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Exploring environmental sustainability of artificial intelligence in radiology: A scoping review

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ABSTRACT

Objective: Artificial intelligence (AI) is increasingly used in radiology, but its environmental implications have not been sufficiently studied, so far. This study aims to synthesize existing literature on the environmental sustainability of AI in radiology and highlights strategies proposed to mitigate its impact.
Methods: A scoping review was conducted following the Joanna Briggs Institute methodology. Searches across MEDLINE, Embase, CINAHL, and Web of Science focused on English and French publications from 2014 to 2024, targeting AI, environmental sustainability, and medical imaging. Eligible studies addressed environmental sustainability of AI in medical imaging. Conference abstracts, non-radiological or non-human studies, and unavailable full texts were excluded. Two independent reviewers assessed titles, abstracts, and full texts, while four reviewers conducted data extraction and analysis.
Results: The search identified 3,723 results, of which 13 met inclusion criteria: nine research articles and four reviews. Four themes emerged: energy consumption (n = 10), carbon footprint (n = 6), computational resources (n = 9), and water consumption (n = 2). Reported metrics included CO2-equivalent emissions, training time, power use effectiveness, equivalent distance travelled by car, energy demands, and water consumption. Strategies to enhance sustainability included lightweight model architectures, quantization and pruning, efficient optimizers, and early stopping. Broader recommendations encompassed integrating carbon and energy metrics into AI evaluation, transitioning to cloud computing, and developing an eco-label for radiology AI systems.
Conclusions: Research on sustainable AI in radiology remains scarce but is rapidly growing. This review highlights key metrics and strategies to guide future research and practice toward more transparent, consistent, and environmentally responsible AI development in radiology.
Abbreviations: AI, Artificial intelligence; CNN, Convolutional neural networks; CT, Computed tomography; CPU, Central Processing Unit; DL, Deep learning; FLOP, Floating-point operation; GHG, Greenhouses gas; GPU, Graphics Processing Unit; LCA, Life Cycle Assessment; LLM, Large Language Model; MeSH, Medical Subject Headings; ML, Machine learning; MRI, Magnetic resonance imaging; NLP, Natural language processing; PUE, Power Usage Effectiveness; TPU, Tensor Processing Unit; USA, United States of America; ViT, Vision Transformer; WUE, Water Usage Effectiveness.

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1. Introduction

Over the decades, human influence on the increased emission of greenhouse gases (GHG) like carbon dioxide and methane has led to significant global changes in weather and climate extremes [1]. In 2014, the carbon footprint of the global health care sector was 2.0 Gt CO2, accounting for 4.4 % of the global net emissions average. Country comparison shows that the United States of America (USA) had the highest percentage of such emissions (7.6 %), followed by Switzerland (6.7 %), while India had the lowest (1.5 %) [2].

Part of these healthcare emissions is attributed to medical imaging [3], and environmental sustainability in radiology has gained in attention. Roletto et al. [4] conducted a systematic review on strategies to reduce energy use and carbon emissions in radiology departments. They found that magnetic resonance imaging (MRI) and computed tomography (CT) scanners were the devices with the highest energy consumption, and the high proportion of the energy was consumed by radiological devices in the idle period. This creates a need to shut down devices when not in clinical activity in order to minimize energy waste [4,5]. In addition, several strategies and recommendations have been discussed to further reduce the carbon footprint of radiology departments, including optimizing technical infrastructure, promoting the use of ultrasound imaging to conserve resources, reducing material waste, fostering a culture of sustainability, and adopting cloud-based image storage to lower energy consumption related to server power and cooling [5–9].

Artificial intelligence (AI) has rapidly become an integral part of radiology landscape, bringing numerous applications to the field such as image analysis, post processing to enhance image quality (e.g., denoising), and natural language processing (NLP) for tasks like information extraction and document classification [10–13]. These advancements contribute to improving diagnostic accuracy, optimizing clinical workflows, and reducing the workload of radiologists. While convolutional neural networks (CNNs) have traditionally dominated AI in medical imaging, the introduction of Vision Transformers (ViT) [14] has generated growing interest. Moreover, transformers are a class of models that has gained a lot of traction due to their performance but they are more computationally demanding [15–17]. The utilization of AI opens possibilities for improving environmental sustainability by reducing examination times, optimization of workflows, and enhancing image quality with decreased contrast injections [18]. However, the increasing application of AI requires strong computational resources to train and operate models and dedicated facilities such as data centers [19], demanding substantial computational energy leading to increased GHG emissions [18,20,21]. This duality was highlighted in the literature, with Van Whynsberghe [19] proposing the concept of Sustainable AI. This concept encompasses AI for sustainability, which refers to opportunities of AI to improve environmental sustainability, and the sustainability of AI, which focuses on reducing the carbon emissions associated with AI.

The environmental impact of AI systems outside imaging has gained much attention. Strubell et al. [22] calculated the training times and the power consumption (kWh) of commonly-used NLP models and compared the estimated CO2 emissions with those of everyday familiar consumption. They showed that NLP models can produce significantly higher CO2 emissions annually than the average American consumption. This has fueled concerns about “red AI”, a term used to describe AI research that prioritizes performance improvements at the expense of massive computational energy consumption [23]. In response, “Green AI” initiatives have emerged to mitigate environmental impacts by taking into account computational costs, CO2 reduction, and sustainable practices [23,24]. These initiatives encourage designing AI systems that balance computational efficiency with performance. A literature review of Alzoubi et al. [24] identified and analyzed 55 green AI initiatives, categorizing them into six major themes. These included *cloud optimization, model efficiency, carbon footprinting green AI tools, sustainability-focused AI development, open-source initiatives, and green AI research and community*. Each theme represents a critical dimension of efforts to minimize AI’s environmental impact, ranging from optimizing cloud resources and enhancing model efficiency to fostering open collaboration and prioritizing sustainability in the AI development.

In healthcare and radiology, relatively few initiatives have been undertaken to provide recommendations for sustainable AI practices. Recently, Doo et al. [18] discussed and proposed a few strategies and opportunities to mitigate AI-related emissions. They also proposed a radiology ecolabel as well as strategies to mitigate AI carbon emissions [18,25]. However, there is currently no literature from the perspective of environmental sustainability that compiles detailed information on published studies in radiology and AI. The aim of this review is to synthesize the literature to identify how environmental sustainability of AI in medical imaging is addressed and if some specific strategies are applied.

