WHITE PAPER

The Artificial Intelligence Era: The Role of Radiologic Technologists and Radiation Therapists

By the HCIAC Corporate Roundtable Subcommittee on Artificial Intelligence

Published by ASRT Foundation, 15000 Central Ave. SE, Albuquerque, NM 87123-3909.

The Artificial Intelligence Era: The Role of Radiologic Technologists and Radiation Therapists

By the HCIAC Corporate Roundtable Subcommittee on Artificial Intelligence

When some people hear of artificial intelligence (AI), their minds jump to sophisticated, overbearing robots that take the place of humans. Although elements of AI and machine learning factor into robotics, the truth is more complex.

The AI depicted in popular books and movies is super-intelligent or advanced. However, for the foreseeable future, AI will be less like a Cylon or Terminator and more like general intelligence in which AI-enabled machines perform cognitive tasks that humans also perform. Most AI applications involve narrow AI, which targets specific problems or tasks. For example, AI methods have contributed to smarter airplane piloting programs that can control repetitive functions such as landing and takeoff. But when a mechanical failure occurs, only a trained human pilot can make a safe and heroic landing on the Hudson river.

The role of AI—and the humans who teach and oversee AI-based medical devices—is similar in health care and medical imaging and radiation therapy. AI in medicine is defined broadly as developing intelligent machines that use computer programs with algorithms that teach the machines using robust data.

This white paper, created by a HCIAC Corporate Roundtable and American Society of Radiologic Technologists (ASRT) task force, aims to inform medical imaging and radiation therapy professionals about AI, with guidance from knowledgeable professionals representing the medical equipment manufacturing industry, ASRT, and the American Registry of Radiologic Technologists (ARRT). For the purposes of this white paper, people who are involved in direct patient care are considered; medical dosimetrists are considered under the auspices of similar reports. Please refer to the glossary for the working definitions the task force used in designing this white paper.

What is AI?

The concept of AI has been around for decades. British mathematician Alan Turing proposed in 1950 that it might be possible for machines to use information to reason, solve problems, and make decisions. His framework is the basis of the Turing Test, which says an AI system learns until indistinguishable from a human being in its ability to hold a conversation. In 1956, a team presented proof of concept on AI at the Dartmouth Summer Research Project on Artificial Intelligence. Also in the 1950s, a team of researchers at Massachusetts Institute of Technology (MIT) began work that would become the MIT Computer Science and Artificial Intelligence Laboratory. These pioneers developed some of the first neural networks and other advances and AI concepts, and research flourished from 1957 until about 1974. Still, advancements were restrained by the limitations of computing power and data available at the time (Cagle, 2019).

Computing power has improved markedly since the past century, and today data runs or factors into nearly every facet of society, to the tune of at least 2.5 quintillion bytes per day and rising (Marr, 2018). The ability to compute has evolved from simple addition to complex

Glossary

Artificial Intelligence Terms and Concepts

Algorithm: A set of instructions designed to perform a specific task. AI relies on algorithms, but a single algorithm does not necessarily constitute AI and machine learning.

Artificial intelligence: Broadly defined as the science and engineering of making intelligent machines. AI uses computer programs and models based on networks of databases in a process that teaches computers. Using data and high-level mathematical functions, the computers incorporate statistical data analysis, labels, and machine learning to enable machines to learn, adapt, and perform tasks previously thought to require human cognitive functions.

AI-enabled: A machine that was designed and developed using AI but that does not continue learning (machine learning) once operational. The FDA calls this type of AI software ***locked***.

Bias: A systematic deviation from the truth (vs variance, which is random deviation). Bias in the data training set will affect the results of algorithms that are run for machine learning, regardless of the algorithms' accuracy. Some bias is inherent in most training data sets, although rare as result. Although bias occurs, it most often occurs unintentionally. In algorithmic bias, a software system reflects the implicit values of the humans creating it or the data sets training it. Once a machine starts learning, its calculations become more complex. The machine might make automatic modifications that lead to bias or variances. A concern about bias is not the end of the software but an opportunity for people to investigate and intervene using a structured approach to correct machine learning. Automation bias also can occur; this bias is the tendency for people to favor decisions generated by machines at the expense of ignoring conflicting data or human decisions.

Labels: Labels add context, information, and value to image data. The labeled data represents ground truth, or prior knowledge, on which to base machine learning. In medical imaging and radiation therapy, labels are study-level descriptors (eg, head CT or abdominal MR) or image-level descriptors (eg, pixels on image 25 represent the kidney). Label sources include image annotations, such as measurements, radiology report findings, electronic health record clinical data, and other data generated by professionals for use in AI.

Machine learning: Use of algorithms that are designed and trained to change their performance (adapt) as it focuses on specific tasks, and ideally improve with exposure to data to achieve AI. The machines are programmed to review large data sets, look for patterns, make predictions, and act on the data. This ability makes the software running them adaptive in behavior (according to the FDA) because the machines learn and change based on new data.

> **Supervised learning:** Labeled training data are input into the machine to facilitate machine learning that can be generalized based on the training data. A teacher or "critic" also can provide feedback and correction as the machine learns.
>
> **Unsupervised learning:** The machine learns based on programmed patterns with no explicit labeling or feedback from a teacher. This type of learning looks for density or clustering of data but learns only the inherent structure of that data.
>
> **Deep learning:** The basis for most image interpretation machine learning that most closely resembles learning by the human brain. The computer learns based on multiple layers of interconnected algorithms categorized into a hierarchy of importance. Deep learning can be supervised, unsupervised, or partially supervised. It is responsible for providing practical applications of machine learning.

Neural network: A neural network is a layered set of algorithms that is modeled to resemble the human brain. The neural network looks for patterns through labeling or clustering of raw data.

Recursion: One of 2 common ways of solving complex problems. In iteration, a problem is converted into a series of steps that occurs in a set order. In recursion, the steps are piled on one another and replicate themselves at smaller scales until they combine to solve the problem.

algorithmic methodologies. These complex computing programs apply multiple abstract levels to metadata and recursion (nonlinear processing) to self-modify, adding context to information (Cagle, 2019).

AI devices run these complex programs that are developed to continuously learn and modify (and ideally improve) based on available data, much like certain aspects of how humans learn. Humans learn experientially from situations and AI learns experientially from data. The performance of AI-based machines improves as they receive more data training, much like a person learns through education and experience. Consider typical radiologic science education, for example. Students receive classroom, or didactic, education that serves as the foundation of their future profession. But their education is incomplete without clinical (practical) experience. It is here that students learn by doing; these cognitive functions are not memorized but involve complex analyses of *cause and effect*, or *if this, then that*.

The key component of AI is machine learning that resembles these cognitive functions, in that a computer or machine continuously can learn from patterns and relationships of data to improve specific tasks. Less certain is whether AI programs can detect anomalies in data and protect data fidelity in learning to perform these tasks as well as, or better than, people. Measures such as the Turing Test might be used for advanced AI, but in medicine, the goal is not to reach this advanced level but to incorporate machine learning into software that can improve effectiveness of patient care.

Examples of AI

Society regularly uses and relies on automated and AI-based devices at home, work, or on the way to work but typically is unaware of the underlying AI technology involved. Many products broadly considered examples of AI actually are AI enabled (programmed with AI but unable to continue learning) but offer a clue to consumer acceptance of AI concepts. For example, some autonomous (self-driving) vehicles use lidar (light detection and ranging), and others use visual recognition and real-time modeling to anticipate obstacles. Yet, these have not fully incorporated machine learning and adapting. Likewise, drones are autonomous but behave based on preprogrammed instructions. Even robotics involves using AI for autonomous movement and management of the robot's state, but most are not learning continuously. Consider these examples of AI-based consumer products:

- Robotic vacuums. The latest Roomba (980 model) uses AI to scan a room's size, spot obstacles, and memorize the most efficient route for cleaning the room's floor (Daley, 2019).
- Banking. Banks use AI to enrich customer experiences with identification and authentication, chatbots or voice assistants, and personalized recommendations. AI also plays a role in detecting fraud (Digalaki, 2019).
- Navigation and maps. A vehicle or smartphone navigation system consists of more than street names and addresses frontloaded into the computer. When drivers take a wrong turn, the app redirects them. Google is using AI to refine directions with global localization and machine learning that will improve accuracy of a vehicle's position and orientation (Reinhardt, 2019).
- Image and facial recognition. Some facial recognition programs based on AI deep learning (based on multiple layers of interconnected algorithms categorized into a hierarchy of importance; most closely resembles human learning) now perform better than humans (Brooke, 2019).
- Trading and investing. Machine learning has evolved at a rapid pace; millions of data points are available historically and in real time on which to base forecasting and other trading decisions. Rather than simply recommending to trade when stocks reach a predetermined level, the AI software initiates the trading action. Nearly 45% of revenues in cash equity trading are electronic (Thomas, 2019).

