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# Revolutionizing Radiation Oncology Through Artificial Intelligence

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ABSTRACT

Artificial Intelligence (AI) is making headlines across the world today. It is helping drive up the stock prices of many companies, inspiring startups, and creating excitement about how it will improve lives. In this article, we review how AI can be used to revolutionize radiation oncology, which relies heavily on computer software and digital data to treat cancer patients using radiation therapy (RT). First, we describe AI and how it functions. Second, we reviewed how AI can have transformative applications in radiation oncology to improve accuracy, efficiency, and precision across (1) treatment planning, (2) segmentation, (3) motion management, (4) quality assurance, (5) personalized treatment, (6) treatment response, and (7) tumor position. Finally, we conclude by describing potential solutions for challenges around data, education, regulation, and security across the rapidly advancing landscape of AI in radiation oncology.

## Introduction

### Cancer

Cancer is a complex disease in which some of the body's normal cells transform by growing and dividing uncontrollably into tumor cells (Ahmedin et al. 2024). The process consists of multiple stages, from cancerous lesions to malignancy. There are various mechanisms that cause cancer, and the prognostic information varies in each patient because of unique molecular signatures in individuals. Furthermore, genetic heterogeneity occurs due to different cancer types, complicating diagnosis and treatment. These reasons provide insight as to why cancer is the second leading cause of deaths in the world, despite the best efforts of thousands of organizations.

There were nearly 20 million new cases of cancer in 2022, and close to 10 million deaths from cancer (National Cancer Institute, 2024). Predictions by the National Cancer Institute (2024) indicate that the annual number of new cancer cases will reach 35 million by 2050, a 77% increase from the 2022 level. In addition to being an important barrier to increasing life expectancy, cancer is associated with substantial societal and economic costs that vary in degree across cancer types and geography.

### Radiation Oncology

Radiation oncology is a branch of medicine that uses ionizing radiation to kill cancer cells or shrink tumors by destroying their genetic material, a process called radiation therapy. It can be used to treat more than 50% of cancer patients, either as a single modality or in combination with other treatments, such as chemotherapy or surgery (Fiagbedzi et al. 2023). Radiation oncologists are doctors who oversee the care of cancer patients undergoing radiation therapy. They use images to determine if RT will benefit a cancer patient, identify the best type of RT for the cancer, create a treatment plan, administer the RT, and follow up with the patient during and after the RT.

RT can be administered inside or outside of a patient's body. The most common type is external beam radiation therapy, which uses high energy beams aimed from a machine, called a linear accelerator, to a precise location on the patient's body. RT that goes inside the body is called brachytherapy, during which a small, solid implant is placed in or near the cancer cells. RT can be used at different times or for different reasons during cancer treatment. For example, when it is used before surgery to shrink a cancer this is called neoadjuvant therapy, when it is used after surgery to stop the growth of any remaining cancer cells this is called adjuvant therapy and when it is used as the only treatment for cancer this is called primary treatment (Mayoclinic, 2024).

## Artificial Intelligence

AI is used every day in a variety of ways. Some of these common AI examples include autonomous driving, phones that recognize our faces, and navigation systems. At a high-level, AI encompasses computer systems capable of performing functions that are typically thought of as intelligent human behaviors, such as learning, reasoning and solving problems. There are four key reasons behind the recent explosion of AI-related activities. (1) Improved algorithms that are more flexible, robust, and capable of solving different types of problems. (2) Increase in quantities of training and test data across industries to create and teach AI models. (3) More powerful technologies, such as Graphics Processing Units (GPUs), cloud computing, and increased computing power to process, store, and manage data. (4) Availability of open-source code libraries which facilitate collaboration as the AI's components are made available for others to use and modify per their own specifications.

The types of AI models used in radiation oncology serve very different needs than those used in people's everyday lives. While it helps AI to be creative, it's most critical function here is to be accurate.