2. Methods

The methodology for this scoping review was structured according to the framework proposed by Arksey and O’Malley [26] and further refined by the Joanna Briggs Institute (JBI) [27]. Structured scoping reviews effectively synthesize findings from various studies, helping to answer research questions and identify gaps in the literature [26]. The protocol for this review is registered on Open Science Framework [28].

2.1. Study selection

The literature research was conducted in the four following databases, MEDLINE, Embase, CINAHL and Web of Science. Primary research articles, literature reviews and opinion articles, published in the last ten years (2014 to 2024), in English and French, were considered. Combinations of keywords and Medical Subject Headings (MeSH) terms related to AI, environmental sustainability, the different fields of medical imaging and radiotherapy were applied. To ensure the inclusion of the most recent studies, an updated search was performed at the end of 2024, complementing the initial search conducted in February 2024. The detailed search strategy can be found in the *Supplementary Material*.

All identified studies were first uploaded to the Rayyan tool [29], where duplicates were removed. The study selection process was performed in two phases illustrated in the PRISMA [30,31] flow diagram (Fig. 1). First, 2 independent reviewers screened the articles in the basis of the title and abstract. Second, the screening was made on full text based on the inclusion criteria. During the review process, conflicts between reviewers were addressed by discussion until a consensus was reached. There was no need for a third reviewer.

2.2. Inclusion and exclusion criteria

Papers were included when they contained information about environmental sustainability of AI applications in medical imaging. Papers were excluded if they were conference abstracts, did not concern radiological medical imaging, focused on non-human population (water micro-organisms, plants, metals, food, chemicals, particles, soil, animals, geology, etc.). Finally, full articles that could not be found or were not available were also excluded.

2.3. Data extraction and analysis

The final set of included studies was independently charted using an extraction table developed by four reviewers. The table was refined following initial testing on two articles and included details such as authors, publication year, environmental impacts, calculation methods, metrics used, and strategies or techniques employed to reduce environmental impact. Sustainability strategies from the original studies were analyzed using the life cycle framework by Mehlin et al. [32], which covers IT infrastructure, data usage, modeling and training, and inference (Table 1). The end-of-life phase was also included, as it is recognized in literature as a critical factor. This phase refers to the retirement of AI models or applications that are no longer in use, which may include turning them off, archiving of reusing parts or components of them to avoid wasted energy and reuse of resources [33].

The results were presented through descriptive analysis and a narrative summary, completed with figures and tables for full visualization.

3. Results

3.1. Included studies

A total of 3,723 articles were initially retrieved from four databases. After duplicate removal, 2,362 articles were screened based on title and abstract; subsequent full-text assessment led to the inclusion of ten articles that fulfilled all predefined criteria. Full-text exclusions were due to wrong outcomes/not related to environmental sustainability (n = 51), incorrect publication types (n = 13), absence of medical imaging (n = 6), inaccessible articles (n = 5), absence of AI application (n = 4) and a

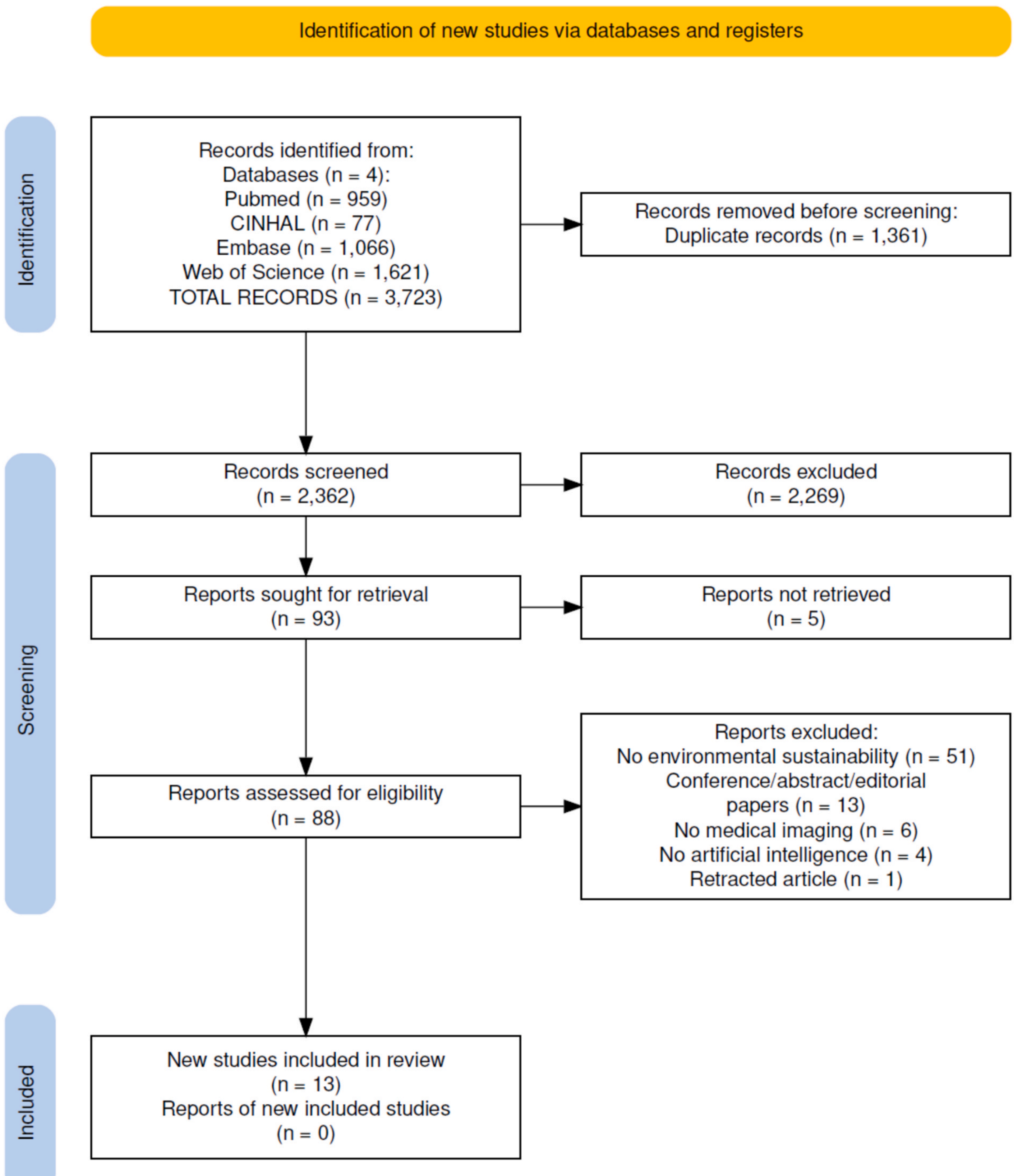


Fig. 1. PRISMA Flow chart.

