

METHODS

Literature searches were performed across eight databases (PubMed, Wiley Online Library, Embase, Web of Science platform, the Cochrane Library, Cumulative Index to Nursing and Allied Health Literature Ultimate, Google Scholar, and MedRxiv) for the period January 2020–June 2026. Full-text sources in the English language were eligible for inclusion. The Joanna Briggs Institute checklists were employed for risk of bias assessment. All data were analyzed using a textual narrative synthesis.

RESULTS

In total, 23 studies were deemed eligible for inclusion. The literature proposed that AI tools in medical imaging could be used to minimize energy consumption by optimizing patient scheduling, decreasing scanner idle times and workstation use, reducing computed tomography over-scanning, contrast agent usage, and radiation dose, harnessing low-field magnetic resonance imaging, and curtailing low-value imaging. However, AI technologies may also impact the environment in harmful ways.

Handling editor: Tuğba Akıncı D'Antonoli

Corresponding author: Christina Malamateniou

E-mail: christina.malamateniou@citystgeorges.ac.uk

Received 26 July 2026; revision requested 19 August 2026; last revision requested 06 October 2026; accepted 07 October 2026.

Epub: : 30.10.2026

DOI: 10.4274/dir.2026.264308

You may cite this article as: Stogiannos N, Konstantinidis K, Ursprung S, et al. Artificial intelligence-powered solutions for environmental sustainability in medical imaging: a scoping review. *Diagn Interv Radiol*. 30 October 2026 DOI: 10.4274/dir.2026.264308 [Epub Ahead of Print].

CONCLUSION
Although AI-powered solutions hold promise for improving sustainability in medical imaging, the true environmental impact remains largely unexplored.

CLINICAL SIGNIFICANCE
The findings of this work further strengthen the dual role of AI adoption in medical imaging related to environmental sustainability.

KEYWORDS
Radiology, sustainability, artificial intelligence, medical imaging, environment, green

Climate change is a complex phenomenon associated with global warming and irregular weather patterns, and it poses severe environmental, societal, economic, and political challenges globally. It also causes an ongoing increase in global temperatures, rising sea levels, and a substantial release of toxic substances in the environment.[1] Greenhouse gas (GHG) emissions are among the major determinants of global environmental change.

Healthcare is a significant contributor to GHG emissions, responsible for almost 5% of global emissions.[2] Therefore, it is imperative to find effective ways to reduce its carbon footprint by implementing policy and practice changes at both the individual and organizational levels. Various suggestions have been documented in the literature; these include, but are not limited to, managing physical waste, reducing commuting, implementing decarbonization measures, and conducting workforce training to change culture.[3]

Medical imaging is among the top carbon footprint contributors within healthcare, with previous data showing that medical imaging can contribute up to 15% of a hospital's electricity consumption (as measured for a specific institution).[4] Radiology accounts for up to 1% of global emissions;[5] computed tomography (CT) and magnetic resonance imaging (MRI) are the principal culprits,[6] contributing an estimated 0.77% of global CO_2 emissions in 2016 (with a projected 30% increase by 2030).[7] MRI scanners consume > 100 MWh per year, and a single scanner spends 31%–38% of its annual energy consumption in a "system-off" state.[8] Moreover, two-thirds of CT energy consumption occurs while the scanner is idle.[5] These inefficiencies are exacerbated by an explosion of AI tools that require data centers, storage, and model training/inference computing power, which substantially contributes to the medical imaging carbon footprint.

Main points

- AI can potentially reduce energy consumption and waste across different imaging modalities.
- There is a significant environmental impact linked with AI-enabled radiology practice.
- However, balancing functionality and sustainability is necessary for all AI-enabled devices in radiology.

The associated storage of medical images on data servers over many years generates GHGs.[9] In addition, the use and disposal of iodinated contrast agents (ICAs) and gadolinium-based contrast agents (GBCAs) may contaminate water systems, requiring further energy to secure cleaner water sources. Interventional radiology may also pose a sizable sustainability burden, since it generates substantial physical waste, mainly associated with single-use surgical supplies.[10] It also presents high energy consumption due to prolonged use of ionizing radiation and the use of ICAs. Finally, there is an urgent need to reduce any travel-related carbon footprint exhibited during major conferences,[11] which attract large numbers of delegates from medical imaging and related specialties. The above challenges have led major societies around the globe to advocate policy changes, such as allowing hybrid attendance, minimizing the length or frequency of events, and promoting global collaboration to achieve environmental sustainability in medical imaging. Environmental sustainability in medical imaging, often called "green radiology," integrates practices that mitigate the negative impact of climate-related changes, supports environment-sparing policies, and takes into account environmental, economic, and social aspects of imaging.[12]

The medical imaging discipline is already being transformed by artificial intelligence (AI)-based solutions, with development and adoption of AI products showing a steady increase over the last few years.[13] These tools can offer increased diagnostic accuracy, optimized workflows, enhanced patient care, and more benefits for clinical practice. At the same time, AI systems require substantial computational power and storage capacity at data centers, and this leads to increased energy consumption and high carbon emissions.[14] Therefore, although AI can offer potential benefits to healthcare delivery, its sustainability should also be thoroughly evaluated and balanced with the proposed benefits stemming from its use.[15,16] AI may, for instance, help curb the environmental impact of medical imaging by addressing current challenges in the field, such as minimizing low-value imaging, reducing energy consumption, optimizing use of resources, or lowering radiation dose.[17,18]

This scoping review aims to map out currently available AI-powered initiatives in medical imaging to help improve environmental sustainability.

Methods

Registration

This scoping review has been retrospectively registered into the Open Science Framework platform (registration number: https://osf.io/mhuc6/overview).