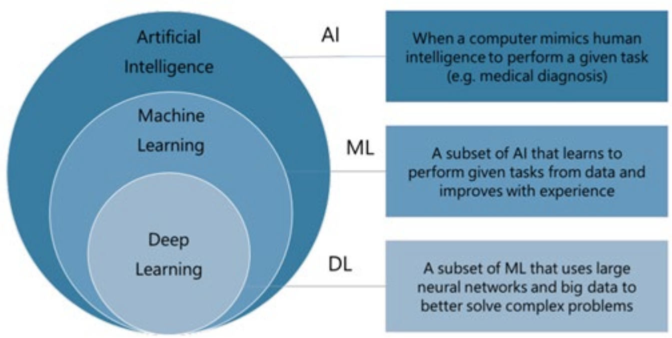


**Figure 1.** Illustrates the hierarchy of AI fields and the relationships between artificial intelligence, machine learning, and deep learning (Gallin et al. 2022).

## Machine Learning

One of the most important technologies in the AI space is machine learning (ML). ML uses mathematical algorithms and data to automatically imitate how humans learn, allowing the system to perform complex tasks without explicit programming (Gallin et al. 2022). As more inputs are given to the system, it gradually becomes more intelligent and accurate through its ability to recognize patterns and relationships between the data.

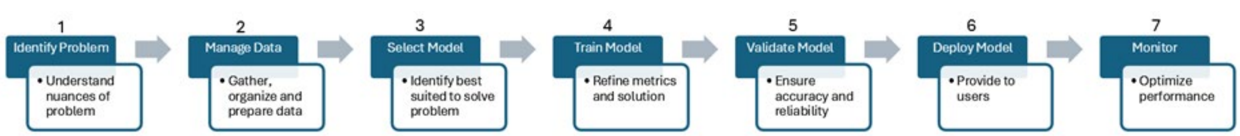


**Figure 2.** Machine Learning Model Process Flowchart.

There are three categories of ML that will help us understand its application in radiation oncology. The primary distinctions between them are in how they are trained and utilized.

Supervised learning creates a model to make predictions based on labeled data, which means that the data is tagged with a collection of variables (features) and specific answers the algorithm should identify on its own. As its name suggests, it has a supervisor or teacher, typically a human, overseeing it. To predict the prices of houses, the values of the labels could include the year built, square footage, number of bedrooms, nearby school ratings, price of the home, and other characteristics. When shown an image of a new house, the model learns, through trial and error, by comparing it to the training examples to predict price. Supervised learning is the most common ML model in radiological sciences, with applications ranging from detection to diagnosis, to therapeutic interventions (Giger et al. 2020).

Sometimes the labeled data may not be easily accessible, too costly, or the algorithm is asked questions where humans are unsure of what they are looking for in the data. This is where unsupervised learning is particularly valuable. Here, a learning model is given only data in which it looks for unknown similarities and differences. The model will attempt to automatically perform data analysis by analyzing useful features to find previously unknown or unseen correlations and patterns to create corresponding groupings. Consider the home price example used in supervised learning. Suppose it included everything except the price of the house; An unsupervised model would be used to cl uster houses into similar groups by year built, number of bedrooms, or location. This would give customers appropriate suggestions for buying when they ask for a "three-bedroom house, built after 2000, in Atlanta."

In reinforcement learning, autonomous AI models attempt to find the optimal way to accomplish a goal or improve their performance on a task based on trial-and-error interactions. It is designed to accomplish a specific goal by optimizing a reward function. The model is not told which actions to take, but rather must discover which actions yield the best reward, by using learnings from past feedback and exploration of new tactics. Using the real estate example established above, suppose an AI model controls a small drone to take pictures and videos of a home for sale. Every time the drone does what it is told, a reward is given for that action. Conversely, every time it bumps into a wall or doesn't take the correct picture, points are deducted. In this manner, the algorithm learns the optimal actions it needs to perform to maximize its reward.