Table 1
Overview of the review papers included & comparison with the current manuscript.

Review paper	Title	Type of publication	Methodology approach	Temporal and Contextual Focus	Main focus	Added value
Doo et al. (2024) [25]	Evaluation of climate-aware metrics tools for radiology informatics and artificial intelligence: toward a potential radiology ecolabel	Framework proposal	Application LCA and the GHG Protocol to radiology informatics. Evaluation of open-source metrics tools	Focus on the critical climate juncture and significant IT carbon footprint	Policy/Standardization Defining an environmental impact framework (LCA, GHG Protocol) and proposing a standardized ecolabel for radiology informatics tools	Defines the environmental accounting standards needed to address GHG emissions in informatics. Proposes the crucial need for a standardized ecolabel.
Doo et al. (2024) [45]	Economic and environmental costs of cloud technologies for medical imaging and radiology artificial intelligence	Economic & Environmental Analysis	Analysis using simulated costs (fictitious rates comparable to major cloud providers). Discussion of cloud architecture and PUE	Discussion on current technological trends (AI/LLMs, robust computing needs)	Infrastructure/Economics Weighing the economic and environmental implications of cloud migration for medical imaging data storage and LLMs	Demonstrates potential for significant financial and environmental savings via the optimized energy consumption (low PUE) of cloud data centers
Doo et al. (2024) [18]	Environmental sustainability and AI in radiology: a double-edged sword	Synthesis article	Structured discussion using published estimates (e.g., GPT-3 training emissions equivalent to 50–191 passenger vehicles/year). Provides action lists (Top 10).	Focus on current explosion of big data and AI applications	Duality/Strategy Highlighting the "Double-Edged Sword" of AI: negative impact (source of GHG) vs. positive potential (lever for operational efficiency).	Frames AI as a tool for operational sustainability (e.g., reducing scanner idle time, optimizing protocols). Calls for transparent efficiency metrics (Energy Star equivalent)
Kaneko et al. (2024) [46]	The Novel Green Learning Artificial Intelligence for Prostate Cancer ImagingA Balanced Alternative to Deep Learning and Radiomics	Narrative review	Narrative classification and comparison of AI methods based on transparency, complexity, and power consumption. Presentation of preliminary GL results.	Recent advances in AI (DL/GL) for PCa imaging	Algorithmic/Specificity PCa Promoting GL as an explainable, lightweight, and sustainable alternative to energy-intensive DL.	Highlights the unsustainable nature of current DL methods. Proposes a lightweight, interpretable model (GL) as a clinical solution
This Manuscript	Exploring environmental sustainability of artificial intelligence in radiology: a scoping review	Scoping review	Strict JBI Methodology: Search in 4 databases (MEDLINE, Embase, CINAHL, Web of Science). Data extraction by four independent reviewers. Strategies classified using the AI LCA framework	Comprehensive synthesis of 10 years of literature: 2014 to 2024.	Synthesis unifying strategies and metrics across the entire AI LCA framework and identifying gaps across four dimensions (Energy, Carbon Footprint, Resources, Water)	This review integrates fragmented literature into a unified framework, synthesizes 12 metrics and 9 strategies from primary studies, and reveals a critical gap: the lack of research on the end-of-life phase.

LCA: Lifecycle assessment – GHG: Greenhouse Gas – PUE: Power Use Effectiveness – GL: Green learning – PCa: Prostate cancer – DL: Deep learning.

retracted article (Fig. 1). No additional relevant documents were found after reviewing the references of the studies included. Finally, 13 papers were included in this review (see main information about the included articles in Supplementary material).

Studies were published in seven different countries: USA (n = 5), China (n = 2), Italy (n = 2), United Kingdom (n = 1), Egypt (n = 1), India (n = 1) and Portugal (n = 1) between 2018 and 2024, demonstrating a gradual increase in publication frequency: one article in 2018, three articles between 2021 and 2022, three articles in 2023 and six articles in 2024. The articles primarily consisted of original research articles (n = 9) and reviews (n = 4), predominantly addressing MRI (n = 5), CT (n = 3), mammography (n = 1), and X-rays (n = 1) (Fig. 2). Three of the reviews did not specify the imaging modalities discussed.

Among the nine original research papers, seven implied deep learning (DL) and two traditional machine learning (ML) architectures. AI tasks included segmentation, classification, diagnosis and image reconstruction (Fig. 2). The four reviews were focused on general AI or on general AI and Large Language Models (LLM).

To clearly demonstrate how this *scoping review* adds value beyond these four existing reviews, a targeted comparative synthesis, which also serves to contextualize the findings presented throughout this study, is provided in Table 1.

3.2. Strategies along AI lifecycle

Table 2 summarizes the data extracted from the research articles included (n = 9), providing the basis for the strategies identified. Most studies employed TensorFlow or PyTorch for model development and execution, primarily utilizing standard Central Processing Units (CPU) and Graphics Processing Units (GPU), already designed for parallel processing. One study went a step further by applying software-based techniques, like pipeline parallelism to better leverage the hardware and improve overall efficiency [37].

Strategies for efficient data usage were rarely addressed. Only three studies mentioned data augmentation techniques, primarily aimed at increasing data variability through multi-center and multi-vendor datasets [34,41] and addressing class imbalance within the data [39]. However, these techniques were not used in the context of reducing environmental impact or training resources demands.

Modeling and training practices varied significantly. The majority of the studies trained models from scratch, with two articles leveraging a pretrained model using specific pretrained parameters [37,41]. Strategies primarily focused on architectural adaptations aimed at reducing complexity, such as minimizing the number of convolutions, employing ML architectures with reduced computational demands. Some articles use skip connections: they create shortcuts that help gradients flow more easily through deep networks, making them easier to train. While they improve stability and enable deeper architectures to converge, they may also slightly increase computational load due to extra gradient paths during backpropagation. Additional optimization techniques included batch normalization, fast optimization algorithms for accelerated convergence, and the use of efficient optimizers. Notably, one study highlighted the application of early stopping to mitigate unnecessary computation during training, which also avoids overfitting [40].