Why Address AI Now?

Since 2015, wider availability and improved computing of graphic processing units as well as speedier parallel processing have enabled an AI explosion. In addition, a nearly infinite repository of data and continuous growth of data collection have facilitated deep learning (Brooke, 2019). Access to greater computing power and increasingly robust data have led to advancements in use of AI for medical imaging and radiation therapy. For the fourth year in a row, Aunt Minnie has voted AI the most significant news event in radiology, saying, "Artificial intelligence is a logical next step in the continued improvement of medical devices that medical imaging and radiation therapy professionals use daily" (Casey, 2019).

AI medical equipment is most effective at replicating or automating specific tasks humans perform. This is a primary advantage of AI—the ability to shorten the time it takes to perform manual, repetitive tasks. Some functions, such as radiation treatment planning, are based on optimization, often requiring subjective analysis of the balance of target coverage and organ sparing, for example (Jarrett, 2019).

Technological advancements and automation form the foundation of the medical imaging and radiation oncology industries. Radiologists and radiation oncologists are experts at analyzing information in medical images to interpret findings or imaging data and arrive at diagnoses or radiation therapy plans. Radiologic technologists and radiation therapists, the professionals who use and monitor operation of the equipment that acquires the images or delivers the radiation treatments, are accustomed to nearly continuous changes in the software and hardware driving medical imaging and radiation therapy systems.

Effectively incorporating AI advancements will not be easy, but AI is perceived to be a necessary advancement for improving patient care. Still, some myths, fears, and perceptions surround consumer and health applications of AI capabilities. Some of these concerns are well founded and require advanced planning for practical and ethical approaches to AI implementation. For example, data privacy and security of consumer and clinical data must become more than a recommendation; concrete steps to ensure data protection must be taken. AI can affect work forces but not necessarily in the way some people fear.

The HCIAC Corporate Roundtable and the ASRT—the 156,000+-member organization for medical imaging and radiation therapy professionals—came together to gather input from the profession, original equipment manufacturers (OEMs), and literature to address concerns and issues related to implementing AI in medical imaging and radiation therapy. The charge of the group was to offer a background document for future challenges and recommendations for technologists and therapists related to implementing AI in the workplace.

About the HCIAC Corporate Roundtable

The HCIAC Corporate Roundtable is an ASRT Foundation program that brings together leading industry manufacturers and other related professionals to address issues facing medical imaging and radiation therapy. For more than 20 years, HCIAC members have come together to develop white papers to effect change that improves the field for all concerned.

In May 2019, HCIAC representatives discussed the future of AI and its potential effects on image quality, patient care, and the role of medical imaging and radiation therapy. The meeting resulted in developing and implementing a survey of ASRT members and forming a task force of individuals representing the profession and industry (see Appendix A). These representatives met for 2 days to discuss the survey results and current and future AI concerns as they pertain to the radiologic sciences.

About the ASRT Survey

In summer 2019, the ASRT Research Department worked with HCIAC members to develop survey questions to pose to practicing radiologic technologists and radiation therapists about AI and machine learning. The team sent the survey to about 20,000 people identifying as radiologic technologists, radiation therapists, and managers from diverse geographic and age groups. The researchers oversampled professionals in younger age groups (19 to 35 years) to ensure representation from that group.

Visit asrt.org/as.rt?sKYXqx to view the survey.

The ASRT survey reported a response rate of 2.1% (+ 4.8% margin of error). The mean age of respondents was 42.9 years, which is within 1 year of the average age of professionals in the ARRT database. Most respondents (54.7%) work in radiography, and 20.7% work in computed tomography. The next specialties

In which disciplines do you actively work?	N	Percent of Cases
Radiography	227	54.7%
Computed Tomography	86	20.7%
Mammography	55	13.3%
Magnetic Resonance Imaging	52	12.5%
Radiation Therapy	51	12.3%
Bone Densitometry	28	6.7%
Vascular-Interventional Radiography	19	4.6%
Nuclear Medicine Technology	11	2.7%
Imaging Informatics/PACS Administrator	11	2.7%
Breast MRI	9	2.2%
Quality Management	8	1.9%
Sonography	8	1.9%
Medical Dosimetry	8	1.9%
Cardiac-Interventional Radiography	5	1.2%
Fusion (e.g., PET-CT, SPECT-CT)	5	1.2%
Breast Sonography	3	.7%
Radiologist Assistant or Radiology Practitioner Assistant	2	.5%
Vascular Sonography	1	.2%
Other:	20	4.8%

Which of the following best describes your job title?	N	Valid Percent
Staff technologist/therapist	285	69.2%
Chief technologist	40	9.7%
Supervisor/assistant chief technologist	24	5.8%
Administrator/manager	21	5.1%
Education program faculty	11	2.7%
Education program director	5	1.2%
Commercial representative (e.g., sales, applications specialist)	3	.7%
Locum tenens (traveling temporary employee)	1	.2%
Other	22	5.3%
Total	412	100.0%

Age	N	Valid Percent
18 to 24	27	6.6%
25 to 33	81	19.7%
34 to 43	100	24.3%
44 to 53	104	25.3%
54 to 62	83	20.2%
63 or older	16	3.9%
Total	412	100.0%

Mean: 42.9 (SD=12.2)
Percentiles: 5th=24.0, 25th=33.0, 50th=43.0, 75th=53.0, 95th=62.0

represented by the highest number of responses were mammography (13.3%), magnetic resonance imaging (12.5%), and radiation therapy (12.3%). Geographic distribution represented all but 4 states. Most respondents (54.5%) work in hospitals. The survey sample represented staff technologists and therapists (69.2%), chief technologists (9.7%), and others including supervisors, administrators and managers, and education program faculty and directors.

In general, the survey found that:

- Respondents are comfortable with technology and use it frequently.
- Most respondents are familiar with the concepts of AI and machine learning.
- Respondents were mixed in their familiarity with AI features on their equipment. Most are confident that those features function correctly and provide trustworthy results; a vocal minority is more skeptical.
- Respondents indicated a lack of standardized process for resolving discrepancies between machine-recommended procedures and technologist judgment.
- Respondents were inclined to see AI as having a beneficial effect on considerations such as safety and quality but worried about a deleterious effect on the more human aspects of the profession, such as patient interaction and creativity.

- Respondents showed no widespread consensus that AI would adversely affect their professional prospects.

Task force members reviewed and discussed the survey results and requested cross-tabulations of specific data. Additional responses are included throughout this paper where appropriate, especially regarding radiologic technologist and radiation therapist perceptions of the role of AI in their work and in patient care.

The State of AI

Although the computing power now exists to make AI more of a reality than it was in decades past, resolution of the practical, ethical, and legal issues surrounding AI implementation still is in its infancy. AI-based methods offer new opportunities for patient care, but efforts are underway to define the degree and method of experience and validation used for existing technologies and clinical tools. For example, use of AI to inform clinical decision-making (eg, suggesting radiographs to review, or patient risk for disease) does not require the same degree of study and validation as does AI diagnostic or treatment methods that replace established approaches in standards of care (JASON, 2017). The ability of a machine to learn introduces a new way of approaching equipment approval, operation, and maintenance because the product's performance changes as it learns.

Data

All AI-based tools rely on the availability of relevant data on which to base learning and decision-making. Computer-based clinical equipment, electronic health records, image data, and disease-tracking registries are examples of the type of data on which developers can base AI programming for medical imaging and radiation therapy. The advent of electronic health records, PACS, and digital medical imaging and radiation therapy systems led to essential policy decisions such as the HIPAA privacy rule. Although the intent of HIPAA applies to AI data, new issues about data privacy and security demand consideration. For example, machines that learn do not forget.

