Environmental Sustainability and AI in Radiology: A Double-Edged Sword

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According to the World Health Organization, climate change is the single biggest health threat facing humanity. The global health care system, including medical imaging, must manage the health effects of climate change while at the same time addressing the large amount of greenhouse gas (GHG) emissions generated in the delivery of care. Data centers and computational efforts are increasingly large contributors to GHG emissions in radiology. This is due to the explosive increase in big data and artificial intelligence (AI) applications that have resulted in large energy requirements for developing and deploying AI models. However, AI also has the potential to improve environmental sustainability in medical imaging. For example, use of AI can shorten MRI scan times with accelerated acquisition times, improve the scheduling efficiency of scanners, and optimize the use of decision-support tools to reduce low-value imaging. The purpose of this *Radiology* in Focus article is to discuss this duality at the intersection of environmental sustainability and AI in radiology. Further discussed are strategies and opportunities to decrease AI-related emissions and to leverage AI to improve sustainability in radiology, with a focus on health equity. Co-benefits of these strategies are explored, including lower cost and improved patient outcomes. Finally, knowledge gaps and areas for future research are highlighted.

The World Health Organization has declared climate change as the single biggest health threat facing humanity (1). Climate change will affect everyone, although individuals and groups who are already the most vulnerable will be impacted the most severely (2).

Most greenhouse gas (GHG) emissions, including carbon dioxide, result from burning fossil fuels for energy use (2). These GHG emissions are typically quantified as carbon dioxide equivalents, which consider the varying global warming potential of other GHGs. The GHGs act like a blanket, making the Earth warmer than it would otherwise be. As a result, GHGs alter the planet's climate, including shifts in precipitation patterns, a rise in average temperature, and extreme events such as heat waves, storms, fires, and floods. As average global temperatures continue to rise, it is imperative to adopt sustainable practices across sectors.

Health care systems, including radiology, are major contributors to the global climate crisis. Health care accounts for 8%–10% of total GHG emissions in the United States, and medical imaging is estimated to account for up to 1% of global GHG emissions (2–4). In diagnostic radiology, most GHG emissions come from the manufacturing of imaging equipment and the energy needed to power it (5). However, due to the explosive increase in the development and adoption of big data and artificial intelligence (AI) applications in radiology, data centers and computational efforts are increasingly large contributors of GHG emissions (6). At the same time, AI can potentially help improve sustainability in radiology by maximizing the efficiency of imaging resources.

It is crucial for both radiologists and AI scientists to grasp the dual nature of AI; while it can serve as a potential tool to enhance sustainability in medical imaging, it also has a negative impact on GHG emissions. This *Radiology* in Focus article aims to shed light on this duality at the intersection of sustainability and AI in radiology (Fig 1). By acknowledging these contrasting aspects, we can make informed decisions and develop strategies to maximize the positive contributions of AI while mitigating its environmental drawbacks.

The Negative Impact of AI in Radiology on Environmental Sustainability

Within health care, radiology has emerged as a leader in exploring the clinical and business potential of AI, with the most AI tools cleared by the U.S. Food and Drug Administration and the most publications related to health care (7). However, until recently, the environmental consequences stemming from these AI activities have been largely overlooked (8,9). It is imperative that we reassess how the development and utilization of AI tools in radiology contribute directly and indirectly to GHG emissions throughout the entire AI and informatics infrastructure. This involves considering aspects such as AI model development and deployment, data storage, and energy source choices. Table 1 provides a summary of the negative impacts of AI on

Abbreviations

AI = artificial intelligence, GHG = greenhouse gas

Summary

Artificial intelligence applications in radiology are associated with the generation of large amounts of greenhouse gas emissions but also hold the potential to improve environmental sustainability if implemented judiciously.

Essentials

- The development and deployment of artificial intelligence (AI) models in radiology is energy-intensive and generates a large amount of greenhouse gas emissions.
- The use of AI tools can improve sustainability in radiology through optimized imaging protocols that result in shorter scan times, improved scheduling efficiency to reduce travel, and integration of decision-support tools to reduce low-value imaging.
- Educational and research initiatives are needed to increase awareness and inform strategies to minimize the environmental impact of AI in radiology.

environmental sustainability, along with mitigating actions. Figure 2 illustrates the negative environmental impacts of radiology AI and highlights key opportunities to use AI as a positive lever to augment sustainability. Importantly, GHG emissions from AI and radiology must be viewed in the context of the overall positive purpose that these serve. In comparison, total global electricity use for crypto assets is estimated between 120 and 240 billion kilowatt-hours per year, resulting in approximately 140 million metric tons of carbon dioxide per year (10).