Research question

The research question of this review was formulated according to the Population, Concept, and Context framework, a universally accepted framework suggested by the Joanna Briggs Institute (JBI) to construct research questions for scoping reviews. In this review, "medical imaging" represents the population of the research question (including MRI, CT, ultrasound, X-rays, nuclear medicine, and interventional radiology), "AI" constitutes the concept (including all AI-powered initiatives and interventions aiming to enhance environmental sustainability), and "sustainability" is operationalized as the context within which the contribution

of these technologies is explored. Therefore, the final research question of this scoping review is: How can AI-powered initiatives contribute to sustainability in medical imaging?

Reporting

Reporting of the findings of this scoping review conforms with the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) extension for scoping reviews.[19]

Search strategy

Searches were performed across eight different electronic bibliographic databases: PubMed, Wiley Online Library, Embase, Web of Science platform, the Cochrane Library, Cumulative Index to Nursing and Allied Health Literature Ultimate, Google Scholar, and the MedRxiv database for preprint work. In addition, handsearching strategies were used to identify relevant sources of evidence published in content-related journals and special issues. Backward citation searching, a well-established technique used when conducting systematic or scoping reviews,[20] was also employed.

Searches were independently performed by three researchers using different combinations of synonyms of "radiology" (e.g., medical imaging, radiography, unique names of medical imaging modalities such as CT, MRI), "AI" [e.g., machine learning, deep learning (DL), algorithms], and "sustainability" (e.g., carbon emissions, environment-friendly, green energy, carbon footprint). An updated literature search was conducted in June 2026 before submission of this scoping review for publication. The search strategy was finalized after iterative discussions within the research team; relevant keywords were used for identification of sources of evidence, and these were appropriately combined into different search strings using Boolean operators (AND/OR/NOT) and relevant filters to limit the results appropriately. Finally, truncations were used to ensure that all variations of keywords would be included in the obtained results. The full search strategy can be found in Supplementary Material 1.

Inclusion and exclusion criteria

Explicit inclusion and exclusion criteria were defined during the conceptualization of this scoping review, and these are listed below (Table 1). For the purpose of this scoping review, AI was defined as any AI-powered intervention helping to reduce the environmental impact of medical imaging, either directly (e.g., AI-enabled power management) or indirectly (e.g., shorter scan times due to AI-based image reconstruction). AIs of any architecture were eligible for inclusion. The energy use of AI models themselves was also within the scope of this review.

Selection process

All identified sources were imported by the researchers into (Rayyan.ai, Cambridge, MA), an AI-powered platform specifically designed for automation and transparency of article screening and selection during reviews.[21] After removal of duplicates, two researchers independently performed screening of titles and abstracts of all the remaining articles against the eligibility criteria of this review. All sources deemed eligible for inclusion in the scoping review were further evaluated at full-text level. Any discrepancies at this stage of the selection process were resolved by the senior authors of this scoping review.

Data extraction

After selection of the sources, two researchers independently populated data extraction tables, extracting data on year of publication, country, study objectives, study design, participants/setting, and outcomes (Supplementary Table 1). A separate data extraction table was created to hold data on AI purpose, AI system used, imaging modality, measured effect with units, comparators, and AI's own cost/energy (Supplementary Table 2). Final confirmation and amendments were actioned by a senior researcher.

Critical appraisal of sources

The JBI Critical Appraisal Tools were employed for risk of bias assessment. Specific tools were used according to the study design of the included studies. Regarding narrative reviews and opinion statements, the dedicated JBI tool for assessing the quality of textual and opinion-based evidence was used. Cross-sectional studies were evaluated using the JBI tool for analytical cross-sectional studies, as this was updated earlier this year. The detailed risk of bias assessment outcome can be seen in Supplementary Material 2.

Synthesis of results

This scoping review followed a narrative synthesis approach for reviewing and synthesizing the findings of all included studies. Narrative synthesis employs a textual approach to summarize and present all findings across different studies, without excluding numerical analyses. This approach aims to arrange heterogeneous sources of evidence into more homogeneous subgroups to facilitate analysis of the findings.[22] In addition, narrative synthesis has proved efficient in converting evidence into practical and clear guidelines.

Results

In total, 23 studies were included in this scoping review. No studies were excluded based on risk of bias assessment. The following PRISMA flow diagram summarizes the process of searching, screening, and selecting sources of evidence (Figure 1).

Study characteristics

Among the 23 included studies, most (n = 15) were narrative-based sources not reporting primary data (narrative reviews, editorials, or scientific statements),[5,6,8,23-34] followed by observational studies (n = 5),[35-39] 2 systematic reviews,[40,41] and 1 scoping review.[42] Publication years ranged from 2023 to 2026. The included studies were from the USA (n = 4), Canada (n = 4), Australia (n = 3), UK (n = 2), Germany (n = 2), the Netherlands (n = 2), Switzerland (n = 2), Japan (n = 1), France (n = 1), Ireland (n = 1), and Norway (n = 1). The majority (n = 22) of the included studies examined AI-enabled ways to improve sustainability in MRI and CT. Two studies discussed AI-enabled environmental sustainability in nuclear medicine.

Table 1. Eligibility criteria

Inclusion criteria
Sources of evidence written in English
Published between January 2020 and June 2026
Only full-text sources
Preprints allowed
Exclusion criteria
Animal and cadaveric studies
Sources not related to artificial intelligence-powered environmental sustainability
Corporate material from vendors that was not part of a peer-reviewed publication

Regarding the sources' classification per AI system type, most included sources discussed DL approaches, with some of them specifically focusing on convolutional neural networks (CNNs) or U-Net architectures, followed by those using large language models (LLMs) and generative adversarial networks. Different types of AI-powered interventions were used in the included studies, with most focusing on accelerating image acquisition, enhancing image quality with AI-enabled methods, or reducing energy consumption and carbon emissions. In addition, LLMs were used to analyze reports.

The main findings identified within the obtained studies are presented below, classified according to whether they were reported in primary or secondary sources of evidence.