The European Union's General Data Protection Regulation (effective May 2018) offered more legal protections to consumers than previously granted. Likewise, the California Consumer Privacy Act (effective January 2020) marked the first such legislation in the United States. Ownership and security of data is complex. If consumer data is pooled to teach a machine, for example, do we require the same right to own our individual data as we do when our individual identity is used with that data? Likewise, if health care AI applications use consumer-collected data as well as health care industry data, the data are secured outside traditional clinical settings. It is likely that, eventually, there will be requirements that AI systems ensure transparency, privacy, and security of data use beyond current software acquisition policies. In addition, data use agreements are examples of ways to specify what parties can and cannot do with a data set.

Raw data (image data before postprocessing and compression) is becoming increasingly important in machine learning; the raw data is not downsampled as it is in rendering techniques and therefore contains more information. Other types of data used in machine learning include demographics, laboratory and imaging reports, and notes in the medical record (eg, physical examination findings) (Syeda-Mahmood, 2018; Jiang, 2017). Clinical data, analytic data, quality measures, and information related to workflow or business operations might be used in machine learning. Examples include radiology report turnaround time, relative value units, and utilization data for computed tomography scanners. Public data gathered from mobile devices and apps, especially from mobile health and fitness apps, also exists. However, much public data and some clinical radiology data are not curated. By curating available data, developers of AI systems can ensure that the training data sets adhere to defined quality criteria and limit variance, focusing on specific tasks (Hosny, 2019).

Preventing Bias

Determining and building the training data sets used for AI-enabled designs and incorporated into machine learning require careful analysis and supervision to prevent bias. Bias can occur with any data set but is more likely if data sets do not accurately and adequately train to reflect a population (eg, patient age, ethnicity, or sex), or medical indications, findings, and biology. For example, clinical trials in the past were criticized for basing heart attack symptoms and typical age of onset primarily on men despite women having different clinical presentations. Likewise, pharmacokinetic differences between men and women mean that pharmaceutical action and adverse effects can differ considerably (Yakerson, 2019). This bias in a training data set would lead to algorithmic bias for AI-enabled heart disease screening or prescription decision systems. Slightly more than 41% of ASRT members surveyed believed that algorithmic bias could affect adoption of AI and machine learning a great deal.

Preventing algorithmic bias is a factor inherent in AI development. The algorithms and systems on which manufacturers base their devices' machine learning processes, along with management of training data sets, is a key concern. The most reliable data on which to base machine learning for imaging devices, for example, comes from radiologists and other radiology professionals. AI can extend this expertise by helping to extract more information on which to base new or better predictions about patients. This data includes the expertise of radiologic technologists and radiation therapists, who are the patient care and technical experts on data related to exposure levels and dose optimization, reject rates, examination trends, and other factors related to image quality and patient safety.

Once an AI system learns to reject data because they do not seem to fit, or are anomalies, the machine gains experience to self-modify. But the AI device cannot reach that point unless people acquire the data and teach the machine which data fit or do not fit. For example, rare findings on CT abdominal scans are lacking in data on which to train the system (European Society, 2019). Supervised machine learning helps note variances and systematic bias.

AI in Health Care

A 2017 poll revealed that more than 50% of global health care leaders expected the role of AI to expand in disease diagnosis and monitoring (Siemens, 2019). AI-enabled equipment already is in use in some imaging applications. Medical imaging accounts for about 10% of the total AI market share and likely will double as a portion of the market by 2024 (Cannavo, 2019). By 2026, the medical imaging AI market is expected to increase to more than $264 billion (Waldron, 2019).

AI in Medical Imaging

Medical imaging and radiation therapy are positioned to take advantage of AI capabilities because of the images acquired, interpreted, used for planning, and stored. Today's images are data (digitally) based, making it easier to identify and build data sets because the data already exist. Cardiac disease diagnosis offers an example: In 2017, Slomka et al predicted a medical imaging transformation in cardiac care that involves:

- processing – extracting image parameters automatically
- assessment – fully quantitative diagnostic scores and risk stratification
- scaling up – adding real-time machine learning metrics that incorporate large databases of clinical and imaging variables that are beyond human cognitive ability
- customization – personalized risk assessments and management plans for patients

Several areas of medical imaging and radiation therapy involve AI-enabled equipment or software. Others are in development and likely a part of the profession's near future. The following examples of AI in medical imaging have been approved and implemented, or are in development:

- Computer-aided detection (CADe) and diagnosis (CADx). CAD represents the earliest clinical applications of AI processes in radiology and is an example of the evolution of AI methods in medical imaging and how AI focuses on specific tasks. Systems typically are programmed to detect signs of disease in a specific area of the body, such as cancer in the breasts on mammograms. Typically, CADe systems alert interpreting radiologists to areas of suspicion or abnormality. CADx systems help assess an area or mass to estimate disease severity, stage, or treatment effectiveness (regression or progression) (Wagner, 2019). Much progress has been made in benign and malignant brain tumor classification. CAD becomes true AI when the program on which it is based begins to learn autonomously, as humans do (European Society, 2019).

- Emergency prescreening. Implementing AI to prescreen patients for pneumothorax involves training programs to rapidly test for and diagnose collapsed lung using data from radiology and pathology images (Daley, 2018; Lovelace, 2019). Up to 62% of requests for portable chest radiographs are marked *stat*, or critical, when they are not. In October 2019, the U.S. Food and Drug Administration (FDA) approved GE's Critical Care Suite, which uses AI to scan chest radiographs and detect pneumothorax and sends the image directly to a radiologist. This process can reduce diagnostic time and lessen the need to mark as many potentially negative images as urgent (Lovelace, 2019).
- Auto positioning. AI technology has automated some tasks associated with positioning, saving time on repetitive, physical tasks. Instead of the technologist positioning a patient's anatomy within crosshairs for CT scanning, automated positioning recognizes, for example, a patient's head. This automation saves time on patient positioning and can aid in dose optimization. The CT table can move automatically to position the patient's body according to the specific protocol. Radiologic technologists must verify and adjust the auto position as needed, particularly in unusual or trauma situations or when imaging pediatric patients (Medgadget, 2018).
- Automatic image slicing for MR. This automation selects slices and reduces the redundant manual steps the MR technologist typically takes. AI-based technology programs slice angles and locations after identifying anatomical structures. The precision of automated positioning can streamline imaging of challenging anatomy such as the optic nerve. A neural network requires tens of thousands of MR images to build the database (GE Healthcare, 2019).
- Automatic detection of anatomical structures. This process can precisely overlay images from different dates or modalities for better comparison and simplified workflows (Siemens, 2019).
- Automating equipment maintenance. Auto reporting of equipment problems or the need for maintenance includes automation of specific tasks such as AI-based monitoring of CT scanners for potential x-ray tube failure. This remote predictive maintenance allows technologists and department administrators time to prepare for maintenance issues such as tube replacement, saving money and avoiding last-minute rescheduling of patient examinations that can occur when there is no tube failure warning (Glassbeam, 2019).

Data mining of relevant information such as radiation dose already is a reality, as are time-intensive tasks such as aggregating electronic medical records and automatic recall or patient rescheduling (Pesapane, 2018). At the 2019 RSNA meeting, 123 vendors participated in an AI Showcase, yet fewer than 1 in 4 AI algorithms had FDA 510(k) certification (Cannavo, 2019). Other applications of AI for medical imaging include breast cancer detection in breast MR imaging, chest radiograph interpretation, brain tumor detection, prostate cancer detection, and characterization of liver lesions on ultrasound (European Society, 2019). Facial recognition concepts are being applied to identifying biomarkers for cancer in blood or on MR scans (Brooke, 2019).

In addition, AI could assist radiologic technologists with dose optimization by facilitating the building of a personalized protocol for patients and estimating radiation risks relative to cumulative dose and patient age or other parameters (European Society, 2019). Neural networks could teach AI systems to map ultralow-dose protocols in CT and re-create the images at a higher resolution (Wagner, 2019). Finally, AI could assist in daily workflow optimization by helping to prioritize examinations based on appropriateness criteria and other factors such as emergency level (European Society, 2019). AI also shows promise in preprocessing steps immediately after image acquisition to improve efficiency and workflow (Hosny, 2019).