AI Model Development and Deployment

The process of training, validating, and deploying AI models demands extensive computational resources, leading to substantial energy consumption and GHG emissions. Nevertheless, there is a lack of specific GHG emission data related to the use of AI in radiology and there are currently no guidelines for selecting sustainable AI software (11–13). To address this, transparent efficiency metrics and reporting standards for radiology AI models, akin to the Energy Star rating for appliances and imaging equipment, are needed to inform scientists, software developers, and radiologists about AI-related GHG emissions (14,15). The energy requirements and associated GHG emissions for AI model development vary depending on the complexity and size of the database; type of AI model; algorithm run time; number, type, and process time of computing cores; amount of memory mobilized; and efficiency of the data center (16). The training phase, which refers to the process of using data to optimize the parameters of an AI model, tends to be very energy-intensive. One AI model's training was estimated to emit more than 626 000 kg of carbon dioxide equivalents, which is nearly five times the lifetime emissions of an average passenger car—including the manufacture of the car itself (17). Conversely, the energy required in the inference phase, where AI models are used to make predictions, scales with use and can occur millions of times and therefore can result in higher overall GHG emissions (18).

Several methods have been suggested for monitoring and estimating GHG emissions resulting from AI activities, among them is a Machine Learning Emissions Calculator *(https://mlco2.github.io/impact/)*. This calculator considers various factors like the type of hardware used, the duration of training, and the geographic region (19). For instance, when applying this approach to a single training run of the large language model Generative Pretrained Transformer 3 (GPT-3), the estimated emissions vary drastically depending on the cloud provider location, ranging from 223 920 to 858 360 kg of carbon dioxide equivalents. To put this in perspective, these emission estimates from a single training run are equivalent to annual emissions from driving 50–191 passenger vehicles (20).

Radiology departments can optimize energy use for AI models by adopting energy-efficient configurations, such as low-power central processing units (CPUs) or graphics processing units (GPUs), to minimize energy use while maintaining optimal performance. It is essential to avoid using architecture that consumes excessive energy, and reducing the number of CPU and/or GPU cores can decrease emissions even though longer execution times might be the trade-off. For example, halving the number of CPU cores from 60 to 30 in an AI simulation reduced GHG emissions by 33%, from approximately 450 g to 300 g of carbon dioxide equivalents, while only minimally increasing the execution time (16). An open-source optimization framework can help identify the best trade-off between energy consumption and training speed, potentially leading to energy savings of 15%–76% for deep learning models (21). Moreover, further strategies to reduce AI energy consumption include tiny machine learning (tinyML), which runs AI models on small, low-powered edge devices, reusing open-source models rather than training new ones, and the evaluation of alternative energy sources (22).

Another challenge in the field is the proliferation of numerous AI models developed independently by different groups to address similar questions. For example, many similar but independent models are designed to identify pulmonary emboli and coronary artery calcium on CT scans (7). Redundant AI models with limited external generalizability generate unnecessary GHG emissions and can waste valuable time and resources. Adding to the complexity, despite the multitude of radiology AI models developed, only a tiny fraction have been integrated into clinical practice to date (23).

Efforts targeted at fostering collaboration and resource sharing would decrease overall GHG emissions associated with AI development while also enhancing the external validity of the resulting models. Encouraging multi-institution collaboration can be achieved through strategies such as centralized data sharing and federated learning models, despite potential challenges related to logistics and regulations (24). The sharing of code and availability of publicly available data sets remain limited, but journals should encourage them as a requirement for the publication of radiology AI-related research. In a study that evaluated code-sharing practices for AI-related articles in RSNA suite journals between 2017 and 2021 (25), only 11% shared reproducible code and only 2% shared both code and complete experimental data. However, rates were higher in 2020 and 2021 than earlier years.