Sustainability outcomes from primary studies

Different sustainability outcomes were reported in the primary studies included in this scoping review. First, DL-based image reconstruction combined with simultaneous multi-slice techniques achieved an energy consumption reduction of 0.39 kWh per scan in patients undergoing routine MRI examinations.[36] This value is being reported as it was mentioned in the primary study, without its exact method being available. In another study, implementing DL sequences across all body regions was measured to lower energy consumption in a range of 31%–72%, and the projected annual carbon footprint savings per scanner were found to be up to 5,422 kg CO_2.[37] Similarly, DL-powered MRI sequences reduced energy per examination, and this reduction was modelled at 21%–65%,[38] according to the acceleration factors, which is further translated into considerable cost savings. In addition, application of UNet++ approaches for breast lesion segmentation in dynamic contrast-enhanced MRI (DCE-MRI) was found to achieve approximately a five-fold reduction in energy consumption, and its calculated carbon footprint was reduced to 0.13 ± 0.03 kg CO_2.[35] When analyzing the reports of chest radiographs, a general-purpose LLM was measured to consume considerably less energy (0.59 kWh vs. 4.16 kWh) when a much smaller parameter size was selected (7 vs. 70 billion parameters).[39]

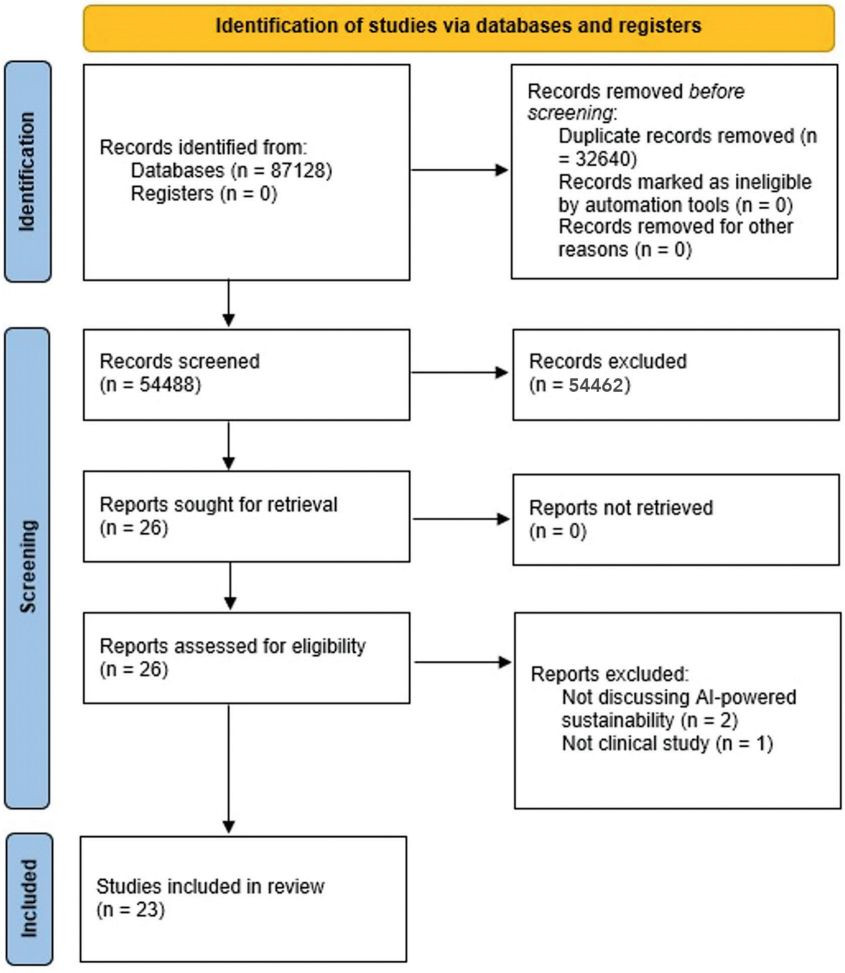

Figure 1. Preferred Reporting Items for Systematic Reviews and Meta-Analyses flow diagram of study identification, screening, and inclusion.

Sustainability outcomes reported in secondary sources

The following sustainability outcomes were reported in secondary sources of evidence (e.g., narrative reviews, systematic reviews). Therefore, they should be interpreted with caution, since they are primarily based on recommendations, rather than evidence-based outcomes. Moreover, the clinical and workflow-related benefits below cannot be associated with a directly proven environmental benefit, since specific metrics for these are not reported in the following sources of evidence. All outcomes have been grouped in relevant themes and categories, according to the patient pathway within the medical imaging department (Figure 2).

Reducing imaging equipment idle time

AI tools can help reduce the overall energy consumption of medical imaging equipment by lowering the energy they consume during idle times; this can be achieved through AI-powered automatic equipment shutdown during expected periods of idle time.[5]

Artificial intelligence-accelerated image acquisition

As stated above, AI-powered acceleration techniques have been reported to have a beneficial impact on sustainability in various ways. For example, AI-assisted image reconstruction techniques can be applied to automate planning of imaging planes to decrease the time needed for this task during the examination,[5,6,30] resulting in less energy required due to shorter examination times. Specific AI-assisted methods have been recommended by many professional societies to accelerate cardiac MRI examinations (CMRs),[23,24] and it was further explained that AI-powered abbreviated protocols for CMRs should focus on outstanding clinical questions only, thus helping to lower the carbon footprint of these examinations.[30]

Another suggested way of reducing MRI scan times is to use half the number of phase-encoding steps,[8] with DL-based image reconstruction techniques showing potential to achieve an annual energy consumption reduction of up to 13%.[8] Regarding CT, advanced DL image reconstruction algorithms have been recommended to be

Figure 2. Main themes and categories derived from textual narrative analysis. *Image created with BioRender. AI, artificial intelligence; GHG, greenhouse gas; CT, computed tomography; SNR, signal-to-noise ratio.

integrated to reduce energy consumption per case.[33]