Only two studies discussed inference-related strategies, such as the utilization of quantization and a pruning approach to reduce computational complexity for a breast lesion segmentation task [37], or deployment sharing via fog computing and the cloud [39]. Notably no studies addressed end-of-life considerations for AI systems.

3.3. Evaluation metrics and tools

Four key categories related to environmental sustainability were identified in the articles: energy consumption (n = 10), computational resource usage (n = 9), carbon footprint (n = 6) and water consumption (n = 2). The included studies utilized a range of metrics to evaluate

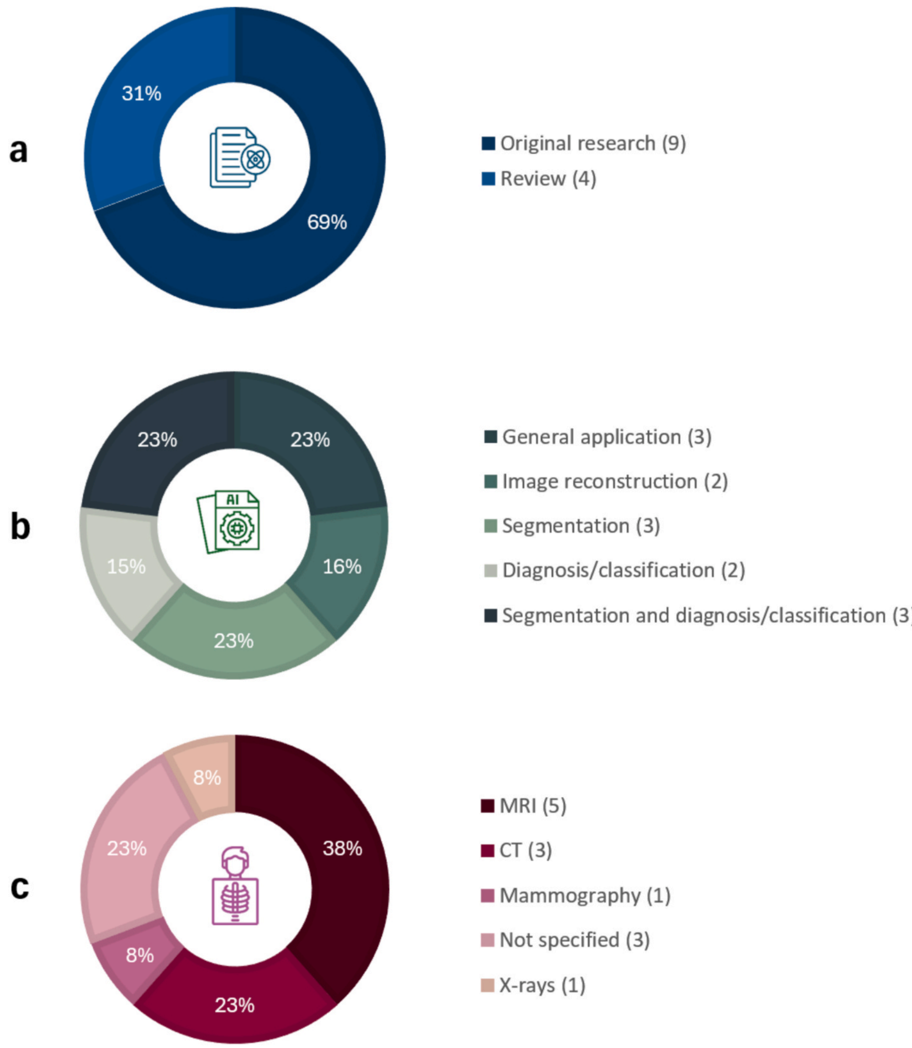


Fig. 2. Type of publications (a), AI task (b), and imaging modality distribution (c) of the included papers.

environmental sustainability across these categories (Table 3). For energy consumption, metrics included energy usage (kWh or J), equivalent car travel distance (km), and Power Usage Effectiveness (PUE). Carbon footprint was assessed through GHG emissions (CO2eq) and carbon sequestration potential (trees/month). Computational resource usage was measured using training, execution, and runtime durations (hours), the number of epochs, floating-point operations (FLOPs), model parameters, and inference time. Specifically, gallons (gal) were used for estimation of water quantity needed for cooling servers or for generating energy. Table 3 offers an overview and definitions of those metrics, as well as the type of impact classified as input, process, or output following the framework of Graedel et al. [43].

Due to the limited number of studies and the substantial variability observed in model architectures, tools employed and environmental sustainability metrics, it was not feasible to reports consistent numerical ranges for the categories reported in Table 3.

Among the original papers, two provided information about the tools used to calculate and evaluate the environmental impact of AI (Table 2), specifically mentioning the Carbon Tracker tool [34,44] and the Green Algorithms website [35]. Two studies emphasized that only the final training phase was considered, without including the training runs required for hyperparameter tuning, model development, and architecture exploration [34,35].

3.4. Recommendations of the papers

A recommendation emerges by incorporating environmental metrics such as energy consumption and carbon footprint as evaluation criteria alongside accuracy and other performance metrics in ML research. According to Bohoran and al. [34], this can help to accelerate innovations in algorithmic efficiency, reduce the adverse environmental impacts of algorithm training, and democratize access to AI research by lowering resource barriers.

Doo et al. [18,25,45] discuss the potential of cloud computing as a cost-effective strategy for radiology AI, pointing out its ability to provide centralized infrastructure while reducing costs associated with hardware ownership, maintenance, and upgrades. They highlight the optimized energy efficiency of modern cloud data centers, achieved through economies of scale, the use of energy-saving algorithms, and the integration of renewable energy sources, which collectively reduce the environmental footprint of radiologic operations. The authors also address the environmental considerations of cloud computing, particularly its water usage, both directly for cooling systems and indirectly through the water demands of non-renewable electricity generation. They note that the choice of data center locations can compete with local water needs and call attention to the lack of transparency in water-use data, which complicates efforts to assess environmental impacts and achieve net-zero emission goals. Additionally, they highlight the capacity of modern cloud data centers to reduce hardware lifecycle

Table 2
Data extraction of the nine research papers included throughout the AI Lifecycle.