**Table 2.** Machine Learning's three main learning models and their common applications in radiation oncology.

| Learning Model | Overview | Examples |
|---|---|---|
| Supervised | Most basic and widely used. Predicts outcomes via training on specific input and expected outputs. | Cancer Diagnosis, pathological analysis, and treatment response prediction. |
| Unsupervised | Often used for exploratory analysis. Groups data by identifying patterns. | Clustering for tumor segmentation, error detection, and radiomics feature extraction. |
| Reinforcement | Accomplishes specific tasks by learning from the consequences of its actions through a feedback and reward system. | Adaptive radiotherapy and treatment planning. |

## Deep Learning

Deep learning (DL) is a specialized branch of ML that is at the core of how many AI models function today. It has propelled breakthroughs across various technologies such as image creation, natural language processing, predictive models, self-driving vehicles, and voice assistants. DL is inspired by the intricate neural networks of the human brain and can be employed for supervised, unsupervised, or reinforcement learning without explicitly being programmed. Human brain cells, called neurons, are a complex and highly interconnected network that send electrical signals to each other to help humans process information ("Aws Amazon," n.d.). DL attempts to mimic this through an Artificial Neural Network (ANN) which uses layers of algorithms and interconnected nodes, called neurons, which work together to process and learn from the input data. Note that this process is analogous to the ANN functioning as a software program containing software modules, called nodes, which solve mathematical calculations. Every ANN has nodes that are spread across at least three layers: (1) an input layer which takes data from external sources that is entered into the ANN to analyze, categorize and process and pass it on to the next layer. (2) a hidden layer that takes data from either an input or hidden layer to process it further and pass it on to the next layer. (3) an output layer that gives the final result in the form of an ANN's response to the data that was entered via the input layer.

As seen in Figure 3, each neuron is connected to other neurons of the following layer, which means that the output of one neuron becomes the input for the next neuron. Each neuron has its own associated weight and threshold. If the output of any individual neuron is above the specified threshold value, that neuron is activated, sending data to the next layer of the network. Otherwise, no data is passed along to the next layer of the ANN ("IBM," n.d.). Each of these connections between neurons has weights which control how much one neuron influences another. These weights are the ANN's way of learning from the input data. As the ANN learns from the data, it adjusts these weights based on how accurate it is relative to the task being performed. These adjustments of weights are done in the hidden layers. Adding additional hidden layers allows the ANN to make more complex computations and decisions. The ANN learns increasingly more about the data as it moves from neuron to another. Using the real estate example discussed earlier, attributes of a house – age, size, location, and other features - are broken down and analyzed by the neurons. The ANN's task is to identify whether the price prediction is correct. It uses the weighting to produce a highly educated guess. The system might be 70% confident the price is between $300-350k, 10% confident it's between $350-400k, and so on. The network architecture then tells the ANN whether it is correct. The system will continue to cycle through this process until it achieves the correct result or is stopped by human intervention.

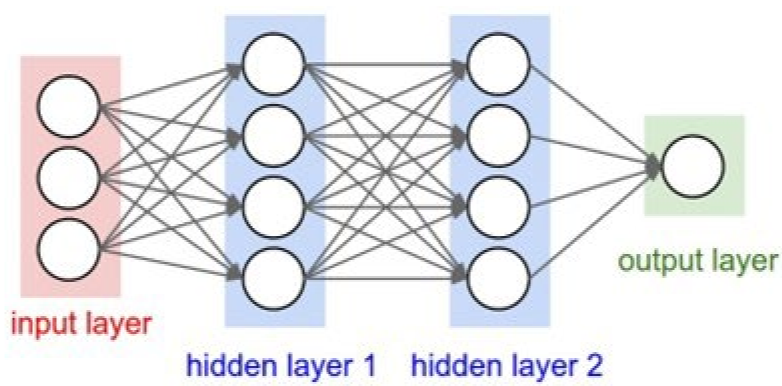


**Figure 3.** Typical 3-layer Neural Network, with three inputs, two hidden layers, and one output layer. The complexity of the Neural Network will depend on the complexities of the underlying patterns in the dataset (Chaudhary. 2024)

## Automation Applications of AI in Radiation Oncology

AI can improve the accuracy, robustness, and speed of the radiation oncology process by aiding in decision making, and efficiently executing lengthy, repetitive tasks (Chopra et al. 2022). Examples of this include making highly subjective work, such as image interpretation more straightforward and reliable, tracking tumor evolution to manage RT, and aggregating narrative text to allow for search and analysis. These AI-enabled technological advancements can improve the patient experience, leading to improved outcomes by reducing the number of treatments or the time per treatment. In addition, it has the potential to free up time for clinicians to take on other tasks, such as education, research, patient counseling, and quality checks. This section focuses on the potential for AI models to transform the radiation oncology workflow by automating certain aspects of treatment planning, segmentation, motion management, and quality assurance.