Image post-processing

AI tools can also assist clinicians after image acquisition; de-noising images that have been accelerated using AI-powered techniques can further contribute to enhanced environmental sustainability,[5,8,30] as it prevents scan repeats due to low image quality or a low signal-to-noise ratio (SNR). In nuclear medicine, AI can generate pseudo-CT attenuation maps to be used in positron emission tomography or single-photon emission CT, thus avoiding CT radiation dose.[29] Automated image analysis can also offer the advantage of otherwise unobtainable pixel-based data (e.g., to improve the estimation of indeterminate pulmonary nodule malignancy risk at chest CT, thus informing whether further interventions are required that could be wasteful).[5] In CMR, AI tools can also perform automated image analysis and reporting to reduce workstation use.[24] Finally, opportunistic screening can be achieved with certain AI solutions; incidental data can be extracted from medical imaging examinations (e.g., coronary artery calcium score quantification from chest CT scans) and contribute to reduced GHG emissions from repeated studies when information was already available on other tests.[5]

Radiation dose reduction

Helical scanning requires irradiation of larger lengths than those planned. This is referred to as over-scanning and can increase radiation dose. Studies found that manual over-scanning (i.e., scan range expanding beyond the target anatomy due to human errors during manual scan range determination) often occurred in chest CT scans, and this was mainly observed in the inferior boundaries of the scan range. A recent systematic review indicated that AI-enabled applications using CNNs facilitated real-time monitoring of scan ranges, reduced over-scanning and radiation dose, and subsequently improved radiation safety.[41]

Low-field magnetic resonance imaging

Recent AI advancements that could allow clinicians to benefit from low-field and ultra-low-field MRI were also discussed in the respective studies. Low-field imaging has lower energy requirements to sustain the static magnetic field and less reliance on gradients for signal encoding, although it exhibits a lower SNR than high-field MRI scanners. However, AI-powered image reconstruction methods can enhance the SNR in low-field systems and generate synthetic images with higher signal and spatial resolution for optimal diagnosis while maintaining a lower energy consumption profile than previous methods.[23] Generative AI systems could provide images with high signal and of comparable clinical value.[24] Such approaches were suggested to allow low-field MRI to evolve as an alternative to higher field strengths, helping to reduce energy consumption.[8]

Workflow optimization

AI tools have been employed to optimize clinical workflows and resource utilization. Clinical decision support systems powered by AI could be used to personalize recommendations and avoid unnecessary imaging examinations that have no clinical value and to reduce low-value imaging.[5,25,34] This could also be achieved by using natural language processing (NLP) tools to decrease low-value and high-cost imaging.[23] Clinical workflows could be further improved with the use of intelligent scheduling algorithms that can optimize imaging equipment usage[8] and reduce equipment idle time.[23,34] The increased diagnostic accuracy provided by AI systems may further contribute to environmental sustainability by reducing repeat scans.[8] Furthermore, AI could be utilized in workforce scheduling, which not only improves employee wellbeing but also reduces unnecessary travel and GHG emissions by clinical staff.[5,6] Where possible, AI-based telemedicine approaches, such as virtual IR clinics, can be employed to reduce patient travel and carbon footprint.[8]

Contrast agents

It has been suggested that AI tools can be used to optimize contrast dosage[27,28,32] in diagnostic imaging and radioisotope dosimetry in nuclear medicine,[6] determine when contrast agent administration is not needed, or generate DL-based virtually enhanced images.[5,23] AI-generated virtual contrast-enhanced images can potentially reduce the amount of ICAs in CT by 50% while maintaining image quality.[5] In another review, DL-based virtual enhancement models were found to achieve delineation between ischemic and non-ischemic fibrosis and scar-

Table 2. Comparative table of antecedent similar reviews

Study	Design	**Search methodology**	Criteria	Results	**Primary focus**	**Metrics reported**	**Added value**
Thomson et al.[43]	Syst. review	MEDLINE and Embase were searched for peer-reviewed sources from 2015 to 2025	Only hospital-based clinical radiology papers Conference papers also included	Eighteen sources of evidence (14 studies, 4 conference abstracts)	Any quantitative measure of artificial intelligence (AI)'s environmental impact	Energy consumption (watts or joules) Carbon emissions (CO_2eq)	No research comparing AI vs. standard care was identified
Champendal et al.[42]	Scoping review	MEDLINE, Embase, Cumulative Index to Nursing and Allied Health Literature Ultimate, and Web of Science were searched from 2014 to 2024	All sources discussing the environmental sustainability of AI applications in medical imaging	Thirteen sources of evidence (9 original studies, 4 reviews)	To explore how the environmental sustainability of AI in medical imaging is addressed	No quantitative sustainability metrics were reported	Lack of studies measuring the true environmental impact of AI
Current study	Scoping review	PubMed, Wiley Online Library, Embase, Web of Science platform, the Cochrane Library, Cumulative Index to Nursing and Allied Health Literature Ultimate, Google Scholar, and MedRxiv from 2020 to 2026	Peer-reviewed literature discussing all AI-powered initiatives to improve environmental sustainability in medical imaging No conference papers included	Twenty-three sources of evidence (15 reviews/scientific statements/ editorials, 5 original studies, 3 systematic/ scoping reviews	To explore how AI can help curb the environmental impact of medical imaging	Energy consumption (kWh) Carbon footprint (kg CO_2)	All possible ways across the patient's pathway in which AI can reduce the environmental burden of medical imaging were reported, with an operational/ clinical focus, rather than trying to quantify environmental outcomes

ring in CMR similar to late gadolinium enhancement.[24,30] DL-based models allow for reduced contrast dosage;[5,26,27,32] for instance, they can predict brain DCE-MRI images using only 10% of the standard GBCA dosage[8] or achieve up to 80% dosage reduction in MR angiography of congenital heart disease.[24] The contrast-to-noise ratio exhibited on MRI images acquired with reduced GBCA dosage can be restored by DL models.[5]