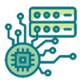
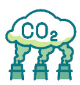
Study	Efficient IT-infrastructure as reported in the study	EfficientData usage	Efficient Modelling/Training	Inference	End-of-life	Sustainability results with metrics and tools used
Bohoran et al. (2023) [34]	**Software**: Tensorflow **Hardware:** NVIDIA RTX A6000 (48 GB) GPU	Data augmentation Multi-center multi-vendor data	Not pretrained **Architecture design**: Compact convolution **Parameters**: Focal Tversky loss, Adam optimizer, He Normal initialization, Batch Normalization	–	–	**Model resource efficiency and carbon footprint:** CO2eq (2093.571 g) Energy (5.984 kWh,) Equivalent distance travelled by car (17.388 km) during final training of 250 epochs, Training time (06:45:11), Average inference time (2.768 ms) **Tool:** Carbontracker tool
Farahat et al. (2023) [35]	**Software**: No indications **Hardware:** Core i7 CPU and 16 Gigabyte (GB) of memory	– Public dataset from TCIA website	Not pretrained **Architecture design**: ML two-stage neural network **Parameters:** Fast optimization algorithm called Levenberg–Marquardt and ELU function, both faster convergence	–	–	**Green complexity analysis**: Energy needed (130.8Wh) and carbon footprint: CO2eq (117.80 g), Carbon sequestration (0.13 tree months) **Tool**: Green algorithm website
Hu et al. (2021) [36]	**Software**: Tensorflow **Hardware**: CPU ES-2640 2,566 memory, and GPU GTX 1080Ti	–	**Architecture design:** Addition of spatial information in Fuzzy C-Means (less noise, faster convergence) **Parameters:** Adam optimizer, Batch Normalization	–	–	Completion time (inference? – unclear) (4.5 s) Total energy consumption of the network (approximately maximum 59 J) **Tool**: no info*
Liu et al. (2018) [37]	**Software:** No indications **Hardware:** Parallel hardware architecture	–	Pretrained **Architecture design**: Cellular Neural Networks for segmentation, Multilayer Perceptron for classification **Parameters**: Particle Swarm Optimization	Quantization and pruning	–	Energy consumption (1038.1 μJ) **Tool:** no info*
Morotti et al. (2021) [38]	**Software:** No indications **Hardware:** NVIDIA GeForce RTX 2080Ti (GPU)	–	Not pretrained **Architecture design**: Light convolutional network, with addition of skip connections. Fewer parameters than residual UNet. **Parameters**: Batch Normalization.	–	–	Number of parameters (85′000), FLOPs (44 x 10^9), training time (53 s) **Tool**: no info*
Pati et al. (2023) [39]	**Software**: Scikit-learn and Keras. **Hardware**: Intel Core i7 processor, Intel Core i5 generationFog computing + Cloud computing	Data augmentation CXR imaging dataset from Kaggle	Not pretrained **Architecture design**: Ensemble learning (multiple neural networks). For image analysis, multiple regular DL architectures (CNN, ResNet101, VGG19.) **Parameters**: Batch Normalization.	Deployment sharing (Fog computing, cloud).	–	Network utilization (8.35 – 25.69 sec), and energy consumption (2.89 – 18.53 W). **Tool:** no info*
Sapienza et al. (2022) [40]	**Software**: PyTorch **Hardware**: Multi core 8 CPU Intel core i7-7700 K at 4.20 GHz, GPU GeForce RTX 2080 (8 GB)	–	Not pretrained **Architecture design**: Autoencoder with skip connections **Parameters**: Batch Normalization, Various initializations, Early Stopping.	–	–	Training time (number of epochs) **Tool**: NA
Ghauri et al. (2024) [41]	**Software**: TensorFlow, PyTorch, Keras **Hardware**: Cloud computing Google Collaboratory	Data augmentation Public data from Kaggle	Pretrained **Architecture design**: CNN **Parameters**: Bayesian optimization	–	–	Carbon footprint CO2eq (140 g) **Tool**: No specific tool was used; only a calculation formula applied (power consumption x running time x carbon intensity = carbon footprint)
Rosa et al. (2024) [42]	**Software**: TensorFlow **Hardware**: NVIDIA	Public data from Kaggle (small dataset)	Not pretrained **Architecture design**: U-Net **Parameters**: Adam optimizer, Batch Normalization, denoising filters	–	–	Computational costs assessed based on the number of training epochs. Application of denoised filters resulted in a reduction of 12 epochs, corresponding to an approximate saving of 16 h of computation. However, the use of denoising filters incurred additional processing time for their application. **Tool**: NA

* No information provided regarding the tool or detailed calculation methodology used for this calculation.
CNN: Convolutional Neural Network – CPU: Central Processing Unit – CXR: Chest X-Ray – FLOPS: Floating-point operations per second – GPU: Graphics Processing Unit – NA: Non-Applicable.

emissions by consolidating IT infrastructure, simplifying recycling and disposal processes, and minimizing pollution from hardware manufacturing. In contrast, Pati et al. [39] presented fog computing, which processes data closer to the source. This approach reduces energy consumption, latency, and bandwidth usage. These characteristics are particularly advantageous for time-sensitive applications, such as COVID-19 diagnostics, by decreasing dependency on centralized servers and extensive data transfers.

Doo et al. [25] highlighted the importance of addressing embodied carbon, defined as emissions from hardware manufacturing,

Table 3
Overview of the metrics used in the articles for each identified environmental sustainability category.

	Metrics (units)	Metrics definition	System model impact type*
 **Energy consumption (n = 10)**	■ Energy spent/Energy needed (kWh or J)	The amount of energy required to perform a task, such as training or inferring a deep learning model [34,35].	■ Input
	■ Equivalent distance travelled by car (km)	The equivalent distance a car would travel using the same amount of energy [34,35].	■ Output
	■ Power Use Effectiveness – PUE	Measures the energy efficiency of a data center by comparing total energy consumption to the energy used by computing equipment alone, with lower values (closer to 1.0) indicating greater efficiency [38].	■ Process
 **Computational resource usage (n = 9)**	■ Training time, running time (h)	Time required to train a machine learning model or run an algorithm [34,35,38].	■ Process
	■ Epochs (n)	Represents a complete iteration on the training data set during the model learning process [34,35,38,40].	■ Process
	■ Floating-point operations – FLOPs	Measure of the computational load of a model or algorithm, used to assess its computational cost [38].	■ Process
	■ Number of parameters (n)	Parameters like weights and biases are learned during training and typically reflect the model size and complexity [38].	■ Process
	■ Running time/Inference time (h)	Time required for a trained model to process new data and generate a prediction [34].	■ Process
 **Carbon footprint (n = 6)**	■ Greenhouse Gas Emissions ($CO2eq$) (g)	Measure the carbon footprint, representing the global warming potential of a quantity of greenhouse gases in CO2 equivalent [34].	■ Output
	■ Carbon sequestration (tree/months)	Estimate the capacity of one or more trees to absorb CO2 over a given period, often linked to the running time of an algorithm [35].	■ Output
 **Water footprint/ consumption (n = 2)**	■ Gallons of water (gal)	Quantifies the water consumption of data centers, whether directly for cooling or indirectly for the production of the non-renewable electricity used [45].	■ Input

* Type of impact regarding AI system classified as input, process, or output following the framework of Graedel et al.[43].

transportation, and disposal. They proposed strategies such as extending hardware lifespan through emission amortization over its operational years, transitioning to modern, energy-efficient equipment or lightweight edge devices, and promoting responsible disposal and recycling practices. Additionally, they noted that cloud computing can further mitigate on-site hardware demands by consolidating IT infrastructure, thereby reducing environmental impacts associated with heavy metal extraction and component manufacturing.