## Treatment Planning

Radiation oncology is a multi-step, sequential process that begins with a patient assessment. The radiation oncologist performs a physical examination and reviews the patient's medical record, with a particular focus on any pertinent imaging, laboratory or pathology findings (Chen et al. 2023). If it is determined that RT is a treatment option, the patient will undergo simulation and treatment planning. Simulation involves medical physicists (MP), radiation therapists and radiation oncologists working together, using various tools and techniques, to simulate the different phases of RT. The goal is to place patients in a reproducible treatment position and obtain imaging to create a treatment plan. A computerized tomography (CT) scan is typically used along with an isocenter, which is a three-dimensional space around which the radiation source will rotate. Once the isocenter is selected, skin marks are placed, with either temporary ink and stickers or permanent tattoos to assist with alignment during RT (Chen et al. 2023). Radiation planning is a complex process that attempts to deliver the highest radiation to the target while delivering the least radiation to noncancerous areas. This process is iterative, as it involves many rounds of trial and error. For example, the initial set of radiation dose distribution usually needs to be modified multiple times until it satisfies the clinical goals before RT can be administered. The skills to create high-quality treatment plans take years of training and practical experience to develop (Giger et al. 2020). AI holds great promise to improve operational efficiency by automatically creating treatment plans of higher consistent quality and standardization.

The amount of information available to clinicians is significantly increasing, often beyond what can be realistically analyzed during a clinical consultation. AI models can review electronic medical records (EMR), analyze historical treatment recommendations based on the patient's health factors, and review other relevant clinical information to help develop treatment options (Dudley et al. 2019). This can assist scheduling radiation therapy sooner than is done today. An AI model created at UT Southwestern recently helped 70 prostate cancer patients start their RT sooner – decreasing the odds of the cancer spreading – by instantly translating complex clinical data into an optimal treatment plan (UT Southwestern, 2020). AI can also extend this scheduling to reshape resource utilization and staffing levels. Treatment in radiation oncology can span several weeks, so it is an area ripe for applying automated scheduling algorithms based on treatment duration, patient preferences, timing of similar procedures for other patients, insurance processes, resource availability, and coordination with other departments.

Part of the simulation steps discussed above entail finding and recording the patient's treatment position. This can create challenges for treatment planning as the patient's previous diagnostic images may have been acquired in a different position. AI models can improve image acquisition, accelerate the image registration process, reduce image registration errors, and decrease imaging time. Barquero et al. (2013) used an AI model to register 4D CT images of the lungs in different phases of inspiration and expiration. This model by Barquero et al. showed registration errors of less than 1mm over 10 validation sets from the same institution, and registration errors of less than 1.6mm over 10 validation sets from other institutions. AI can also help optimize the dose efficiency by predicting the radiation sensitivity of a tumor, thereby optimizing radiation on the target while sparing the noncancerous areas.

## Segmentation

When RT is prescribed, clinicians trace along the border of the areas of the body to be treated and avoided within a treatment software application. This process, known as segmentation, involves the accurate delineation of tumors, target volumes, and organs at risk (OAR) for effective treatment planning and reducing the risk of radiation-induced toxicity. However, manual segmentation of these structures, which is the current standard of care, is repetitive, tedious, time-consuming, and prone to inter- and intra-observer variability depending on the skill of the clinician, which can contribute to suboptimal treatment outcomes (Ceci et al. 2023). An AI model used by Cheng et al. (2021) achieved automatic delineation of nasopharyngeal carcinoma with an accuracy of 79%, which is comparable to that of radiotherapy specialists. AI models can assist in the faster adoption of segmentation best practices and recommendations by integrating them into future application releases, helping to socialize these standards across the industry. Auto-segmentation can also be used as a training tool to coach residents and clinicians with less experience.