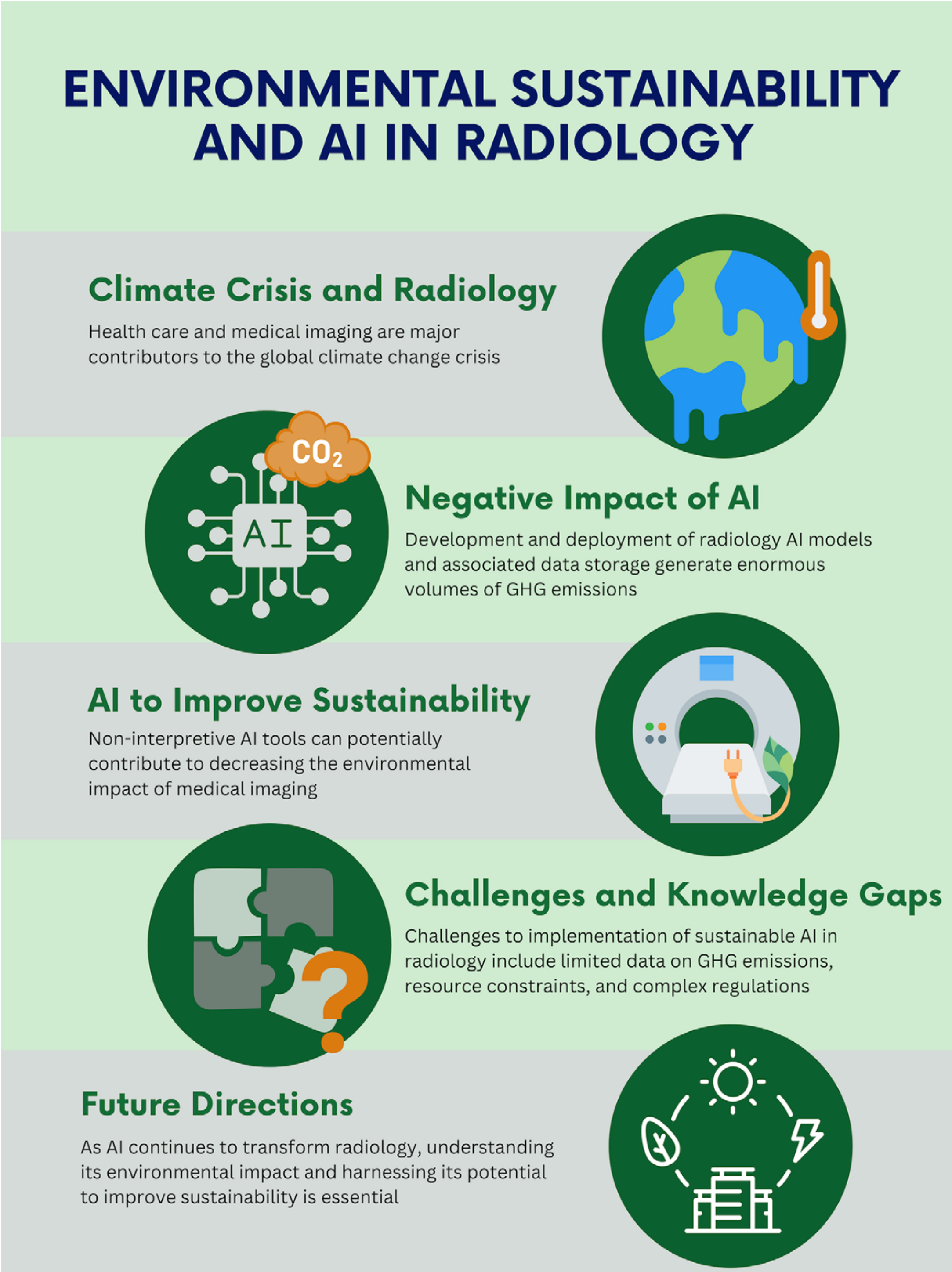

Figure 1: Summary of the intersection of environmental sustainability and artificial intelligence (AI) in radiology. GHG = greenhouse gas.

Data Storage

Exponential growth in medical imaging data and high demand for accessible labeled data for AI model training have created substantial challenges for data storage infrastructure. Traditionally, radiology departments have relied on local on-premise storage solutions, which often require constant upgrades and maintenance, resulting in waste. In recent years, cloud-based and hybrid storage solutions have gained popularity due to their scalability and flexibility. While cloud-based data centers provide the necessary computational power to store and process large volumes of medical imaging data, they consume large amounts of energy to power their operations (26,27). The total global emissions from cloud-based storage are now larger than that for the entire airline industry (17).

Cloud-based data storage involves storing data in large-scale data centers, which are massive buildings filled with hard drives.

Table 1: Negative Impact of AI on Environmental Sustainability: Challenges, Actions, and Outcomes

Challenge	Action	Outcome
AI Model Development and Deployment		
Development and deployment of AI models consumes large amounts of energy	Select energy-efficient configurations, such as low-power CPU, to minimize energy use while maintaining optimal performance	Halving the number of CPU cores from 60 to 30 for an AI model reduced GHG emissions by 33% (16)
There are no radiology-specific tools available to estimate AI-related GHG emissions	Modify online general AI GHG calculators for radiology AI applications, considering type of hardware, training hours, and geographic region (19)	Using accurate estimates of GHG emissions related to radiology AI models can inform strategies on lower energy techniques
There are no current guidelines for selecting sustainable radiology AI software	Develop transparent efficiency metrics and reporting standards for radiology AI models, like an Energy Star rating	Estimated GHG emission metrics related to radiology AI tools can guide purchasing decisions (14,15)
Redundant AI models waste resources and generate unnecessary GHG emissions	Strategies to foster multi-institution collaboration include centralized data sharing and federated learning models and requirements by journals for code and data sharing (24)	Targeted efforts to foster collaboration and share resources could decrease overall GHG emissions, improving the external validity of resulting AI models
Data Storage		
Massive data storage needs per exponential growth in medical imaging and AI data	Minimize storage requirements by optimizing data compression	Deduplicating and compressing data reduces storage needs and associated energy consumption
Data centers and data transmission networks use a lot of energy	Evaluate energy-efficient data storage alternatives; implement tiered storage systems based on frequency of access	More energy-efficient data storage can decrease cost and GHG emissions
Current calculators available to estimate data storage are not specific to radiology	Further study is needed to evaluate the impact of data storage options related to AI applications in radiology	Accurate estimates of GHG emissions related to data storage in radiology can inform purchasing decisions
Multiple data storage options exist with limited transparency on total GHG emissions	Explore partnerships with cloud service providers committed to renewable energy sources and energy-conscious service scheduling	GHG emissions related to data storage vary depending on the data center provider and location
Energy Source Choices		
Underlying AI energy sources determine the environmental impact	Train AI models in locations with renewable energy choices and low-carbon intensity grids (22)	Renewable energy sources can substantially decrease overall GHG emissions from AI models
Cooling and ventilation systems are 40% of a data center's energy consumption (30,31)	Select data centers in cooler climates to minimize the energy needed for cooling systems to efficiently dissipate heat (32)	Reduced energy and GHG emissions related to data center cooling translate to overall lower energy and more sustainability

Note.—AI = artificial intelligence, CO_2e = carbon dioxide equivalent, CPU = central processing unit, GHG = greenhouse gas.