Discussion

Previous work has been published on AI-enabled medical imaging and environmental sustainability. A narrative literature review highlighted critical aspects of AI-related environmental sustainability in medical imaging.[5] However, our work followed a robust and comprehensive approach, employing a scoping review methodology. Furthermore, a recent systematic review found that environmental sustainability is seldom evaluated; of 4,449 citations, only 18 studies met the inclusion criteria, 6 reported quantitative outcomes, and algorithms designed to be "lightweight" generated 2.19–17.15 times less carbon emissions and 1.60–751.62 times less energy than standard models.[43] However, this work focused mainly on clinical radiological studies using AI tools to support diagnosis and on quantitative metrics of environmental sustainability. Similarly, a recent scoping review focused on any sources of evidence discussing the environmental impact of AI in medical imaging, although quantitative metrics from primary studies were not reported.[42] Our study focused on exploring ways in which AI can have a positive environmental impact on medical imaging, having a clinical/operational focus and following the patients' pathway to guide radiographers through this AI-enabled process. Any strictly computational/quantitative-focused literature was not the primary focus of this review. Moreover, our study was the only one to perform broader searches across eight databases. Table 2 provides a brief comparison between our scoping review and its two antecedent reviews.

This scoping review revealed not only AI's environmental cost, as developing and deploying AI models requires substantial computing power and therefore large amounts of energy,[5] but also its potential for more sustainable clinical services in medical imaging. AI can shorten scans through abbreviated acquisitions, improve scanner scheduling, and reduce low-value imaging. These opposing forces constitute the so-called "AI sustainability paradox": the need to weigh the environmental burden of AI against its ability to reduce energy consumption.[44]

Environmental footprint of artificial intelligence beyond the scanner

The environmental footprint of AI itself encompasses multiple stages of the AI lifecycle. Training, validation, and deployment of AI models demand significant computing power; for instance, training one NLP model using a neural architecture search can emit more than 626,000 pounds of CO_2-e,[45] which is approximately five times the lifetime emissions of an average car; carbon intensity varies by location, although newer estimates are considerably lower than they were. A single GPT-3 training produces between 223,920 and 858,360 kg CO_2-e,[5] depending on the data center's energy source. Inference, which is executed millions of times, can cumulatively exceed training emissions. Selecting energy-efficient hardware (e.g., halving CPU cores can reduce emissions by 33%) and optimizing algorithms through pruning, quantization, or model distillation can save 15%–76% of energy.[5] Inference with lightweight models on low-power edge devices, reusing open-source models, and using federated learning further reduces the computational burden.[42] Nevertheless, transparent reporting of model energy consumption remains rare. Beyond computing, cloud data centers supporting AI training and storage emit large amounts of carbon. According to the International Energy Agency, global data centers emit 180

Table 3. Recommendations to enhance sustainability in medical imaging

Category	Action
Mandate lifecycle assessments and carbon labelling for artificial intelligence (AI) tools	Regulatory agencies and purchasing bodies should require vendors to report energy use and carbon emissions for training and inference. The environmental impact should be split into in-hospital and out-of-hospital emissions. Transparent and standardized metrics will allow comparison of AI models and drive innovation toward lightweight architectures.
Integrate environmental sustainability into AI education curricula	Medical schools, radiology residency programs, healthcare schools for allied health professionals, and continuing education courses should teach carbon accounting, green computing techniques, and the environmental implications of AI. Course curricula should include sustainability alongside ethics and bias to prepare a workforce that can balance environmental costs and clinical benefits.
Optimize imaging protocols and reduce low-value imaging	Implement AI-accelerated protocols that shorten scan times and energy use without sacrificing diagnostic quality. Implement clinical decision support systems that incorporate environmental impact to avoid unnecessary or low-value scans. When multiple modalities offer similar clinical value, choose the method with the lowest radiation dose and environmental impact.
Improve data and hardware efficiency	Use lightweight algorithms, edge computing, and federated learning to minimize training and inference emissions. Adopt tiered storage, data compression, and renewable-powered data centers to reduce the footprint of data storage. Procure equipment with modular upgrades, and implement idle-mode management strategies to extend device lifespans.
Engage stakeholders through policy, certification and collaboration	Professional societies should develop toolkits and certifications (e.g., Green ID) to support departments in adopting sustainable practices. Policymakers should integrate sustainability into reimbursement and accreditation criteria. Collaboration between medical imaging professionals, industry, engineers, and patients is essential to align sustainability goals with clinical outcomes. Building a culture of environmental stewardship and establishing research frameworks with standardized reporting will generate the robust evidence base needed to benchmark progress and accelerate the adoption of green medical imaging practices.

million tonnes of CO_2.[46] Strategies such as tiered storage, compression, deduplication, and leveraging renewable-energy-powered providers[42] can mitigate these emissions.

Lifecycle impact beyond the hospital

Comprehensive lifecycle assessments estimating the overall environmental impact of medical devices are not yet standardized.[42] Although the production of imaging equipment is resource- and energy-intensive, the impact per examination over a 10–15-year lifespan of the product is thought to be low compared with the ongoing energy use. However, estimates of the grey energy of medical imaging equipment—the environmental footprint resulting from its production—are imprecise owing to a scarcity of information on equipment weight and composition.[47] Nonetheless, pathways for upgrading equipment and prolonging its useful lifespan, as well as sustainable manufacturing practices that anticipate recyclability, can contribute to a reduced overall environmental impact.

Even in the daily running of CT scanners, the majority of energy is consumed outside of the hospital. This includes the generation and transmission of electricity and the production of consumables, such as single-use materials, textiles, and contrast agents.[48] Consequently, approximately three-quarters of the environmental impact of CT scanning is caused outside of hospitals.[48]

Sustainability strategies in medical imaging beyond artificial intelligence

Efforts to decarbonize medical imaging should not rely solely on AI. Basic "turn-it-off" strategies, which switch scanners to low-power modes during nights and weekends, can reduce energy consumption. Equipment procurement should prioritize modular upgrades and low-energy components to extend lifespan and avoid premature replacement. Hospitals are establishing sustainability officers, developing procurement policies that favor recycled packaging, and promoting recycling or proper disposal of e-waste. Medical imaging departments should embed climate literacy into training, emphasizing the four pillars of green radiology: reducing energy, water, and helium use; recycling waste (including contrast); fostering environmentally friendly behavior; and reducing ionizing radiation. Renewables-powered data centers and evaporative cooling can further reduce the footprint, and more open and transparent reporting from both research and industry about the environmental impact of imaging and AI tools is urgently needed to guide purchasing and practice decisions.