AI in Radiation Therapy

Radiation therapy is in many ways leading AI advancements in oncology, partly because of the role of imaging modalities in screening and diagnosis, but also because of AI-based methods to facilitate steps such as segmentation and treatment planning and delivery (Rattan, 2019). AI deep-learning methods are poised to support clinical decision support, automated image-guided adaptive therapy, and data mining in real time, as well as (Fornell, 2019):

- Multiscan methods. CT scanning is critical to planning. Using neural networks, AI can enable radiation therapists to acquire multiple cone-beam CT (CBCT) images and merge them for matching (Rattan, 2019). Neural networks can directly map CBCT images to planning CT images (Jarrett, 2019). A voxel-based prediction and dose mimicking method has been studied for head and neck radiation therapy planning. The ability to rapidly merge multiple scans online through deep learning is helpful in adaptive radiation therapy to account for respiratory motion (Rattan, 2019). In addition, online factors such as pretreatment patient positioning, anatomical changes, and treatment response of tumors can help align onboard imaging to the planning CT (Jarrett, 2019).
- Real-time fiducial tracking. Smart biomaterials can improve the next generation of fiducial markers. In short, a smart biomaterial can respond to physiological changes or stimuli. Functionalized nanoparticles can be activated to boost radiation therapy effectiveness. Investigations are underway for coating or loading nanoparticles into fiducial markers. Tracking the fiducial markers in real time for auto beam holds can improve treatment accuracy and minimize damage to nearby tissues or organs (Ng, 2014).
- Autocontouring of structures. Automating this task equates to better treatment plans. Typically, segmenting tumor regions and normal tissue is a manual task. The procedure can be lengthy and subjective, varying by operator, which can lead to uncertainty in treatment plans. Early steps to automate segmentation relied solely on the information contained in each image, but later methods are incorporating prior knowledge, which is machine learning. For example, an AI-based system incorporates information on relative anatomy or expected size variations in organs. The system learns the structure labeling of each image voxel and uses mathematical models to merge the information with prior knowledge (Jarrett, 2019). Autocontouring can replace timely manual work for radiation therapy staff and offer more standardized contouring.

Deep-learning approaches also show promise in image recognition, object classification, and disease detection (GE Healthcare Radiation, 2019). AI likely will improve efficiency of the complex workflow of radiation therapy and improve treatment monitoring, which is critical in evaluating radiation therapy effectiveness (Hosny, 2019).

Improved Patient Care

By using machine learning to automate repetitive tasks, AI can lessen time restraints on medical imaging and radiation therapy staff. This automation can result in more time for patient care and interaction as well as shorter examination times, thus improving patient satisfaction and time to emergency diagnosis.

Benefits

The current and potential effects of AI on patient care are indisputable. AI technologies are proving helpful in patient care by analyzing data that facilitates better public and individual health. Data can support digital health and positive patient experiences, a top priority of 80% of chief information officers surveyed in 2018 (Heath, 2018). This support includes development of patient engagement technology such as wearables and biosensors such as Fitbit, along with similar health tracking apps (Heath, 2018).

One of the strengths of AI in medicine is the ability of AI-based systems to rapidly process thousands more data points than a person ever could. People base these critical decisions partly on learned experience. But a physician might never have encountered a patient who has a precise and rare combination of clinical indicators for a particular disease. Once AI systems can learn, they can store and process much more data than can the brain of a physician who sees on average 30 patients a day.

Internet-based health indicators can use consumer health tracking information for public health research that rises above and beyond traditional data and ability. Social markers can fill gaps remaining in improving health and well-being of patients with data unavailable in health care sources. AI can gather population data to integrate information about communities and populations for improved epidemiology and better prevention and management of chronic diseases (Shaban-Nejad, 2018).

Positive patient experiences from AI also come from provider-facing technologies such as care coordination or clinical decision support (Heath, 2018). For example, AI-based patient navigation can sift through patient reports and medical records, relieving professional patient navigators of time-consuming activities spent reading pathology and radiology reports. These systems can save navigators up to 3 hours a day that used to be spent identifying patients in need of cancer care navigation and queue patients for navigators to begin contacting and assisting. Ultimately, the time saved provides more time for patient interaction (Heath, 2019).

A radiologist evaluates data such as available patient history, previous images, and current images to arrive at a finding. AI can evaluate hundreds or thousands of data points related to a specific patient or imaging signs for unusual pathology. As a result, personalized patient care is an attractive benefit of AI. Rapid decision-making in AI-based software can help provide more personalized clinical care and more personalized radiology and radiation therapy encounters, from positioning to radiation dose and treatment plans.

Machine learning techniques can analyze large quantities of data related to radiation therapy clinical and treatment variables for patients (ASTRO, 2019; Rattan, 2019). Knowledge-based adaptive planning can incorporate imaging data with relevant clinical, dosimetry, and tumor biology data to personalize treatment while minimizing radiation toxicity and improving tumor control (Rattan, 2019). Patients undergoing radiation therapy for head and neck cancers can experience considerable weight loss and require feeding tubes. An AI model enables precision oncology by predicting risk for weight loss, feeding tube placement, and unplanned hospitalizations after radiation therapy before treatment begins (ASTRO, 2019).

Challenges

Plenty of challenges await development and widespread adoption of AI in medicine. No other medical specialty has experience using AI in patient care at the scale at which medical imaging is poised to reach. Radiologic sciences are at the forefront of AI advancements, and professionals working in medical imaging and radiation therapy will serve as pioneers of sorts (Mitchell, 2019).

AI is different from previous advances; despite the technology's capabilities, the information contained in a machine learning system never is complete or totally comprehensive. A machine can make decisions only when the programming reaches a tipping point at which facts confirm or deny the queried information. So, although the AI equipment might be able to analyze more information more rapidly, the machine lacks a person's recognition that "this is all we need to know and we must decide," as well as the ability to make judgment calls.

Additional challenges include:

- Creating ethical guidelines on interaction with equipment, managing and reporting discrepancies, and use of patient data. Initial work has begun, but ethical and liability issues could continue to arise as AI capabilities are more fully realized and implemented.
- Ensuring patient data privacy and security at the institution and industry levels. Data privacy and security concerns involve cybersecurity threats, data ownership and rights (such as opting out or deleting information), and a "for the greater good" philosophy, which means demonstrating that a particular AI system has the right to or a need for the information it collects.
- Developing policies for consistent patient transparency regarding AI tools. This task requires traceable and explainable systems and the ability of professionals to explain the tools. Policies also should maintain a focus on considering patient preferences.

- Paying attention to possible automation or algorithmic bias and how to prevent or monitor for bias.
- Developing a system for integration of AI tools with patient-specific data to encourage personalized care and avoid algorithmic bias.
- Providing methods for integrating medical imaging and radiation therapy professional input in machine learning to maintain a focus on patient safety and to prevent dose creep.
- Informing and addressing health care professionals' concerns about AI and possible reluctance to accept the technology.
- Accepting radiologic science professionals' concerns about workforce disruption and addressing education and evolution of tasks and roles.
- Accepting and preparing for an evolution of health care professional roles and ensuring appropriate education is available to support learning to interact with AI tools.

AI technology must be carefully trained and highly supervised, involving the workforce the equipment supports. This practice emphasizes the need for people and AI devices to work together and for a healthy level of trust and skepticism from medical imaging and radiation therapy professionals. Implementing the AI/human approach poses challenges that OEMs and professionals in medical imaging and radiation therapy must address.

OEM Role

Undergoing traditional clinical trials and regulations for market approval of medical devices are only part of the AI adoption process (JASON, 2017). Manufacturers of medical equipment integrating AI technology must weather a transitional FDA approval process. Traditionally, FDA policies regarding software as a medical device ensures safe and effective technology. In the past, when design changes occurred specific to software that had been cleared under a 510(k) notification, the FDA's Center for Devices and Radiological Health issued guidance on determining whether software modifications pose risks to users and patients (ie, introduces a new risk, increases potential harm from an existing risk, or significantly affects clinical functionality or performance) (FDA, 2019; FDA Framework, 2019).