There are millions of these data centers around the world, and they require substantial amounts of energy to maintain continuous server operations. In 2012, the energy cost of data transfer and cloud-based storage was estimated at approximately 3–7 kWh/GB compared with 0.000005 kWh/GB to save data to a personal hard drive (28). Currently, the energy associated with cloud storage varies depending on the infrastructure and vendor.

Health care networks must carefully evaluate their data storage choices to enhance environmental sustainability. Considering energy-efficient alternatives and optimizing data compression techniques can reduce storage requirements and energy consumption. Implementing deduplication to remove duplicate or redundant data and compressing the remaining data can be effective. In addition, adoption of a tiered storage system can help allocate data based on its frequency of access. To accomplish this, health care networks can store frequently accessed data on faster, energy-efficient storage devices and archive less frequently accessed data on slower storage media that require less power. Radiology practices can further contribute to sustainability by partnering with cloud service providers committed to renewable energy sources and energy-conscious service scheduling. By taking these measures, health care networks can potentially improve data storage efficiency while minimizing their environmental impact. This is summarized in Figure 3.

Energy Source Choices

The environmental impact of AI and informatics infrastructure greatly depends on the energy sources that power them (2). Energy is estimated to account for more than 75% of total GHG emissions globally, with fossil fuels representing 80% of

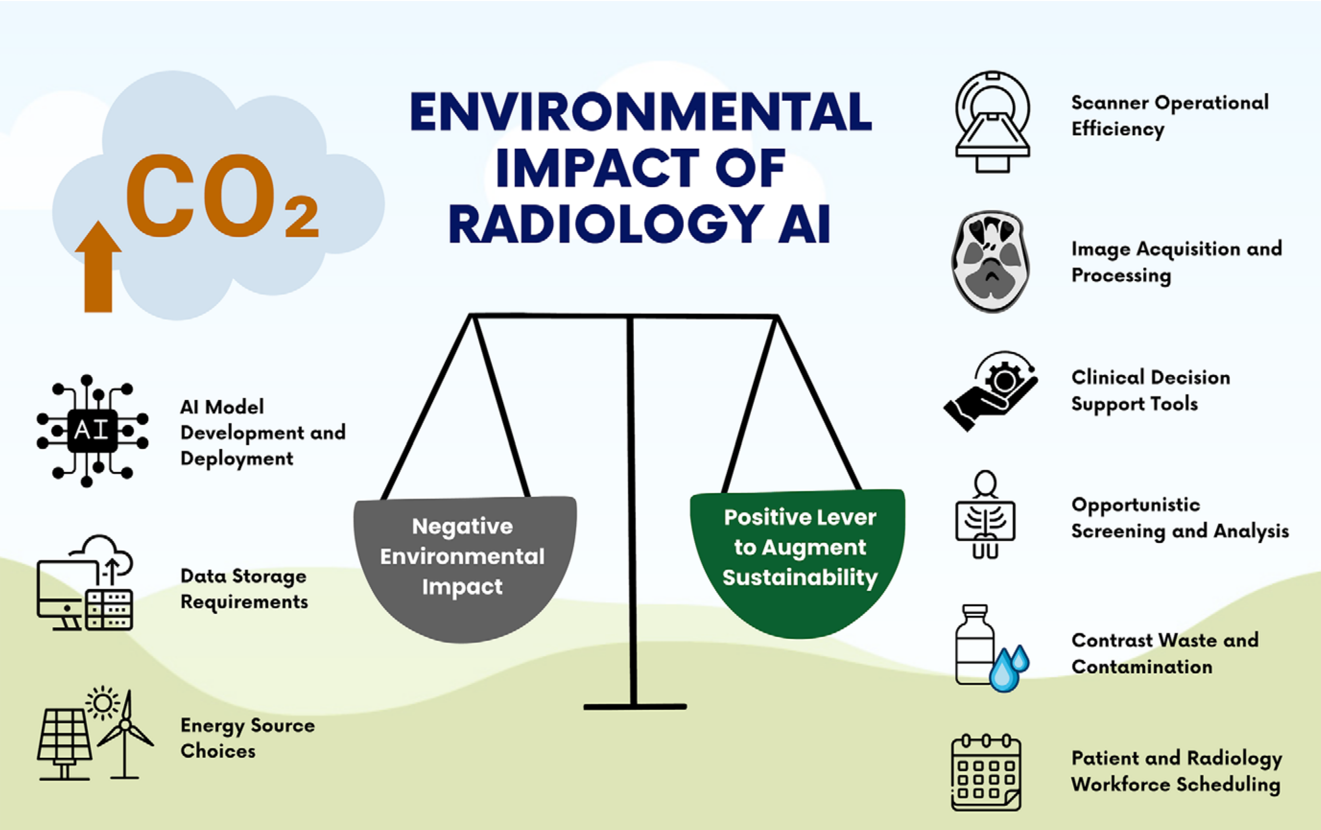

Figure 2: Summary of how artificial intelligence (AI) in radiology has a negative impact on the environment, with key opportunities and actions to improve sustainability using AI in radiology.