Education, transparency, and accountability

Despite growing environmental concerns, integration of sustainable practices into AI or medical imaging education remains minimal. The widely adopted AI Literacy Course for radiology residents focuses on algorithmic bias and ethics but does not explicitly address environmental impact. Similarly, in a first-year medical student AI course, topics include fundamentals, prompt engineering, and ethical use of generative AI, again without consideration for sustainability. Educators should incorporate climate literacy, environmental cost accounting, and sustainable healthcare principles into curricula. The Society for Cardiovascular Magnetic Resonance calls for carbon cost and environmental awareness to be incorporated into medical education and CMR training programs.[24]

Transparency is equally critical in an environment where environmental metrics are rarely disclosed for both AI tools and medical devices. Recent work proposed the development of energy and carbon efficiency ratings for AI models and standardized ecolabels, analogous to the Energy Star program for consumer devices.[49] Vendors should report the carbon footprint of their products (physical and software) alongside clinical performance, enabling purchasers to compare tools on sustainability as well as accuracy and cost. The European Society of Radiology's Green ID initiative exemplifies this approach;[50] it certifies medical imaging departments' sustainability practices based on criteria covering energy, waste, and pro-

curement, and it aims to translate awareness into actionable changes.

Professional bodies have recognized the need for collective action. A 2025 multi-society position paper (from the American College of Radiology, Asian Oceanian Society of Radiology, European Society of Radiology, International Society of Radiology, and others) calls for urgent, measurable changes to medical imaging practice and outlines priority actions: improve climate literacy, conduct research into resource usage and low-value imaging, develop toolkits for departments, collaborate with industry on emissions metrics and circular economy approaches, and engage patients.[7] The paper stresses that sustainable imaging must not exacerbate global inequities; CT and MR imaging account for only 0.77% of global CO_2 emissions, yet access to CT and MRI varies tenfold across regions.[7] Medical imaging professionals should advocate renewable energy, invest in low-carbon equipment, and integrate sustainability into quality assurance frameworks.

Some limitations remain for this scoping review. First, the evidence base remains extremely small: of 87,128 identified citations, only 23 studies met the inclusion criteria. Eighteen of the included studies reported secondary data in narrative-based sources or systematic/scoping reviews. Although scoping reviews are primarily used to identify and map existing evidence, irrespective of source design, this scarcity of primary data, coupled with the early-stage nature of most interventions, means the review cannot provide robust pooled estimates of effect. However, many of these reviews focused on specific aspects of the medical imaging pipeline, whereas our work offers a bird's-eye view to support a more comprehensive approach directly reporting on different medical imaging modalities and scopes of practice (from scheduling of scans to post-processing). Second, because of the study design, the included studies were highly heterogeneous in terms of modalities (mostly MRI and CT), AI techniques, and sustainability metrics (energy use, scan time, carbon emissions, and image quality). Such variability precluded a formal meta-analysis. In addition, an author overlap analysis revealed that a single researcher is listed as a co-author in 6 of the included studies, three more researchers are included in 3 of the obtained studies, whereas eight other researchers are presented in 2 different studies in this scoping review. This means that the 23 included studies do not represent completely independent research groups, which limits author independence. An evidence overlap also exists, since most secondary sources have cited the same primary studies more than once. Finally, language biases are possible because only English-language publications were included, and heterogeneity in reporting further limits confidence in the evidence.

Future research

Five of the included articles mentioned quantitative environmental factors at one time point and did not provide lifecycle or carbon footprint assessments; consequently, it remains unclear whether the energy saved by more efficient imaging offsets the emissions from training and running AI models. Furthermore, none of the included studies directly compared AI-enabled pathways to standard care and most lacked long-term follow-up; therefore, the clinical and environmental impact of these technologies relative to current practice is uncertain. Finally, the focus of published literature on MRI, CT, and nuclear medicine means that the findings may not be applicable to radiography or mammography, which use lower energy and have different sustainability challenges. The latter are high-volume modalities due to the screening programs in breast and lung cancer; therefore, although individual energy savings per person may be marginal, they can build up quickly over time in population studies. Lifecycle assessments performed on radiography and fluoroscopy equipment have shown a substantial amount of GHG emissions. Therefore, longitudinal sustainability studies, directly comparing standard clinical practice with AI-enabled care and exploring different modalities and contexts, should be prioritized in the future.

Future policy and practice directions and recommendations

This scoping review demonstrated that AI-enabled sustainability in medical imaging is still in its infancy, with most AI studies not measuring direct environmental outcomes and with considerable knowledge gaps remaining. To progress from promising pilots to widespread adoption, we propose the following practical recommendations (Table 3).

Healthcare—particularly medical imaging—has a large environmental footprint. The increasing adoption of AI plays a dual role. Although AI may increase energy consumption through training, validation, and the deployment of AI tools, this may be balanced out with potential energy, carbon emission, and consumables savings through improved workflows and efficient use of resources. Clinicians, researchers, policymakers, and vendors have a responsibility to reduce and report the environmental impact of AI to support sustainable medical imaging practices. Training, lifecycle assessments of medical devices, and appropriate governance can enable stakeholders to make environmentally conscious decisions, since current evidence is lacking regarding the true savings of AI tools in clinical practice and any differences with the standard care pathway.

Footnotes

Conflict of interest disclosure

The authors declared no conflicts of interest.