However, because traditional medical devices are not designed for adaptive intelligence and machine learning, the agency is developing a modified regulatory framework for AI approval. The new process needs to maintain reasonable assurance of safety and performance while allowing the software to learn continuously and evolve to improve patient care (FDA, 2019; FDA Framework, 2019).

The proposed framework (as of fall 2019) begins to define types of modifications (eg, performance inputs and intended use) and emphasizes a total product lifecycle regulatory approach for AI and machine learning-based software. To accommodate the nature of machine learning algorithms to continuously improve performance, the FDA recommends the following principles of a total product lifecycle regulatory approach:

- Clear expectations on quality systems and good machine learning practices established.
- The premarket review for software that requires submission should demonstrate reasonable assurance of safety and effectiveness and include manufacturer expectations for continually managing patient risks throughout the equipment's lifecycle.
- Manufacturers should monitor AI devices and, as part of development, incorporate a risk management approach based on FDA's guidance for deciding when to submit a 510(k) for software changes.
- Enable transparency regarding continued safety and effectiveness to users and the FDA with postmarket real-world performance reporting (FDA Framework, 2019).

All OEMs will complete a new predetermined change plan as part of their premarket submissions. The plan should include anticipated modifications facilitated by the device's AI and the associated methodology for implementing those changes to manage patient risk and device performance. The agency will apply a risk-based strategy to enforcing requirements related to the AI devices, focusing on higher-risk software functions (eg, diagnosis as higher risk than decision-making aids) and those involving logic that might not be fully transparent to the device user (Hale, 2019). The full framework is available at https://www.fda.gov/media/122535/.

The new adaptive nature of machine learning also emphasizes collaboration with customers and the role medical imaging and radiation therapy professionals will have in supervised learning for devices. Developers of AI-based systems must be vigilant about preventing and monitoring potential data set shifts, unintended bias, and the challenges and potential bias involved in generalizing data to new populations (eg, adult data sets applied to children).

Long-term study will be required to evaluate patient outcomes from clinical systems and human-algorithm interactions (Ridley, 2019). This task will require cooperation between OEMs and customers that goes beyond applications training; in essence, the professionals who clinically use the equipment will help teach the systems to perform safely and accurately. OEMs also must build in mechanisms for human intervention, such as overriding a decision made by the AI device and tracking those overrides. These steps ensure that the equipment and the professionals who use it both learn. As a result, OEMs developing AI medical imaging and radiation therapy devices should:

- Assist in guiding equipment operators on AI-enabled device operation and quality assurance.
- Commit to helping educators, education programs, and practicing professionals prepare for AI.
- Attempt to use standard definitions and differentiations of AI-enabled and AI/machine learning devices.
- Foster best practices in AI device design and marketing.

Medical Imaging and Radiation Therapy Professional Roles

Clearly, OEMs will rely heavily on their users in decisions about labeling and gathering data and supervised learning for AI-based devices. Likewise, the users will help monitor adaptability, variances, and long-term outcomes. This need for medical imaging and radiation therapy professionals to help oversee and improve AI devices can complement the role of these professionals.

Overcoming Fears

No consensus from ASRT survey respondents demonstrates widespread concern that AI will adversely affect their professional prospects. Still, an average of 24% of respondents believed AI and machine learning features would reduce their role, and slightly more than 31% believed the technology would reduce the role of the profession in general. Specifically, an average of 30.4% said automation from AI and machine learning would reduce their staffing levels, and 38.3% believed the technology would reduce staffing levels for the profession. A plurality (46.4%) do not expect AI will change staffing levels in the profession.

Verbatim responses explained some staffing fears:

> *People will become obsolete if machines do all the work.*

> *The more the equipment does for you, the less of a tech you become. While tech[nology] can be great, it also reduces the skill set of the technologist.*

> *If this technology can perform our jobs, then the need to have staff will decrease. Employers may have the opportunity to make cutbacks and decrease the number of employees needed.*

ASRT members are not alone; 1 of the greatest fears associated with AI is that people affected will lose their jobs because of the advancements (European North American, 2019). Although this is possible, especially in jobs in which people perform repetitive tasks, it is important to remember that, by definition, AI and machine learning focus on specific tasks. There is no current or foreseen technologist robot with the broad role of replacing trained and registered people to perform patient care, medical imaging examinations, or radiation therapy treatments. In general, industry developers of AI devices foresee changes to the role of radiology and radiation therapy staff, but not a reduction in the need for professionals.

How do you think AI/ML/automated features will affect the scope of your current role?

	My role				The profession, in general			
	Reduce	No Change	Expand	Total N	Reduce	No change	Expand	Total N
18 to 24	19.2%	50.0%	30.8%	26	19.2%	42.3%	38.5%	26
25 to 33	31.6%	46.8%	21.5%	79	39.2%	39.2%	21.5%	79
34 to 43	33.0%	42.9%	24.2%	91	36.7%	35.6%	27.8%	90
44 to 53	21.3%	60.6%	18.1%	94	25.3%	42.9%	31.9%	91
54 to 62	11.8%	61.8%	26.3%	76	26.4%	36.1%	37.5%	72
63 or older	20.0%	80.0%		10	40.0%	30.0%	30.0%	10
All ages	24.2%	53.5%	22.3%	376	31.3%	38.6%	30.2%	368

How do you think AI/ML/automated features will affect staffing levels?

	My role				The profession, in general			
	Reduce	No Change	Expand	Total N	Reduce	No change	Expand	Total N
18 to 24	23.1%	69.2%	7.7%	26	26.9%	57.7%	15.4%	26
25 to 33	34.2%	57.0%	8.9%	79	35.4%	46.8%	17.7%	79
34 to 43	38.2%	58.4%	3.4%	89	49.4%	39.1%	11.5%	87
44 to 53	29.0%	67.7%	3.2%	93	36.0%	47.2%	16.9%	89
54 to 62	26.3%	64.5%	9.2%	76	37.7%	47.8%	14.5%	69
63 or older	30.0%	70.0%		10	20.0%	60.0%	20.0%	10
All ages	31.4%	62.7%	5.9%	373	38.3%	46.4%	15.3%	360

In addition to the cooperative role professionals must play in overseeing AI-based systems, the following scenarios are likely:

- Staffing levels have stabilized; it is unlikely they will decline, particularly based on aging patient population models and new capabilities of the technology that could improve patient care and outcomes.
- Learned skills, especially as the final decision-maker on patient exposure and diagnostic quality of images, are necessary to teach and operate AI-based equipment and supervised machine learning.
- Even with improved workflow, most efficiency should apply to repetitive, manual tasks, saving more time for patient care, troubleshooting, and equipment supervision and quality control.
- Radiologic technologists and radiation therapists will have an essential role in preventing dose creep and ensuring patient safety.

To date, most AI-enabled tasks have applied to disease prediction on images, which falls within the scope of radiologist practice. A key point has been made that there is a difference between diagnosis and prediction vs action and recommendation (Pesapane, 2018). The same concept is important as AI enters more of the radiologic technologist and radiation therapist domain.

A 2017 poll revealed that 65% of American adults felt uncomfortable delegating medical diagnosis to computers with AI (European North American, 2019). These opinions likely will shift somewhat as AI becomes more mainstream in health care and consumer goods but solidly demonstrate an unwillingness of patients to let go of human involvement in clinical care. A 2019 study on workers and automation concluded that employees do not experience wage reduction as a result of automation, and that automation can affect relatively few workers over time (Bessen, 2019). AI-based automation causes initial disruption in workforces but has not hurt most industries. For example, AI has automated many background tasks in banking, yet banks continue to open branches and employ workers, although employees might focus less on teller duties and more on customer and vendor relationships or promoting new products and capabilities (Berruti).