the total global energy supply (29). Renewable energy sources, including solar, wind, hydropower, biofuels, and others, are replenished by nature and emit little to no GHGs or pollutants into the air.

The noncarbon energy intensity of the grid varies widely depending on location and time. For example, AI models trained in the United States may rely heavily on energy from fossil fuels, leading to the generation of large volumes of GHG emissions. However, training the same model in other places like Quebec, Canada, where the primary energy source is hydroelectric power, would result in a much lower carbon footprint (22).

The physical location of information technology infrastructure is another important consideration, not only related to the local carbon intensity of the grid but also with respect to the need for cooling. Approximately 40% of a data center's energy consumption goes into powering its cooling and ventilation systems (30,31). Therefore, locating a data center in a cooler climate can reduce the energy needed for the cooling system to efficiently dissipate heat (32).

AI as a Positive Lever to Augment Sustainability in Radiology

The use of AI also has the potential to contribute to sustainability efforts in radiology, particularly through non–pixel-based use cases, including noninterpretive applications such as study protocolling or worklist prioritization (33). Noninterpretive AI tools provide radiologists with several potential opportunities to reduce GHG emissions and to decrease the environmental impact of imaging along the continuum of care. This is summarized in Table 2.

Operational Efficiency

CT and MRI scanners consume substantial amounts of energy even when they are not actively acquiring imaging data. Approximately two-thirds of energy use in CT occurs in a nonproductive idle state, and one-third of energy use for MRI occurs during the system-off state (34). Because the metadata of radiology examinations are standardized within scanner log files and Digital Imaging and Communications in Medicine, or DICOM, headers, AI models can potentially decrease idle time, improving the operational efficiency of scanners while reducing GHG emissions and cost (35). In theory, system use states and nonproductive idle mode time intervals could be monitored and predicted by using recognizing patterns of examination time stamps, either at a single scanner level or at a larger institutional scale (36). As a result, AI tools could switch between system states, with automatic system shutdowns during pre-expected periods of idle time, as well as automatic scanner start-up and quality checks at the most energy-efficient time points. Similarly, it could be possible to use AI tools to monitor other energy-consuming devices in radiology departments, such as picture archiving and communication system workstations, with automated shutdown when not in use to minimize nonproductive energy consumption (37).