Supplementary Material 1 Link: https://d2v96fxpocvxx.cloudfront.net/68ab204c-182b-49da-b227-bc7efe058632/content-images/b24277a2-1511-4c45-860c-df3d3920de57.pdf

Supplementary Material 2 Link: https://d2v96fxpocvxx.cloudfront.net/68ab204c-182b-49da-b227-bc7efe058632/content-images/c8959d06-3f1c-4f05-a19d-2be405bf2516.pdf

Supplementary Table 1, 2 Link: https://d2v96fxpocvxx.cloudfront.net/b37683d5-c547-4565-8c20-fa38c0b1ec76/content-images/40537812-b159-4a62-b89b-aeab63199512.pdf

References

1. Abdul-Nabi SS, Al Karaki V, Khalil A, El Zahran T. Climate change and its environmental and health effects from 2015 to 2022: a scoping review. *Heliyon*. 2025;11(3):e42315. [Crossref]
2. Rodríguez-Jiménez L, Romero-Martín M, Spruell T, Steley Z, Gómez-Salgado J. The carbon footprint of healthcare settings: a systematic review. *J Adv Nurs*. 2023;79(8):2830-2844. [Crossref]
3. Braithwaite J, Smith CL, Leask E, et al. Strategies and tactics to reduce the impact of healthcare on climate change: systematic review. *BMJ*. 2024;387:e081284. [Crossref]
4. Zalis ME, Slutzman JE. Technical and administrative advances to promote sustainable radiology. *J Am Coll Radiol*. 2024;21(2):274-279. [Crossref]
5. Doo FX, Vosshenrich J, Cook TS, et al. Environmental sustainability and AI in radiology: a double-edged sword. *Radiology*. 2024;310(2):e232030. [Crossref]
6. Leswick DA, Kulanthaivelu R, Jamil H, et al. Enhancing environmental sustainability in diagnostic radiology: focus on CT, MRI,

and nuclear medicine. Can Assoc Radiol J. 2025;76(4):595-602. [Crossref]