To enhance computational efficiency, Doo et al. [25] proposed running workloads on fewer, highly utilized servers and leveraging edge computing to optimize tasks based on regional demand or time of day. Techniques like early stopping and gaussian initialization were also identified as effective approaches to minimize training time and resource consumption [40].

Finally, to promote standardization and accountability in sustainable AI, the development of a standardized ecolabel for radiology AI tools was proposed, to provide a consistent framework for assessing energy and carbon efficiency [25]. Collaborative efforts among radiologists, technologists, and industry partners have been emphasized as crucial for advancing sustainability initiatives and incorporating environmental considerations into AI development [25].

4. Discussion

This review highlights that sustainable AI in radiology is still a relatively underexplored topic, though interest appears to be growing with many of the publications only in 2024. Similar findings were reported by Verdecchia et al. [47], who found few publications focusing on computer vision in their systematic review.

Among the original research identified, only two papers explicitly aimed to measurably reduce the carbon footprint of their AI systems. Although the overall volume of research remains limited, the findings of this scoping review highlight emerging trends and considerations for sustainable AI in radiology.

4.1. Current gaps

The studies employed AI across various imaging modalities (MRI, CT, mammography, and X-rays), but the assessment of environmental impact remains inconsistent and often incomplete with limited consideration of the complete AI lifecycle. Most studies focus primarily on the training phase, with minimal attention to data preparation, inference, and end-of-life considerations.

To accurately evaluate the carbon footprint of AI systems, a comprehensive lifecycle assessment (LCA) of AI system is needed [32,33,48,49]. Existing studies, such as Bannour et al. [33] and Wu et al. [48] have proposed frameworks that considered emissions arising from hardware production and use, data processing, training, inference and end-of-life equipment. Mehlin et al. [32] further provided an overview of energy-efficient approaches along the DL lifecycle that includes IT-infrastructure, data, modeling, training and deployment. However, there is still no clear or complete approach. In practice, some different stages of the AI lifecycle are not clearly separated, as many techniques can contribute to reducing energy consumption across several phases.

To reduce the costs associated with data collection, annotation, and training, several techniques have been proposed. These include data augmentation, active learning, which minimizes data requirements by selectively using the most informative (highest information gain) examples during training; and the use of pretrained models, which leverage knowledge from existing models to reduce training demands [32,50]. However, while data augmentation can help reduce the need for collecting, annotating, and storing new data, it should be used thoughtfully, as some strong data augmentation techniques can significantly be computationally expensive [51].

Additionally, algorithm and model architecture optimization significantly impact energy efficiency. Various techniques have been explored, primarily focusing on reducing model complexity (e.g., the number of layers), using primarily pretrained architectures, optimizing hyperparameter selection, implementing early stopping mechanisms, and quantization and pruning methods to create more compact and computationally efficient AI models without sacrificing performance. Additionally, for hyperparameter optimization, random search remains a good baseline strategy, particularly when the number of parameters increases, however grid search becomes inefficient due to the exponential increase in search [52]. These efforts align with general research trends outside of radiology, like the development of energy-efficient AI models and the integration of green computing practices [53]. While model optimization strategies are widely discussed in literature, no standardized approach has been established, and no comparison of the approaches has been made to systematically reduce the carbon footprint and computational energy consumption of AI models in radiology.

A study on digital pathology, revealed that large and multi-task DL models emit significantly higher GHG than smaller models limited to a specific task [54]. It is not always necessary to rely on large models to perform a task, because simpler approaches, such as statistical methods or logistic regression, can sometimes be sufficient. Choosing the right model wisely for a given task is essential.

As highlighted in the results, the inference phase of AI models, despite requiring less time compared to training, has received limited attention in discussions of environmental sustainability [49,55]. However, it can still consume substantial energy, especially in cases of widespread deployment, such as ChatGPT, where energy usage escalates due to the surge in user requests [49,56]. In contrast, inference tends to be less problematic in the context of typical radiological applications where models are deployed locally and utilized on a per examination basis. Nonetheless as the field explores broader integration of generative AI for tasks like report or image generation, sustainability must extend beyond the training phase.

No article has mentioned end-of-life regarding AI systems and the end of their operational life. This may be attributed to the fact that most articles focused on the development phase than implementation. As a result, there is little guidance on how to responsibly decommission AI systems no longer in use including datasets and infrastructure in clinical environments. It would therefore be beneficial to promote the reuse or mutualization of data and model components to reduce the environmental footprint linked to redundant computation and storage.

4.2. Current state within sustainability assessment

Four interconnected dimensions of environmental impact in AI radiology systems were found in this work: energy consumption, computational resources, carbon footprint and water consumption. These dimensions are closely linked, with some impacts occurring primarily at the input stage of the AI system lifecycle (water and energy consumption), computational resource at the process stage, and carbon emissions as output.

4.2.1. Energy Consumption and Optimization:

Energy efficiency in AI systems improves mainly through algorithmic and hardware optimization [52]. Energy consumption is assessed using specific open-source tools (for example the open-source Carbontracker tool [44]) that estimates energy used for a specific task, and offer comparisons, such as converting energy use into the equivalent distance traveled by car, to contextualize the environmental impact. In the field of radiology, future research could benefit from comparative analysis of the energy demands of AI models relative to those of traditional imaging modalities. An illustrative example was provided by Kocak et al. [57], who compared the energy consumption of LLMs against CT and MRI scans.