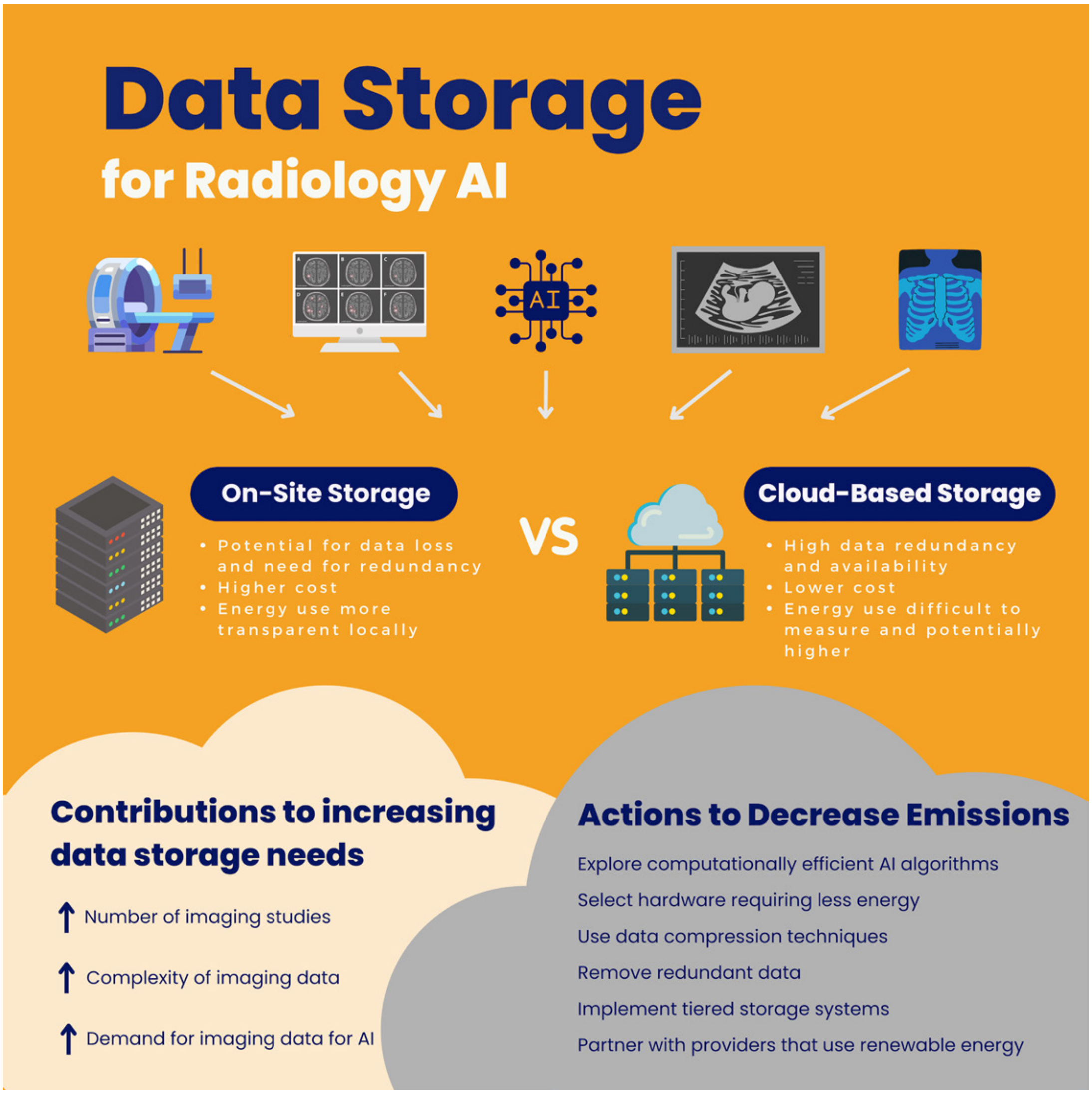

Figure 3: Summary of on-site and cloud-based data storage options for artificial intelligence (AI) in radiology, why data storage needs are increasing, and recommended actions to decrease the resulting greenhouse gas emissions.

Optimized Image Acquisition and Processing

The use of AI tools can also optimize image acquisition and processing. Given that active scan duration is typically proportional to energy consumption, image acquisition time savings also result in lower GHG emissions and cost, with the additional benefit of improved patient comfort. For MRI, AI-based applications have the potential to reduce scanning times without sacrificing diagnostic quality, therefore decreasing use-phase emissions (5). Examples include AI-guided de-noising of accelerated acquisitions and AI-guided rapid or fully automated planning of imaging planes such as anatomic landmark identification in cardiac MRI (38,39). These AI techniques are also applicable to low-field-strength MRI units, which have lower GHG emissions in production and use phases (5). They offer the potential to increase global access to MRI due to their lower costs (5,40). AI tools also have the ability to transform images across modalities, potentially reducing the need for additional imaging and thereby reducing GHG emissions. For example, creation of synthetic CT images from an existing MRI study performed for cancer staging could eliminate the need for an additional CT study for radiation treatment planning (41).

In theory, AI tools could also be used to analyze patterns between image acquisition and energy consumption to improve our understanding of how changes in imaging parameters (eg, tube voltage for CT or number of signals acquired for MRI) affect energy consumption during image acquisition. By combining these insights with existing knowledge on how scanner parameter manipulations affect image quality or radiation dose, one could predict new parameters such as estimated energy consumption and estimated carbon dioxide equivalents for each sequence to optimize overall energy profiles.

Radiology Clinical Decision Support Tools

AI-powered clinical decision support tools can help minimize low-value imaging, thereby decreasing GHG emissions and lowering health care costs. Approximately 20% of medical imaging tests are considered low value, that is, they provide little to no benefit to patients, have the potential to result in harm, and

Table 2: Summary of Key Opportunities and Actions to Improve Sustainability Using AI in Radiology

Opportunity	Action	Impact
Operational Efficiency		
CT and MRI scanners consume a substantial amount of energy even when idle	AI tools could switch between system states with automatic system shutdowns during pre-expected periods of idle time	Reduced idle time will reduce GHG emissions, lower costs, and improve practice efficiency
Image Acquisition and Processing		
Scan duration is typically proportional to energy consumption	AI-based applications can reduce MRI scan times (eg, de-noising of accelerated acquisitions, automated planning of imaging planes (38,39)	Reduced scan time results in lower energy use and GHG emissions, lower cost, and improved patient comfort
Image acquisition parameters impact energy consumption	AI tools could be used to analyze patterns between image acquisition and energy consumption to improve our understanding of how changes in imaging parameters affect energy consumption	These insights could be used to predict carbon dioxide equivalents for each sequence to optimize energy profiles
Radiology Clinical Decision Support Tools		
Low-value imaging does not improve patient outcomes but contributes to unnecessary GHG emissions	AI-powered clinical decision support tools can personalize recommendation guidelines to avoid imaging that may not add value (44)	Avoiding low-value imaging reduces waste and GHG emissions while lowering health care costs
Opportunistic Screening and Image Analysis		
Large amounts of pixel-based data are not used in routine clinical evaluation	AI tools can facilitate opportunistic screening to extract useful data incidental to the indication for the imaging study (47)	This information can potentially be leveraged to improve patient outcomes, lower GHG emissions and costs, and increase patient satisfaction (52)
Contrast Agent Waste and Contamination		
Contrast agents have important environmental impacts including water body contamination	AI tools could optimize image contrast, determine when a contrast agent is not needed, or generate deep learning–based virtually enhanced images (60)	Reduction of contrast agent usage mitigates their environmental impact and lowers costs
Patient and Radiology Workforce Scheduling		
Transportation is associated with substantial GHG emissions	AI can help reduce travel-related GHG emissions with optimized scheduling and no-show prediction modeling (63)	Decreased travel-related GHG emissions and less radiologist burnout (65)