The HCIAC Corporate Roundtable discussion emphasized that AI is a data decision tool that provides another way of automating some tasks. Medical imaging and radiation therapy professionals have many responsibilities and perform many steps that AI tools cannot address. Only the person present can walk patients into an imaging or therapy room and converse with them about his or her weekend. Further, the automation afforded by AI tools enables more focus on the patient. Medical imaging and radiation therapy roles likely will develop to ensure AI is working correctly (daily quality assurance), help train the AI equipment, and enhance patient contact time as a result of reduced burden afforded by AI automation

Embrace and Adapt

Social and medical history are replete with examples of disruptive technologies that have improved lives and patient care. Medical imaging and radiation therapy professionals should embrace the positive role of AI in patient care and its assistance with manual and repetitive tasks, leaving them time to perform more value-added responsibilities. Professionals still will practice the science and techniques for which they were trained with the help of relatable, pertinent, and predictive tools. The combination of equipment with machine learning and the educated professional will help radiologic science staff work smarter while providing the essential human element of patient care.

As all imaging information (and indeed most of the services used in everyday life) has evolved to rely on digital data, radiology and radiation therapy will be more heavily data focused. Radiologists and radiologic technologists will make decisions in conjunction with intelligent devices but not independently of them. In addition, data labeling to drive machine learning and neural networks relies on user actions to collect the most useful labeled data sets.

To adapt to AI advances, medical imaging and radiation therapy professionals can ask themselves, "How do I make my future role more relevant?" In particular, all interested radiologic technologists and radiation therapists should research and prepare for an expanded role as AI becomes more prevalent in medical imaging and radiation oncology. At the least, radiologic science students and professionals should begin to learn more about AI basics and capabilities so they can adopt a healthy level of trust and be transparent with patients. In addition, they can plan for a more solid or expanded future role; education in data analytics could help professionals advance to lead positions, for example. Numerous job enrichment, cross-training, and leadership opportunities are foreseen for those who embrace the technology.

Adapting will require varying levels of education for radiologic science professionals. Although a vast majority (94.7%) of survey respondents define AI and machine learning similarly to the standard definition provided in the survey, applying the concepts to their daily work and equipment changes will require continuing education. The ASRT survey also revealed that most (54.8%) respondents received training on AI features through onsite education. About 32% said they had received no training, and 10.4% reported having trained offsite at a vendor facility. Educators, industry leaders, and the registry must work together to develop curricula and content specifications pertinent to AI.

A Healthy Level of Trust

Although medical imaging and radiation therapy professionals should embrace the potential advancements coming in AI, they should not become complacent to the point they depend on AI devices solely. This action can lead to *automation bias*, which is the tendency for people to favor decisions generated by machines at the expense of ignoring conflicting data or human decisions. Automation bias can occur in any industry.

In general, how much do you trust AI/ML/ automated features at work?		
	N	Valid Percent
Completely	7	1.8%
A great deal	120	30.9%
Somewhat	203	52.3%
Very little	41	10.6%
Not at all	17	4.4%
Total	388	100.0%

In addition to blindly agreeing with machine decisions, some people can over-rely on the technology or fail to monitor it as they should. Automation bias can lead to errors of omission and commission. Omission errors occur when the people involved fail to notice or choose to disregard an AI device's failure or variance. Commission errors occur when the professional involved accepts or implements an AI device's decision despite training and evidence to the contrary. It is critical that all professionals operating AI-based equipment maintain a healthy level of trust and skepticism, overcoming fears about the technology while not becoming dependent on it.

It is encouraging to know that ASRT members responding to the ASRT survey appear to already represent a healthy level of trust when it comes to AI. When asked how much they trust AI/machine learning/automated features at work, only 1.8% of respondents stated they trust AI "completely." Nearly 31% said they trust it "a great deal" and 52% "somewhat." A total of 15% of respondents said they trust AI "very little" or "not at all." Most of the respondents (83%) appear to have an appropriate level of trust in the technology, an excellent indicator that the profession is poised to embrace and supervise AI-based devices without depending on them entirely.

Verbatim responses to this and similar survey questions included the following paraphrased statement: "I think my profession will expand with more AI and machine learning-enabled efficiency such as auto processing so I can spend more time on patient care." However, many verbatim responses voiced a fear of becoming a "button pusher," a scenario that is unlikely as they work with AI devices. However, respondents to the ASRT survey also indicated that standardized processes for resolving discrepancies between machine-recommended procedures and technologist judgment are lacking. Radiologic technologists and radiation therapists should work closely with senior staff to establish methods, policies, and procedures regarding variances or errors.

IEEE has stated that intelligent and autonomous systems "should always subordinate to human judgment and control" (European North American, 2019). Although any professional operating AI-based devices supervises their operation and learning, the industry will need technologists and therapists to refine and maintain the technology. It is possible that a spike in the growth of new specialists to support AI will occur, much like there was when PACS became mainstream technology. Although staffing of some roles (eg, file room clerks) was negatively affected, technologists adapted to new workflows and some became PACS administrators.

Maintaining a Patient Focus

When clinical devices and processes are improved by AI, maintaining a patient focus reiterates the reason behind the technology. Numerous examples of changes and advancements that positively affect patients fill the relatively young histories of radiology and radiation oncology practice. As the person in charge of the diagnostic imaging or radiation treatment encounter, these professionals can and must be transparent about the process with patients.

In the ASRT survey, 30.8% of respondents believed AI would have a negative effect on patient interaction. Patients have clearly stated they will not accept human-free medical care. However, patients must trust the humans who oversee AI equipment. It is critical that radiologic technologists, radiation therapists, and all members of the care teams follow ethical approaches to AI so they can be transparent about the benefits and potential risks of AI technology. Being transparent also requires having the knowledge to explain the tool to patients.

As industry ethics foundations are developed with efforts such as this white paper, medical imaging and radiation therapy professionals should continue relying on their relative practice standards and codes of ethics regarding patient data privacy, patient safety, image quality, and promoting the common good of patients.

Ethics

Ensuring ethical use of AI-based devices relies on current ethical statements for professionals and the founding principles of AI. Numerous efforts have resulted in various but similar sets of founding principles of AI for OEMs and others. Overlapping themes, based mostly in current bioethics principles, include (Floridi, 2019):

- beneficence, by promoting well-being, preserving dignity, implementing AI for the benefit of humanity
- nonmaleficence (do no harm), by ensuring privacy, security, operating within secure constraints, and avoiding misuse
- autonomy, by ceding some decision-making power to the technology but striking a balance between that autonomy and human delegation of power, plus retention of enough human power to prevent impairing human freedom
- justice, by promoting prosperity while avoiding unfairness, including preventing discrimination
- explicability, or holding the decision-making ability of AI to account, by ensuring transparency and accountability

In addition to established founding principles for AI, initial ethics papers and statements have been released for medical imaging. A joint statement by European and North American radiology societies, including the American College of Radiology, Radiological Society of North America, American Association of Physicists in Medicine, the Society for Imaging Informatics in Medicine, and others, was published in 2019. The core team behind the document reviewed ethics literature from computer science, medicine, and ethical scholarship. The multisociety statement thoroughly addresses current and future ethical issues relevant to AI in medical imaging and can help inform future policies or regulations.

United States-based radiologic technologists and radiation therapists are guided by ASRT practice standards and the ARRT Standard of Ethics, including the Code of Ethics. Ethical application of AI falls within the code based on delivering patient care in a professional manner and for the full respect of the dignity of mankind; using equipment for the purposes for which it was designed; assessing situations and exercising care and discretion; acting as an agent by observing and communicating; and acting and operating equipment within standards of practice. In addition, the code of ethics emphasizes continually striving to improve knowledge and skills by participating in continuing education and investigating new aspects of professional practice (ARRT Code).

Standards and ethics are well established and serve as the basis for medical imaging and radiation therapy professionals, and ethics documents have been composed by physicians, physicists, and other leaders in the industry. Therefore, the HCIAC Corporate Roundtable AI task force believes the following statement is most applicable to summarize ethical use of AI for radiologic science professionals:

> *With respect to the founding principles and ethics of medical imaging and radiation therapy, AI shall be used to augment the science of these professions and leverage the latest advancements in technology while continuing to engage and empower technologists and therapists to provide enhanced patient care.*

Specifically, medical imaging and radiation therapy professionals should gain the knowledge needed to interact with and supervise AI-based medical devices and act appropriately in managing the devices and reporting discrepancies. In agreement with established ethics regarding patient care, these professionals also should dedicate to sharing appropriate data while protecting patient privacy and feel comfortable explaining AI processes for full patient transparency.