## Motion Management

During RT treatment delivery, clinicians need to ensure that the treatment plan is being properly executed so that the radiation dose delivered matches what and where it was planned. One of the most significant factors that can trigger adjustment includes the patient's inaccurate positioning and anatomical changes. People move. Children often cannot hold still. Motion management during RT is intended to improve accurate dose delivery to moving tumor targets while limiting radiation exposure to unintended tissue. In the past, clinicians used to take motion into account by covering the target with large margins, despite the risk of high-dose delivery to OARs. AI can leverage the clinical history of the patient being treated and data from treatments of similar cancer types to develop robust models to help with motion management and image-guided RT.

Real time tumor tracking can be enhanced with AI to model breathing patterns and to predict tumor motion. This is important for lung cancer, the leading cause of cancer-related deaths in the United States (National Cancer Institute, 2024). Cone beam computed tomography (CBCT) is widely used to visualize the position target in the patient receiving RT. However, it produces low quality images that are not as accurate as those from the planning scans. An AI-based model is being used by clinicians to enhance the resolution of CBCT images and provide a more accurate depiction of the target area (Choi et al. 2023).

Another key area of radiation therapy that can be transformed by AI is called adaptive radiation therapy. This is where the patient's images are taken upon arrival and their radiation plan may change to accommodate the natural, everyday changes that occur in their anatomy. Human anatomy changes quickly through normal bodily processes based on what patients eat or drink. Slight changes in the body during treatment can significantly impact RT effectiveness by the cancer getting less radiation than planned or OAR getting unnecessary radiation. One such AI model, Ethos, has helped address this issue by fine-tuning the program's RT process. Ethos creates images of the patient's anatomy that day, segmenting the cancerous organs and tissue (Mirel, 2024). It then computes a new dose plan calculation that is tailored to each patient. This can also reduce the amount of radiation treatments and treatment time for patients so that they are treated less frequently and more efficiently each time.

## Quality Assurance

Quality assurance (QA) is integrated into the RT workflow to prevent errors, while ensuring the accurate and safe delivery of radiation as prescribed (Fiagbedzi et al. 2023). As modern RT has become increasingly sophisticated, the number of QA tasks have also increased. MPs perform most of these tasks, which include the evaluation of the treatment plan, quality assurance of equipment, and ensuring radiation protection of patients and staff by accounting for and analyzing potential risks during the planning and delivery of RT. These responsibilities typically follow the guidelines of national and international bodies, such as the American College of Radiology (ACR) and International Atomic Energy Agency (IAEA). AI models have the potential to automate and improve the workflow for many of these time consuming, repetitive QA processes.

One of the most important steps in QA involves a chart review process of the RT plans, which occurs prior to and during treatment. It has been suggested that over half of incident reports and 33% of near-mis incidents originate in the treatment preparation process (Conroy et al. 2020). This is often attributed to the large amount of information that requires attention for each chart, the repetitive nature of the work, and the short amount of time that it must be done in. It has also been reported that only 25-38% of detectable errors were identified at this stage (Conroy et al. 2020). AI models can help improve the chart review process by (1) using unsupervised and reinforcement learning to identify outliers by comparing similar RT plans and (2) identifying steps in the workflow that are prone to introduce errors by analyzing the large amounts of data available today. AI can also help with the quality assurance of RT delivery systems. One recent AI model successfully predicted errors in an image guidance system (Chuang et al. 2015), while another predicted errors for external beam radiation treatments (Chan et al. 2017). As future applications of AI models improve the automated quality assurance of these delivery systems, the role of the MP is likely to evolve to include less of these tasks and more around the overall treatment process.