Data centers are major energy consumers, mostly for cooling systems [58], and remain powered by fossil fuels [59]. At radiology level, utilizing primarily cloud computing can be more energy-efficient because hyperscale providers operate optimized data centers with advanced cooling and lower PUE values. However, in the healthcare context, transferring sensitive radiology data to the cloud raises inherent challenges, including secure and anonymized transmission, and in some cases the requirement of patient consent [60].

4.2.2. Computational resource usage:

Efficient management of computational resources depends on the model complexity typically defined with the number of parameters and FLOPs, along with architectural choice and some specific hyperparameters, impacting training duration and resource demands. Thus, AI systems applied in radiology should provide a clear and transparent description of these elements. Despite this, the hidden costs associated with training and fine-tuning models for clinical deployment are often difficult to quantify because they are not reported but must not be overlooked.

4.2.3. Carbon Footprint Considerations:

Carbon footprint calculation includes both the energy needed for the algorithm and carbon intensity. The results are expressed in terms of GHG emissions measured in grams of CO2-equivalent (g CO2eq). These estimations were calculated using tools such as CarbonTracker [44] and the Green Algorithms calculator [61]. Notably, the Green Algorithms tool also incorporates an estimate of carbon sequestration, which quantifies the time a tree would need to absorb the CO2 emitted by running a given algorithm providing an intuitive and environmentally relevant metric.

When compared with GHG emissions from radiological modalities [4,9,62], the estimated emissions associated with the AI algorithms reviewed in this paper are generally lower than those of MRI or CT scans per examination. In some cases, they are comparable to the emissions from a standard ultrasound US or X-ray examination. In general, the more complex and larger a model is, the more emissions of CO2 [63]. There is a need to review systematically AI applications in radiology to have a better estimation of their GHG emissions in clinical practice.

Furthermore, data centers have become also major contributors to GHG emissions [64]. It is then important to build adequate data management practices, such as minimizing redundant storage, using centralized and low-carbon storage infrastructure [18,53,64]. Lannelongue et al. [65] highlighted the importance of interinstitutional collaborations, particularly in regions with access to low-carbon electricity, as carbon intensity varies significantly by geographic location. Hosting energy-intensive tasks in countries with greener energy grids can thus yield substantial reductions of emissions.

4.2.4. Water consumption:

In addition to carbon emissions, AI systems impose other environmental costs, such as resource depletion and water consumption mainly because of data centers [25,45]. Training large models such as GPT-3 demands thousands of water liters for cooling servers and generating the electricity required to power them, resulting in a substantial impact that has often gone overlooked [66]. Li et al. [66] provided a comprehensive methodology for estimating the water footprint of AI systems and gave an overview of the values of PUE and Water Usage Effectiveness (WUE) for various data centers.

While ongoing research focuses on developing energy-efficient models, there is no consensus yet on standardized metrics for measuring energy efficiency and carbon emissions. However, researchers are increasingly encouraged to consider energy efficiency and carbon emissions as part of model evaluation, promoting high-performance models with lower energy consumption [32,34]. Systematically reporting energy consumption enhances transparency and fosters accountability in the development of AI systems [53,65]. Various tools have been developed to assess AI-related energy consumption and carbon emissions, but variability between them was observed [33,67]. Among the existing tools for evaluating the carbon footprint of NLP methods, a significant limitation lies in the underestimation of emissions, particularly those from the production and end-of-life phases of hardware [33]. Emissions associated with the manufacturing and disposal of GPUs and Tensor Processing Units (TPU), which represent a substantial portion of AI's environmental impact, are often overlooked. Notably, no publications were found that estimated GHG emissions specifically for the production phase of these hardware components [33,67]. Furthermore, most of these tools focused on the training phase of AI models, leaving other critical sources of emissions, such as hardware production, data storage, and disposal processes, underrepresented in assessments [67]. As highlighted by Bolte et al. [68], the training and deployment of AI models contribute to electronic waste, land degradation, and the extraction of rare earth minerals required for hardware manufacturing, practices that intensify ecological damage through habitat disruption, pollution and habitants delocalization.