Note.—AI = artificial intelligence, GHG = greenhouse gas.

generate unnecessary GHG emissions (42,43). Once AI models become more personalized by combining individual risk factors, laboratory test results, genetics, and appropriate use criteria, they could provide personalized recommendation guidelines to avoid imaging that may not add value (44). Moving beyond typical dichotomous decision processes in appropriate use criteria, AI can improve risk stratification using prior information to guide the choice of imaging tests (45). However, multicomponent interventions are likely needed to reduce low-value imaging (46).

Opportunistic Screening and Image Analysis

The use of AI tools can also facilitate opportunistic screening to extract useful data incidental to the indication for the imaging study (47). For example, AI tools can quantify coronary artery calcium at nongated chest CT (48) and bone mineral density for osteoporosis screening at abdominal CT (49). Similarly, AI has also enabled automated image analysis for previously time-consuming tasks and extraction of otherwise unobtainable pixel-based data. For example, AI tools have been used to improve the estimation of indeterminate pulmonary nodule malignancy risk at chest CT and predict prostate cancer aggressiveness using MRI (50,51). This information can potentially inform diagnosis, guide treatment decisions, and improve patient outcomes, theoretically resulting in lower GHG emissions and costs along with increased patient satisfaction (52). However, the downstream impact of AI deployment on subsequent investigation requires careful evaluation to ensure that these tools do not inadvertently result in over-investigation of incidental findings.

Contrast Agent Waste and Contamination

Contrast agents have important environmental impacts that AI tools can potentially mitigate. For example, gadolinium-based contrast agents used in MRI and iodinated contrast agents used in CT can contaminate water bodies, as traditional water treatment methods do not adequately remove them (5,53). Furthermore, iodine is a nonrenewable resource that is in high demand for imaging and interventional applications, although there are currently limited programs for recovery and reuse (54). Contrast agents used in US pose a distinct environmental challenge, as some are GHGs and therefore