Radiologic technologists and radiation therapists should respect institutional and practice standards and protocols regarding equipment use, including standards for machine learning as these arise. Adhering to practice standards, codes of ethics, and established institutional procedures also ensures better patient safety and reduces potential liability of radiologic technologists and radiation therapists operating AI equipment.

Future

Market predictions in 2017 suggested an upcoming boom in innovative AI applications in medical imaging by 2022 to 2027 (Siemens, 2019). At the 2019 RSNA meeting, an AI Showcase included 123 vendors, nearly double the number exhibiting in 2018 (Cannavo, 2019). As of early 2020, AI is beginning to bridge the gap between acquiring data and meaningful interpretation of data (Rattan, 2019).

Applying AI to advanced imaging modalities such as CT and MR is in initial phases but already showing great promise, such as early results on differentiating benign from malignant nodules on chest CT scans, along with neurologic and psychiatric uses. Incorporating AI into MR has shown promise at predicting survival in patients with cervical cancer and amyotrophic lateral sclerosis (Pesapane, 2018). Machine learning is being proposed or evaluated for radiation therapy error prevention, treatment planning, and automatic organ segmentation (Rattan, 2019). The use of machine learning and artificial neural networks is likely to increase the growth of AI in health care exponentially.

Summary

The computing capabilities and quantities of data now available can facilitate AI advancements previously thought unachievable. Predictions include estimating that employees in 20% of all companies will oversee neural networks by 2020 (Wagner, 2019). As all radiologic science professionals and OEMs prepare for future change, they should consider the following:

- Artificial intelligence is a logical next step in the continued improvement of medical devices radiologic science professionals use daily.
- The potential exists to increase public awareness of AI and machine learning and ensure transparency about technology with patients.
- Radiologic technologists and radiation therapists should participate in or lead efforts to maintain quality of AI-based devices and to incorporate AI into quality programs, particularly for patient radiation dose.
- Medical imaging and radiation therapy professionals are poised for role or workforce changes but will be aware and prepared; new opportunities likely will arise, especially for those professionals who choose to adapt and learn.
- Stakeholders must come together as groups to encourage beneficial use of AI in line with established codes of ethics, established joint statements on AI in medical imaging, and founding principles of AI:
- As OEMs face strong market forces and regulatory changes, they should inform and work with radiologic technologists and radiation therapists to guide AI-relevant policies, procedures, and deep learning for AI devices.
- Radiologic technologists and radiation therapists should become involved in laying the groundwork for ethical, practical, patient safety, and clinical aspects of AI in their responsibilities and for the betterment of patient care.
- Further work is needed as industry, radiologic science professionals, and institutional leaders work together to meet the challenges of AI specific to medical imaging and radiation therapy in terms of patient data privacy, security, and patient safety.
- Regarding ethics and AI: With respect to the founding principles and ethics of medical imaging and radiation therapy, AI shall be used to augment the science of these professions and leverage the latest advancements in technology while continuing to engage and empower technologists and therapists to provide enhanced patient care.

References and Resources

1. American College of Radiology Data Science Institute. (n.d.). Retrieved from https://www.acrdsi.org/. Accessed November 1, 2019.
2. American Society of Radiologic Technologists (ASRT). 2019 Artificial Intelligence Survey. Retrieved from https://www.asrt.org/as.rt?sKYXqx.
3. Anyoha R. (n.d.). The history of artificial intelligence: Can machines think? Harvard University. Retrieved from http://sitn.hms.harvard.edu/flash/2017/history-artificial-intelligence/. Accessed October 15, 2019.
4. ARRT Code of ethics. (n.d.). American Registry of Radiologic Technologists. Retrieved from https://www.arrt.org/docs/default-source/governing-documents/code-of-ethics.pdf?sfvrsn=71f304fc_14. Accessed October 18, 2019.

5. Artificial intelligence accurately predicts radiation treatment side effects for patients with head and neck cancers. (2019). Retrieved from https://www.astro.org/News-and-Publications/News-and-Media-Center/News-Releases/2019/Artificial-Intelligence-accurately-predicts-radiat. Accessed November 4, 2019.
6. Berruti F, Ross E, Weinberg A. (2017). The transformative power of automation in banking. McKinsey and Company. Retrieved from https://www.mckinsey.com/industries/financial-services/our-insights/the-transformative-power-of-automation-in-banking. Accessed November 10, 2019.
7. Bessen J, Goos M, Salomons A, van der Berge W. (2019). What happens to workers at firms that automate? [PDF file]. Retrieved from https://www.cpb.nl/sites/default/files/omnidownload/CPB-Discussion-Paper-390-Automatic-Reaction-What-Happens-to-Workers-at-Firms-that-Automate.pdf. Accessed December 5, 2019.
8. Brooke D. (2019). Difference between artificial intelligence, machine learning and deep learning. Retrieved from https://learnworthy.net/difference-between-artificial-intelligence-machine-learning-and-deep-learning/. Accessed October 8, 2019.
9. Cagle K. (2019). What is artificial intelligence? Retrieved from https://www.forbes.com/sites/cognitiveworld/2019/08/20/what-is-artificial-intelligence/#48dca851306f. Accessed October 8, 2019.
10. Cannavo MJ. (2019). RSNA's AI Showcase provides a deep experience. Retrieved from https://www.auntminnie.com/index.aspx?sec=ser&sub=def&pag=dis&ItemID=127556. Accessed December 4, 2019.
11. Casey B, Ridely EL, Yee KM, Forrest W. (2019). Winners of 20th annual Minnies are radiology's best. Retrieved from https://www.auntminnie.com/index.aspx?sec=nws&sub=rad&pag=dis&ItemID=126852. Accessed October 22, 2019.
12. Daley S. (2018). 19 examples of artificial intelligence shaking up business as usual. Retrieved from https://builtin.com/artificial-intelligence/examples-ai-in-industry. Accessed October 31, 2019.
13. Digalaki E. (2019). The $450B opportunity for the applications of artificial intelligence in the banking sector and examples of how banks are using AI. Retrieved from https://www.europeanbusinessreview.eu/page.asp?pid=3297. Accessed October 20, 2019.
14. Geis RJ, Brady AP, Wu CC, et al. (2019). Ethics of artificial intelligence in radiology: Summary of the joint European and North American multisociety statement. *Radiology, 293(2), 437-440*. doi:10.1148/radiol.2019191586
15. European Society of Radiology (ESR). (2019). What the radiologist should know about artificial intelligence – an ESR white paper. *Insights Imaging, 10(44), 1-8*. doi:10.1186/s13244-019-0738-2
16. Artificial intelligence and machine learning in software as a medical device. (2019). Retrieved from https://www.fda.gov/medical-devices/software-medical-device-samd/artificial-intelligence-and-machine-learning-software-medical-device. Accessed November 10, 2019.
17. Proposed Regulatory Framework for Modifications to Artificial Intelligence/Machine Learning (AI/ML)-Based Software as a Medical Device (SaMd). (n.d.). Retrieved from https://www.fda.gov/media/122535/download. Accessed December 2, 2019.
18. Floridi L, Cowls J. (2019). A unified framework of five principles for AI in society. *Harvard Data Science Review, 1(1).* Retrieved from https://hdsr.mitpress.mit.edu/pub/l0jsh9d1. Accessed November 12, 2019.
19. Fornell D. (2018). Key technology trends in radiation therapy at ASTRO 2018. Retrieved from https://www.itnonline.com/content/blogs/dave-fornell-itn-editor-astro/key-technology-trends-radiation-therapy-astro-2018. Accessed November 10, 2019.
20. Glassbeam announces artificial intelligence application for healthcare provider market. (2018). Retrieved from https://www.glassbeam.com/press/glassbeam-announces-artificial-intelligence-application-healthcare-provider-market. Accessed October 20, 2019.
21. No matter how you slice it, this AI tech is changing MR neuro imaging. (2019). Retrieved from http://newsroom.gehealthcare.com/this-ai-tech-is-changing-mr-neuro-imaging/. Accessed November 3, 2019.
22. Could AI improve radiation oncology contouring accuracy? (2019). Retrieved from https://www.gehealthcare.com/article/could-ai-improve-radiation-oncology-contouring-accuracy. Accessed November 3, 2019.
23. Hale C. (2019). FDA delivers regulatory guidance on AI software and clinical decision-making tools. Retrieved from https://www.fiercebiotech.com/medtech/fda-delivers-regulatory-guidance-ai-software-and-clinical-decisionmaking-aids. Accessed November 15, 2019.
24. Heath S. (2018). Patient experience, technology top the list of CIO priorities. Retrieved from https://patientengagementhit.com/news/patient-experience-technology-top-the-list-of-cio-priorities. Accessed November 2, 2019.
25. Heath S. How artificial intelligence helps CIOs drive patient experiences. (2019). Retrieved from https://patientengagementhit.com/news/how-artificial-intelligence-helps-cios-drive-patient-experiences. Accessed November 2, 2019.