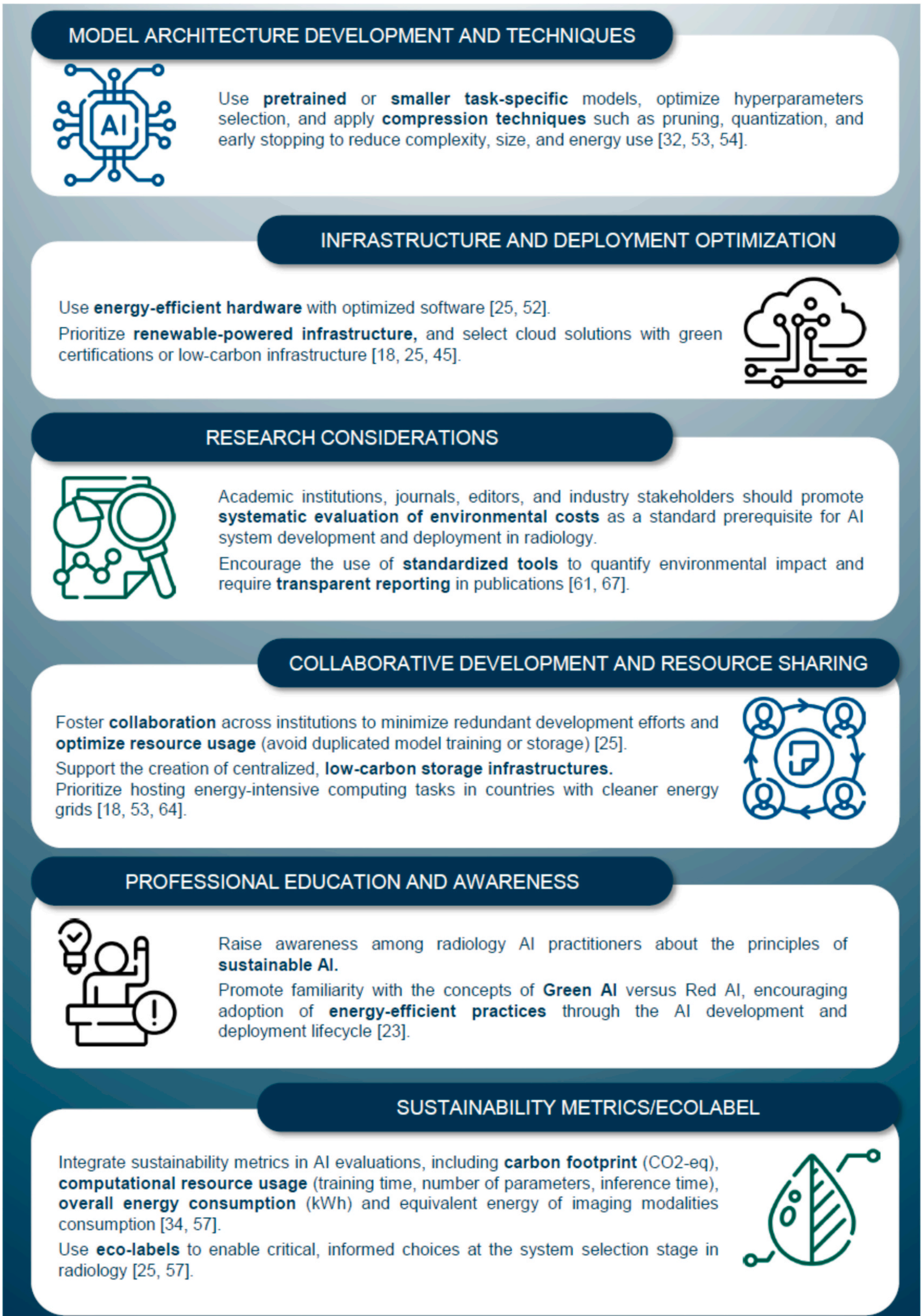


Fig. 3. Practical strategies proposed for integrating Green AI principles.

4.3. Future directions and recommendations for sustainable AI in radiology

While the ethical landscape surrounding AI development has gained increasing attention, environmental sustainability remains an under-represented dimension [69]. As reported by Ueda et al. [53], formalized policies and global initiatives that embed sustainability within AI governance are needed, particularly in healthcare. To prevent greenwashing, transparency and standardization in reporting are essential. Radiologists and radiographers are well-positioned to engage in the process stage of the AI lifecycle; we therefore propose targeted strategies to mitigate environmental impacts (Fig. 3).

Model architecture development and technique: the first strategy, widely adopted in literature, is to act at the model architecture level by using simpler or already pretrained models, and also optimized hyperparameters selection [32,53,54]. For example, employing lightweight architecture or smaller task-specific models that can reduce computational complexity and energy consumption while maintaining competitive performances.

Infrastructure and deployment optimization: When deploying and implementing AI, it is also important to use modern energy-efficient hardware [25,52,57]. Additionally, organizations should prioritize renewable-powered infrastructure when possible and choose cloud providers with green certifications [18,25,45]. It is also crucial to think about end-of-life of AI systems, including associated datasets, and to establish for example guidelines for sustainable decommissioning and the reuse of AI system components.

Research considerations: In our opinion, academic institutions, journals, and industry stakeholders should promote the systematic evaluation of environmental costs as a standard prerequisite for AI system development and deployment in radiology. For example, research funding agencies should require applicants to assess and report on the environmental sustainability impact of their projects. Similarly, for publications, alongside traditional performance metrics such as accuracy or AUC, researchers should also include sustainability metrics [61,67].

Collaborative development and resource sharing: Institutions should collaborate to reduce redundant development and optimize resource use, for instance by sharing models and data instead of repeating training or storage [25]. They should also support centralized, low-carbon storage solutions and host energy-intensive computations in regions with cleaner energy grids, minimizing the environmental impact of AI activities [18,53,64].

Professional education and awareness: It is also important to raise awareness about the principles of green AI through education [23], and for example integrate this topic in the AI training programs and courses available for radiology.

Sustainability metrics/ecolabel: Finally, the concept of an ecolabel proposed by Doo et al. [25] represents a valuable proposition, particularly in promoting transparency and enabling users to make informed decisions regarding the use of AI systems. We argue that this perspective could be further extended by integrating sustainability-related metrics into AI Model facts which is a structured documentation framework designed to communicate important model characteristics to end-users, including clinicians [70]. Such integration would allow for the inclusion of key environmental indicators such as CO2-equivalent emissions, the number of model parameters, training and inference times, and whether specific energy-efficient techniques were applied.

4.4. Limitations

This review is limited by the small number of currently available studies and the absence of standardized reporting methods. Nonetheless, it provides a good foundation for assessing current trends in literature and guiding future research, particularly in enabling comparisons. The included articles cover the period from 2018 to 2024, reflecting an increase in publication frequency in recent years. However, due to the rapid evolution of AI and sustainability frameworks, results from different years cannot be directly compared, This work focuses exclusively on the environmental dimension of sustainability, without addressing the social or economic pillars, which are equally important [68]. Additionally, the methodological quality of the articles included was not assessed, due to the nature and scope of this review.

5. Conclusion

To the best of our knowledge, this is the first study to explore the current landscape of environmental sustainability in AI applications within radiology imaging. Despite the limited number of studies available, clear gaps and challenges were identified, underscoring the need for a more structured and transparent approach to sustainable AI development. Based on the findings, a set of strategies is proposed to guide future AI research toward the active integration of environmentally sustainable practices.

Building truly sustainable AI systems means looking beyond just optimizing models to consider the full footprint, from hardware production, infrastructure maintenance, and even research activities. Acknowledging this impact is only the first step, lasting change depends on shared responsibility, community collaboration, and strong institutional. By fostering a culture of sustainability in AI research and practice, we can collectively shape a more responsible and environmentally aware future for technology in radiology.

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CRediT authorship contribution statement

Mélanie Champendal: Writing – review & editing, Writing – original draft, Methodology, Investigation, Formal analysis, Conceptualization. **Belinda Lokaj:** Writing – review & editing, Writing – original draft, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Valentin Durand de Gevigney:** Writing – review & editing, Writing – original draft, Investigation, Formal analysis, Conceptualization. **Gaël Brulé:** Writing – review & editing, Supervision. **Jamil Zaghir:** Writing – review & editing, Investigation, Formal analysis. **Polina Boiko:** Writing – review & editing. **Christian Lovis:** Writing – review & editing, Supervision. **Henning Müller:** Writing – review & editing, Supervision. **Jérôme Schmid:** Writing – review & editing, Supervision. **Ricardo Teresa Ribeiro:** Writing – review & editing, Supervision.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Declaration of generative AI in scientific writing.

- Statement: During the preparation of this work the author(s) used ChatGPT in order to rephrase sentences, check syntax and correct spelling. After using this tool/service, the author(s) reviewed and edited the content as needed and take(s) full responsibility for the content of the published article.

Appendix A. Supplementary data

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