## Predictive Applications of AI in Radiation Oncology

AI's ability to accurately and efficiently analyze large amounts of medical images and patient data has the potential to guide treatment decisions and improve patient outcomes. In this section, we will review how this data can be used to predict various clinical phenomena in radiation oncology that enables the creation of personalized treatment plans specific to each patient's profile, predict patient outcomes, and track tumors to make timely RT adjustments.

### Personalized Treatment

Personalized medicine in radiation oncology involves tailoring RT to individual patients based on their unique clinical, genetic, and molecular characteristics. This approach improves quality of life, increases survival rates, and spares healthy surrounding tissue and organs compared to generic, one-size-fits all methods. One of the important aspects of personalized RT plans is radiation dose optimization. The integration of AI models with imaging technologies has allowed for improving imagine quality, thereby enabling clinicians to administer the appropriate amount of dosage. A recent AI solution used three-dimensional dose distributions based on mapped organs and target areas to predict and automate more personalized treatments (Mirel, 2024). This improved efficiency and patient satisfaction, lowered treatment time for patients, and allowed clinical teams to have more patient-facing time and focus on treatment quality.

### Treatment Response

Predicting treatment responses for RT are mainly characterized as tumor control probability (TCP) and normal tissues complication probability (NTCP), which should be maximized/minimized, respectively, to achieve desired outcomes (Nuraini et al. 2019). Leveraging a patient's EMR and existing data sources for genomics, imaging, patient outcomes, and treatment plans. AI models can be used to improve the efficiency of RT and mitigate scheduling delays. Fan et al. (2020) recently combined an AI model with radiomics to build a predictive model that can evaluate the response to treatment of bladder cancer. Another AI model successfully predicted clinical outcomes for patients with rectal cancer undergoing upfront chemoradiation (Elahinia et al. 2018).

### Tumor Position

One of the biggest challenges in radiation oncology is how to adjust the radiation treatment plan during treatment in response to changes in anatomy. Kill the cancerous tissue with RT and leave the healthy tissue untouched (Mirel, 2024). These are simple RT goals but executing them can be made difficult because the patient's picture - the literal position of their anatomy - can change daily, says Mirel. Further, there is often a time lag of a few microseconds between accessing the tumor movement to finally correcting for it. AI models can assist in solving these problems by analyzing different aspects of target motion to predict future positions and optimize treatment delivery. Recently, ML approaches that integrate radiomics have been developed to analyze medical images. Radiomics is an emerging field that extracts quantitative features, such as shape, size, and texture, from medical images that can be used for diagnostic and prognostic purposes. AI can analyze this information to predict tumor tracking based on factors such as tumor position and patient anatomy. Chang et al. (2024) created an AI model, equipped with data of breathing patterns, that predicts the movements more accurately and decreases the computation time for tracking to be more accurate.

## Current Limitations and Potential Solutions

AI holds great promise in advancing the field of radiation oncology, potentially leading to more effective treatments and improved patient outcomes. While the number of AI applications in this field continues to increase, their clinical use remains low. Many of these solutions are still in the technological incubation state and require much more clinical validation. In this section, we will review key constraints, gaps, and risks that need to be addressed for AI models to deliver in clinical settings at scale and with consistency.

### Cost

The investment for turning a promising AI model into a certified solution for radiation oncology is an arduous, expensive process. This includes the cost of the data required to train computer algorithms, the technologies to refine and deploy the AI model, tools to protect the data and intellectual property, staff training, and workflow adoption. Teams should identify ways to reduce the cost and time of AI implementation by leveraging industry best practices and exploiting synergies with relevant organizations.

### Data Bias

We need to ensure that AI models account for diverse clinical populations to reduce implicit biases, disparities, and inequities that are already baked into our societies. Existing datasets used to train AI are often biased towards certain races and ethnicities (Trafton, 2024). This can have severe consequences, as was recently shown for an AI system that diagnosed people with darker skin with lower accuracy because there was less data on people with diverse skin colors (Trafton, 2024). We also know that gender, geographic location, and socioeconomic conditions impact cancer risk and treatment. Moving forward, there is a need for broadly accepted and adopted standards for the development of AI models to mitigate bias and ensure reproducibility across the population, in which they could ultimately be implemented.