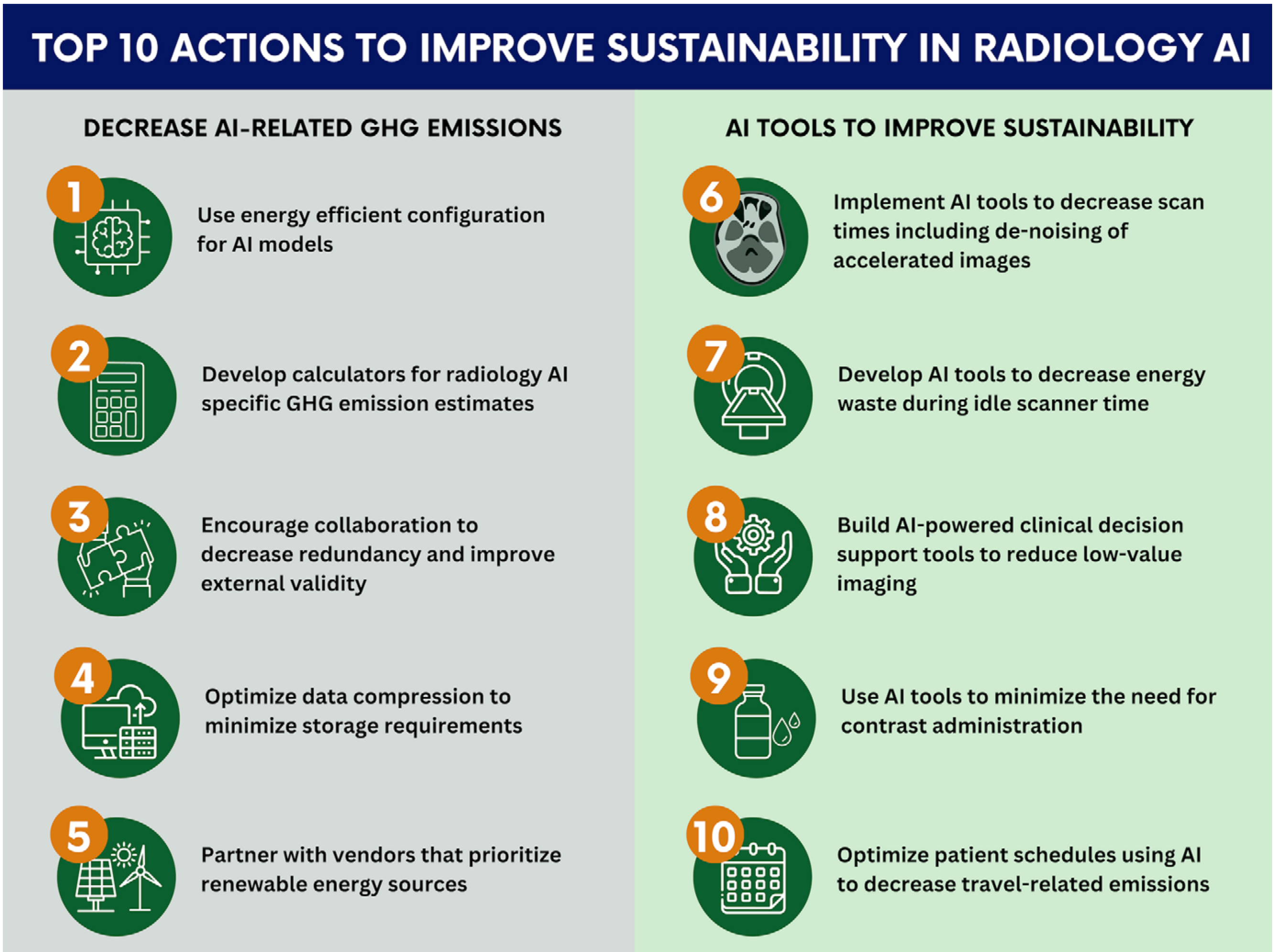

Figure 4: Diagram shows top 10 actions to improve the sustainability of artificial intelligence (AI) in radiology, with a focus on decreasing greenhouse gas (GHG) emissions and using AI tools to optimize image acquisition and processing.

contribute directly to emissions. For example, sulfur hexafluoride is a commercially available US contrast agent and is itself a GHG with very high global warming potential (more than 22 000 times higher than carbon dioxide) and a very long lifetime (55,56). Therefore, even small amounts can have large negative effects on the environment.

The use of AI tools could optimize image contrast, similar to the administration of exogenous contrast agents, or determine which imaging studies can be performed without contrast agents without sacrificing diagnostic performance (33). For example, using AI-generated virtual contrast-enhanced images can reduce the amount of iodinated contrast agents for CT by 50% while maintaining image quality (57). Similarly, using AI can restore the signal-to-noise ratio for MRI scans acquired with lower doses of gadolinium-based contrast agents (58,59). Also, it may be possible to eliminate the need for contrast agent administration altogether with deep learning–based virtually enhanced MRI (60). Reducing contrast agent use mitigates their direct environmental impact along with the co-benefits of lower cost and reduced GHG emissions related to avoided production, packaging, and distribution.

Patient and Radiology Workforce Scheduling

The use of AI tools can help reduce travel-related GHG emissions by maximizing resource utilization for both patients and radiologists through smart scheduling. For example, AI models can analyze patient characteristics, clinical urgency, available resources, and environmental factors and suggest optimal patient schedules (61,62). Improved coordination of imaging tests with other outpatient appointments could reduce GHG emissions from transport if the number of required visits is reduced (63). These AI tools also have the potential to reduce patient no-shows for imaging appointments (62). No-show prediction modeling could identify patients for targeted interventions, such as additional personalized phone reminders, to decrease wasted energy and lower costs while improving patient access to medical resources. In the United States, AI-guided preauthorization of imaging tests could optimize patient scheduling and minimize scanner idle time as well as unnecessary travel (64). Finally, AI-based workforce scheduling could also decrease GHG emissions related to radiologist travel, with the potential to boost engagement and reduce burnout (65).

Figure 4 outlines the top 10 actions to improve sustainability in radiology AI.

Knowledge Gaps and Next Steps Toward a Sustainable Future for AI and Radiology

Several gaps remain to be addressed before AI in radiology is optimized for a sustainable future. Educational initiatives are essential to increase awareness in the radiology AI community regarding the relationship between technology infrastructure choices and GHG emissions. Further research is also needed on the optimal measurement of AI-related GHG emissions and the downstream impact of AI deployment in clinical practice.

Resource constraints pose challenges to the adoption of sustainable practices in radiology AI, as upgrading hardware often requires up-front financial investment. By leveraging shared computational resources or collaborating on sustainability initiatives, radiology practices can overcome resource limitations. Importantly, many strategies to decrease GHG emissions in radiology have an associated benefit of lower cost once implemented due to lower electricity use and decreased waste.

Last, complex regulations and policies can impede progress in implementing sustainable AI practices. Radiology AI leaders must navigate the evolving landscape of ethical and legal concerns as well as environmental regulations, which can be daunting. Radiologists should work collectively to engage with stakeholders to advocate for policy decisions and a regulatory framework that fosters and promotes sustainable AI practices and environmental sustainability as key strategic priorities.

Conclusion

Artificial intelligence (AI) is an increasingly large contributor to the environmental footprint of medical imaging. As AI continues to transform radiology, it is essential that we continue to address its environmental impact and harness its potential to improve sustainability.

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