7. Rockall AG, Allen B, Brown MJ, et al. Sustainability in radiology: position paper and call to action from ACR, AOSR, ASR, CAR, CIR, ESR, ESRNM, ISR, IS3R, RANZCR, and RSNA. *Eur Radiol.* 2025;35(9):5427-5436. [Crossref]
8. Chaban YV, Vosshenrich J, McKee H, et al. Environmental sustainability and MRI: challenges, opportunities, and a call for action. *J Magn Reson Imaging.* 2024;59(4):1149-1167. [Crossref]
9. Jia Y, Deng M, Burger R, et al. Greenhouse gas emissions due to long-term data storage of CT with reformats and strategies for mitigation. *Eur Radiol.* 2026;36(3):2186-2197. [Crossref]
10. Chua ALB, Amin R, Zhang J, Thiel CL, Gross JS. The environmental impact of interventional radiology: an evaluation of greenhouse gas emissions from an academic interventional radiology practice. *J Vasc Interv Radiol.* 2021;32(6):907-915.e3. [Crossref]
11. Yakar D, Kwee TC. Carbon footprint of the RSNA annual meeting. Eur J Radiol. 2020;125:108869. [Crossref]
12. Abuzaid MM, Almuqbil N. Charting a sustainable future in radiology: evaluating radiologists' knowledge, attitudes, and practices toward environmental responsibility. *Insights Imaging.* 2025;16(1):39. [Crossref]
13. Antonissen N, Tryfonos O, Houben IB, Jacobs C, de Rooij M, van Leeuwen KG. Artificial intelligence in radiology: 173 commercially available products and their scientific evidence. *Eur Radiol.* 2026;36(1):526-536. [Crossref]
14. Richie C. Environmentally sustainable development and use of artificial intelligence in health care. *Bioethics.* 2022;36(5):547-555. [Crossref]
15. Truhn D, Müller-Franzes G, Kather JN. The ecological footprint of medical AI. *Eur Radiol.* 2024;34(2):1176-1178. [Crossref]
16. Dietrich N, Hanneman K. Greener by design: weighing the environmental impact of radiology AI development. *Can Assoc Radiol J.* 2026;77(2):267-268. [Crossref]
17. Heye T, Meyer MT, Merkle EM, Vosshenrich J. Turn it off! A simple method to save energy and CO_2 emissions in a hospital setting with focus on radiology by monitoring nonproductive energy-consuming devices. *Radiology.* 2023;307(4):e230162. [Crossref]
18. Kjelle E, Andersen ER, Krokeide AM, et al. Characterizing and quantifying low-value diagnostic imaging internationally: a scoping review. *BMC Med Imaging.* 2022;22(1):73. [Crossref]
19. Tricco AC, Lillie E, Zarin W, et al. PRISMA extension for scoping reviews (PRISMA-ScR): checklist and explanation. *Ann Intern Med.* 2018;169(7):467-473. [Crossref]
20. Briscoe S, Bethel A, Rogers M. Conduct and reporting of citation searching in Cochrane systematic reviews: a cross-sectional study. *Res Synth Methods.* 2020;11(2):169-180. [Crossref]
21. Ouzzani M, Hammady H, Fedorowicz Z, Elmagarmid A. Rayyan-a web and mobile app for systematic reviews. *Syst Rev.* 2016;5(1):210. [Crossref]
22. Essex R, Bruce G, Dibley M, et al. A systematic scoping review and textual narrative synthesis of the qualitative evidence related to adolescent idiopathic scoliosis. *Int J Orthop Trauma Nurs.* 2022;45:100921. [Crossref]
23. Mastrodicasa D, van Assen M, Huisman M, et al. Use of AI in cardiac CT and MRI: a scientific statement from the ESCR, EuSoMII, NASCI, SCCT, SCMR, SIIM, and RSNA. *Radiology.* 2025;314(1):e240516. [Crossref]
24. Hanneman K, Picano E, Campbell-Washburn AE, et al. Society for Cardiovascular Magnetic Resonance recommendations toward environmentally sustainable cardiovascular magnetic resonance. *J Cardiovasc Magn Reson.* 2025;27(1):101840. [Crossref] Erratum in: *J Cardiovasc Magn Reson.* 2025;27(2):101991. [Crossref]
25. Ueda D, Walston SL, Fujita S, et al. Climate change and artificial intelligence in healthcare: review and recommendations towards a sustainable future. *Diagn Interv Imaging.* 2024;105(11):453-459. [Crossref]
26. Bendszus M, Laghi A, Munuera J, Tanenbaum LN, Taouli B, Thoeny HC. MRI gadolinium-based contrast media: meeting radiological, clinical, and environmental needs. *J Magn Reson Imaging.* 2024;60(5):1774-1785. [Crossref]
27. Ben Salem D, Soyer P, Vernhet Kovaczick H. The effect of radiology on climate change: can AI help us move toward a green future? *Diagn Interv Imaging.* 2024;105(11):415-416. [Crossref]
28. Najjar R. Clinical applications, safety profiles, and future developments of contrast agents in modern radiology: a comprehensive review. *iRADIOLOGY.* 2024;2(5):430-468. [Crossref]
29. Currie GM, Hawk KE, Rohren EM. The potential role of artificial intelligence in sustainability of nuclear medicine. *Radiography (Lond).* 2024;30 Suppl 1:119-124. [Crossref]
30. Gunasekaran S, Szava-Kovats A, Battey T, et al. Cardiovascular Imaging, climate change, and environmental sustainability. *Radiol Cardiothorac Imaging.* 2024;6(3):e240135. [Crossref]
31. Mariampillai J, Rockall A, Manuellian C, et al. The green and sustainable radiology department. *Radiologie (Heidelb).* 2023;63(Suppl 2):21-26. [Crossref]
32. Pichler V, Martinho RP, Temming L, Segers T, Wurm FR, Koshkina O. The environmental impact of medical imaging agents and the roadmap to sustainable medical imaging. *Adv Sci (Weinh).* 2025;12(9):e2404411. [Crossref]
33. Currie GM. Beyond green: sustainability in nuclear medicine practice. *Br J Radiol.* 2025;98(1176):2023-2033. [Crossref]
34. Tsai A. Leveraging AI solutions for sustainable practice in pediatric radiology: a practical guide and an educational tool. *Pediatr Radiol.* 2026;56(4):705-717. [Crossref]
35. Narimani S, Hoff SR, Kurz KD, Gjesdal KI, Geisler J, Grøvik E. Sustainable deep learning-based breast lesion segmentation: impact of breast region segmentation on performance. *BMC Med Imaging.* 2025;25(1):406. [Crossref]
36. Reschke P, Gotta J, Gruenewald LD, et al. Deep learning in knee MRI: a prospective study to enhance efficiency, diagnostic confidence and sustainability. *Acad Radiol.* 2025;32(6):3585-3596. [Crossref]
37. Afat S, Wohlers J, Herrmann J, et al. Reducing energy consumption in musculoskeletal MRI using shorter scan protocols, optimized magnet cooling patterns, and deep learning sequences. *Eur Radiol.* 2025;35(4):1993-2004. [Crossref]
38. Woolen SA, Deshpande V, Becker AE, et al. Low-carbon MRI: acceleration strategies to reduce emissions and expand imaging capacity. *Radiology.* 2025;315(1):e243453. [Crossref]
39. Doo FX, Savani D, Kanhere A, et al. Optimal large language model characteristics to balance accuracy and energy use for sustainable medical applications. *Radiology.* 2024;312(2):e240320. [Crossref]
40. Anudjo MNK, Vitale C, Elshami W, et al. Considerations for environmental sustainability in clinical radiology and radiotherapy practice: a systematic literature review and recommendations for a greener practice. *Radiography (Lond).* 2023;29(6):1077-1092. [Crossref]
41. Bani-Ahmad M, England A, McLaughlin L, et al. AI-driven assessment of over-scanning in chest CT: a systematic review and meta-analysis. *Eur J Radiol Open.* 2025;15:100674. [Crossref]
42. Champendal M, Lokaj B, de Gevigney VD, et al. Exploring environmental sustainability of artificial intelligence in radiology: a scoping review. *Eur J Radiol.* 2026;194:112558. [Crossref]
43. Thomson RM, Perdomo-Lampignano J, Fisher E, et al. Evaluating the environmental sustainability of AI in radiology: a systematic review of current practice. *BMJ Digit Health AI.* 2025;1(1):e000073. doi: 10.1136/bmjdhai-2025-000073
44. Kocak B, Ponsiglione A, Romeo V, Ugga L, Huisman M, Cuocolo R. Radiology AI and sustainability paradox: environmental, economic, and social dimensions. Insights Imaging. 2025;16(1):88. [Crossref]
45. Strubell E, Ganesh A, McCallum A. Energy and policy considerations for deep learning in NLP. In: Proceedings of the 57th Annual Meeting of the Association for Computational Linguistics.

Florence, Italy: Association for Computational Linguistics; 2019. p. 3645-3650 [Crossref]

46. International Energy Agency. Energy and AI [Internet]. Paris: International Energy Agency; 2025. Accessed 2026 Sep 7. [Crossref]

47. McAlister S, McGain F, Petersen M, et al. The carbon footprint of hospital diagnostic imaging in Australia. *Lancet Reg Health West Pac.* 2022;24:100459. [Crossref]

48. Esmaeili A, Twomey JM, Overcash MR, Soltani SA, McGuire C, Ali K. Scope for energy improvement for hospital imaging services in the USA. *J Health Serv Res Policy.* 2015;20(2):67-73. [Crossref]

49. Doo FX, Parekh VS, Kanhere A, et al. Evaluation of climate-aware metrics tools for radiology informatics and artificial intelligence: toward a potential radiology ecolabel. *J Am Coll Radiol.* 2024;21(2):239-247. [Crossref]

50. European Society of Radiology. Green Imaging Department [Internet]. Vienna: European Society of Radiology. Accessed 2025 Oct 13. [Crossref]