### Data Quality and Quantity

The accuracy of AI models depends on the quality, quantity, and diversity of the training data (Gallin et al. 2022). Medical data, such as imaging, genomics, and RT treatment plans, in radiation oncology can be rich with information. For example, the adoption of EMRs has generated a rich source of data that can be used to train AI models. However, it can be challenging to obtain this data as they often contain sensitive patient information and require rigorous ethical and privacy considerations. In addition, radiation oncology datasets have generally been smaller and more limited than the datasets other professions may use to fine-tune their AI algorithms (Chen et al. 2023). Therefore, it is important to identify governance that takes a risk-managed approach to collect, identify, and store data so that it can be appropriately used to train the AI and facilitate dissemination of information. Efforts such as The Cancer Imaging Archive (TCIA) have enabled oncology-specific data to be shared across different organizations, but the potential has yet to be recognized due to interoperability issues and the lack of widely- accepted common data models (Clark et al. 2014). Methods of addressing these issues of incomplete, missing or sparse data could include supporting open access codebases, creating standardized datasets, promoting data sharing across institutional and international borders, and incentivizing release of datasets for academic and scientific activity.

## Data Privacy

Data gathering and accessibility are some of the first steps in developing an AI model. Due to the highly sensitive personal health information (PHI) in medical records, the issue of patient privacy often restricts the availability of data, which in turn limits training the AI model, ultimately hindering the full potential of AI. There are also significant privacy implications of unintended third-party data use that will become more common with AI adoption (Murdoch, 2021). Solutions to these issues can include anonymizing the data and introducing global standards to address geographic-specific regulatory requirements.

## Data Security

Given PHI is among the most private and legally protected forms of data, there are significant concerns about the vulnerability of these AI models that can lead to incorrect medical advice, privacy breaches, and even endanger patients' lives ("Exabeam," n.d.). This requires the need to create specific guidelines that clearly answer questions such as: who has access to which data, what can they do with that data, where is the data stored, and how long is the data available. To protect confidentiality and intellectual property from hacker or misuse, it is vital to comply with healthcare regulatory regulations and standards for data protection, such as HIPPA in the United States, encryption, secure authentication, regular security assessments, and training for staff to recognize and prevent cyber threats ("Exabeam," n.d.).

## Education

As AI models are expected to transform radiation oncology, there will be an increase in the demand for education to stay current with these advancements. Radiation oncology practitioners and future graduates will need to possess the necessary knowledge and skills to understand the changes taking place in technology and its impact to their clinical roles and workflows in order to successfully partner with these AI models. Accordingly, curricula will need to be updated to teach ML techniques, tools, and oversight, just as programs have previously included specialized instruction in radiobiology and physics (Bridge et al. 2019). The need for an increase in emotional intelligence and soft skills will also be important as clinical staff devote more time to patient interactions.

## Explainable and Interpretable Models

Clinical teams don't always know how an AI model reached its solution, or programmers have difficulty understanding why an AI algorithm produced incorrect results. The "black box problem" is a term used to describe these situations where an AI model's internal workings and decision-making processes are not transparent to humans (Glover, 2024). It will be imperative for project teams - from the technologists creating and managing the algorithms, to the medical professionals - to understand the reasoning behind the AI's conclusions in a transparent manner. Understanding the AI model's decision-making process is crucial as it will build confidence and trust in the model, allowing doctors to optimize patient treatment.

## Regulation

As AI becomes more prevalent for radiation oncology, regulators must establish and harmonize policies that accommodate the benefits, constraints, and risks of AI technology without slowing down innovation that ensures patient safety. While certain countries and regions have established their own frameworks, discrepancies in regulations internationally must be addressed for AI to truly deliver on its potential. We need to establish universally standardized regulation that alleviates issues around data (accessibility, anonymity, management, ownership, privacy, quality, and security), intellectual property management of the AI models, transition from testing to approvals, and manufacturing. A successful example of this coordination was when the American College of Radiology (ACR) launched the Data Science Institute (DSI) to collaborate with global partners to define clinically meaningful AI use cases, set standards for medical imaging AI interoperability, certify algorithms, and address regulatory, legal, and ethical issues that accompany medical imaging AI (American College of Radiology, 2019).