26. Hosny A, Parmar C, Quackenbush J, Schwartz LH, Aerts HJWL. (2018). Artificial intelligence in radiology. *Nat Rev Cancer*,18(8),500-510. doi:10.1038/s41568-018-0016-5
27. Rethinking privacy for the AI era. (2019). Retrieved from https://www.forbes.com/sites/insights-intelai/2019/03/27/rethinking-privacy-for-the-ai-era/#4c91de117f0a. Accessed December 2, 2019.
28. Jarrett D, Stride E, Vallis K, Gooding MJ. (2019). Applications and limitations of machine learning in radiation oncology. [published online ahead of print]. *Br J Radiol*, 92, 1-12. doi:10.1259/bjr.20190001
29. Artificial Intelligence for Health and Health Care [PDF file]. (2017). Retrieved from https://www.healthit.gov/sites/default/files/jsr-17-task-002_aiforhealthandhealthcare12122017.pdf. Accessed October 10, 2019.
30. Jiang F, Jiang Y, Zhi H, et al. (2017). Artificial intelligence in healthcare: Past, present and future. *Stroke Vasc Neurol*, 2(4), 230-243. doi:10.1136/svn-2017-000101
31. Lovelace B. GE's health unit wins first FDA clearance for AI-powered x-ray system. CNBC. (2019). Retrieved from https://www.cnbc.com/2019/09/12/ges-health-unit-wins-first-fda-clearance-for-ai-powered-x-ray-system.html. Accessed November 19, 2019.
32. Marr B. How much data do we create every day? The mind-blowing stats everyone should read. (2018). Retrieved from https://www.forbes.com/sites/bernardmarr/2018/05/21/how-much-data-do-we-create-every-day-the-mind-blowing-stats-everyone-should-read/#59e361da60ba. Accessed October 23, 2019.
33. Siemens SOMATOM Edge Plus CT uses AI and 3D camera to auto position patients. (2018). https://www.medgadget.com/2018/04/siemens-somatom-edge-plus-ct-uses-ai-and-3d-camera-to-auto-position-patients.html. Accessed October 30, 2019.
34. McKendrick J. (2019). Only humans can provide the intelligence in artificial intelligence. Retrieved from https://www.forbes.com/sites/joemckendrick/2019/06/30/only-humans-can-provide-the-intelligence-in-artificial-intelligence/#70c123162997. Accessed October 1, 2019.
35. Mitchell JW. Addressing the ethical challenges of AI at RSNA. (2019). Retrieved from https://www.dotmed.com/news/story/49421. Accessed December 4, 2019.
36. Ng M, Brown E, Williams A, Chao M, Lawrentschuk N, Chee R. (2014). Fiducial markers and spacers in prostate radiotherapy: current applications. *BJU Int*, 113(suppl 2), 13-20. doi:10.1111/bju.12624
37. Pesapane F, Codari M, Sardanelli F. (2018). Artificial intelligence in medical imaging: Threat or opportunity? Radiologists again at the forefront of innovation in medicine. *Eur Radiol Exp*, 2(1), 35. doi:10.1186/s41747-018-0061-6
38. Rattan R, Kateria T, Banerjee S, et al. (2019). Artificial intelligence in oncology, its scope and future prospects with specific reference to radiation oncology. *BJR Open*, 1, 20180031. doi:10.1259/bjro.20180031
39. Reinhardt T. (2019). Using global localization to improve navigation. https://ai.googleblog.com/2019/02/using-global-localization-to-improve.html. Accessed October 30, 2019.
40. Ridley EL. (2019). AI needs robust clinical evaluation in healthcare. https://www.auntminnie.com/index.aspx?sec=log&itemID=127077. Accessed November 6, 2019.
41. Shaban-Nejad A, Michalowski M, Buckeridge DL. (2018). Health intelligence: how artificial intelligence transforms population and personalized health. *NPJ Digit Med,* 1(53), 1-2. doi:10.1038/s41746-018-0058-9
42. Artificial intelligence in healthcare: Transforming data into knowledge for better care. (n.d.). Retrieved from https://www.siemens-healthineers.com/en-us/digital-health-solutions/value-themes/artificial-intelligence-in-healthcare. Accessed October 8, 2019.
43. Slomka PJ, Dey D, Sitek A, Motwani M, Berman DS, Germano G. (2017). Cardiac imaging: Working towards fully-automated machine analysis & interpretation. *Expert Rev Med Devices*, 14(3), 197-212. doi:10.1080/17434440.2017.1300057
44. Syeda-Mahmood T. (2018). Role of big data and machine learning in diagnostic decision support in radiology. *J Am Coll Radiol*, 15(3 Pt B), 569-576. doi:10.1016/j.jacr.2018.01.028
45. Thomas M. (2019). How AI trading technology is making stock market investors smarter—and richer. Retrieved from https://builtin.com/artificial-intelligence/ai-trading-stock-market-tech. Accessed October 30, 2019.
46. Wagner JB. (2019). Artificial intelligence in medical imaging. *Radiol Technol*, 90(5), 489-501.
47. Waldron T. (2019). Three surprising ways healthcare is using AI. Retrieved from https://blog.definitivehc.com/ways-healthcare-using-ai?utm_campaign=Customer%20Newsletter&utm_source=hs_email&utm_medium=email&utm_content=78099605&_hsenc=p2ANqtz-9AeeKh8uf55WRagvjR7ZT3RErfEHvn5dvzuMwuXc3WlhdJoYtvFVXcdt-Ou4CXzY0CX9_vtrXFMTRFEi7UBSBBDMLJeoOqDocdPzgimOJD3pFAQeJav619zZUpfGQuW7I. Accessed October 30, 2019.
48. Yakerson A. (2019). Women in clinical trials: a review of policy development and health equity in the Canadian context. [published online ahead of print]. *Int J Equity Health*, 18(1), 1-8. doi:10.1186/s12939-019-0954-x

Appendix A

HCIAC Roundtable Representatives

Canon Medical Systems USA
Lori Webb, Sr. Product Line Advisor
Lou Bonincontri, Sr. Manager Clinical Applications, CT

Elekta
Paul Naine, Director, Global Clinical Operations
Rui Lopes, Director, Business Development

GE Healthcare
Tiffany DuGal, Customer Operations Marketing Manager

Hitachi Healthcare Americas
Dave Wilson, Director, Corporate Communications

Hologic
Kendra Potts, Field Product Specialist

Philips Healthcare
Aideen O'Sullivan, Senior Manager, Radiation Oncology, AMI and CT
Terry Fonner, Senior Manager, Clinical Services – Midwest Zone

Siemens Healthineers
Lyle Muhammad, Director of Education Services; Head of Clinical Practice-Syngo Radiology and Cardiology
Carnessa Ottelin, Education and Workforce Solutions, EWS Solutions Manager

Varian
Ann McElvaney, Clinical Operations Manager
Alex Salima, e-Learning Content Developer

ARRT
Jeff McLeod, Director, Examination Requirements and Psychometrics

ASRT
Craig St. George, Director of Education
John Culbertson, Director of Research
Michael Jennings, Senior Research Analyst

ASRT Foundation
Steven Hardy, COO
Carol Kennedy, Foundation Director
Janet McEwen, Director of Corporate Relations

Contract Writer
Teresa Odle, ELS