## Conclusion

Although we understand more about cancer today than at other points in history, it continues to be a leading cause of death around the world (National Cancer Institute, 2024). This ongoing demand for cancer treatment options, pressure to reduce the cost of healthcare, and the significant image-based and data-intensive nature of radiation oncology are some of the major drivers for its adoption of AI.

Recent advancements in computing power, robust algorithms, and data aggregation and analysis are empowering AI to revolutionize the world through innovative solutions and products. Under the umbrella of AI, ML and ML are transforming radiation oncology to help alleviate suffering, save lives, and decrease economic and societal burdens. AI models can accurately and efficiently process vast amounts of patient data and medical images. These two areas are crucial for a field, like radiation oncology, that relies on nuanced clinical decision making and is characterized by subjectivity through its many time-consuming and manual steps. Methods to improve image acquisition, image registration, and image quality through AI-powered models have the potential to improve RT accuracy and patient outcomes, while reducing imaging time (Islam et al. 2021). Radiomics, an emerging field used for quantitative analysis of imaging data, is heavily dependent on machine learning. This integration of radiomics and AI can be used for automated image analysis and predicting RT outcomes. Radiation delivery is using AI to forge novel techniques in guiding patient setup and monitoring target position through motion management and image guidance methods to ensure effective, safe dosage (Mirel, 2024). One of the most difficult areas of radiation oncology, treatment planning, has shown promise in delivering improved quality, increased efficiency, and reduced variability through automated-treatment plan creation (UT Southwestern, 2020). This has the potential to allow for faster, more precise planning, thereby administering treatment sooner to patients or reducing the number of treatments needed. Recent advancements in natural language processing (NLP) can assist with treatment optimization by analyzing the data in a patient's electronic medical record and historical information on other patients to enhance the precision and effectiveness of RT. This integration of AI in radiation oncology also holds great promise for enhanced patient care and clinical efficiency by delivering greater personalization of treatments and providing prediction outcomes.

As the AI landscape grows, we must continue to be alert in resolving issues such as data biases, quality, privacy, and security. Radiation oncology generally has less datasets than other professions to train their AI algorithms (Giger et al. 2020). Additionally, the completeness and quality of this data can cause issues around accuracy and biases. To address these challenges, a few government and public agencies have taken steps to promote policies that enable data sharing and standardization across institutional and organizational borders. Understanding how an AI model reaches its conclusions is important to ensure clinician acceptance and patient safety. This issue is exacerbated for deep neural networks, given the complicated multi-layer structures and numerous, numerical operations performed by each layer (Chaudhary, 2024). Teams building and maintaining the AI models should construct them such that the code and formulas are available and comprehensible so that teams can understand how the algorithm arrives at its conclusion. Before implementing AI systems in clinical settings, it is essential to ensure that they are safe, secure, and not prone to errors that could put patients' health at risk (Gallin et al. 2022). Education and training of staff will be necessary for them to integrate AI-powered tools into their clinical practices. The potential impacts of AI on job security are important considerations. It is imperative to understand that AI complements, rather than replaces, human expertise in radiation oncology. Clinicians' experience, judgment, and knowledge should continue to be emphasized. Ultimately, AI is another tool in the radiation oncology toolkit, enhancing and supporting the capabilities of these healthcare providers. For example, less time may be spent on quality assurance or treatment planning, while more time may be spent on patient consultation, teaching, and research. The constraints, gaps, and risks discussed in this article are some of the reasons that require the need for an evolving regulatory domain which ensures increased collaboration between experts in government, medicine, and technology. We need to balance the difference in pace between creating and implementing new regulations compared to the time it takes to build or update AI models. The future is bright for radiation oncology as it moves towards increased usage of AI-powered technology to decrease inefficiencies, empower clinicians with better tools, improve patient outcomes, and reduce healthcare costs across the cancer continuum.

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