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In This Issue

10

Features

Society News

Departments

VOLUME 22 • NUMBER 2

ASTRO news

AMERICAN SOCIETY FOR RADIATION ONCOLOGY

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EDITOR'S*notes*

BY NAJEEB MOHIDEEN, MD, FASTRO
SENIOR EDITOR, *ASTRONEWS*

AI on the Horizon

ARTIFICIAL INTELLIGENCE (AI) INSPIRES HOPE AND FEAR IN ALMOST EQUAL MEASURE. The idea that machines will become advanced enough to think like humans is no longer fantasy. Alexa, we're told, is learning every day, by listening to all our conversations. Digital technology has disrupted every sphere of our lives. Doctors, insurers and technology companies are using it to reshape health care. The hope is that, on the one hand, AI and data-driven predictions can improve patient care and lead to better outcomes. On the other, we could create efficiencies in an industry that currently accounts for 18% of the U.S. gross domestic product. One can see how AI could change patient scheduling, operations, billing, etc., but can it really make inroads into complex clinical situations such as cancer patient management? And, how might that impact radiation oncology? That's the theme of this issue, and it extends the engagement that began with the ASTRO membership at Dr. Paul Harari's 2018 ASTRO Annual Meeting Presidential Symposium.

Any conversation has to start with an understanding of the language and terminology, which can be confusing. Carlos Cardenas and Kristy Brock help unravel this with a brief introduction to AI for the radiation oncologist. We then move through our process of care and get a fascinating glimpse into the impact of AI in the treatment planning process from the physics team at Northwell Health and MD Anderson Cancer Center. This is an area where there is great potential to improve standardization of plans and increase quality of care across the community. Sewit Teckie discusses the promises and pitfalls and the technology that will evolve to move clinical care and access to the patient's fingertips. Olivier Morin and his group list the current shortcomings with Electronic Health Records (EHRs) that limit the ability to use the information for broad development of data science and AI in the treatment of cancer and discuss their MEDomics concept as a possible solution. Andre Dekker discusses the need to come together to share data and describes a platform that would enable this using routine clinical cancer data and AI methods to gain new knowledge. How will this impact patient care? Marisa Kollmeier gives us a glimpse into the real-world experience that emerged from Memorial Sloan Kettering's collaboration with IBM using the company's Watson computer system. Contextually aware bots could potentially respond to the needs of patients by comparing their requests or problems to huge databases of layered neural information. A key to unlock this potential is the research efforts in semantic interoperability, enabling the exchange of data with unambiguous, shared meaning from EHRs to research databases for consistent interpretations.

While AI has the potential to improve quality, efficiency and patient outcomes and to decrease costs, it will also produce new possibilities, consequences and questions. It has the potential to alter professional relationships, patient engagement, knowledge hierarchies and the labor market. Additionally, it may add to the disparities that exist in health care due to concentration of AI resources. Our specialty has a responsibility to thoroughly examine this data-driven, human-plus-machine, decision-making future for unintended consequences. We are ultimately responsible for what happens to patients and will need to acquire new skills to manage these ecosystems. The potential for catastrophe shouldn't be underestimated as with the advanced avionics on the modern aircraft or accidents with self-driving cars.

The ethics of data are fundamental to AI in medicine. Mittelstadt et al. identified five key areas of concern: 1) informed consent; 2) privacy and data protection; 3) ownership; 4) objectivity; and 5) the gap between those who have or lack the resources to use large datasets. Other data issues include bias against group-level subsets on the basis of gender, ethnic or economic group, the importance of trust in assessing data ethics, and providing meaningful and moral access rights to data.[1] As a specialty, should we be working on necessary guardrails, lest it be taken out of our hands to the detriment of patients? This would include a code of ethics and practices for AI and data-sharing policies.

ASTRO has already taken a step in this direction. As Dawit Tegbaru writes, ASTRO published a data-sharing policy and best practice guide for authors submitting to its journals. Data availability statements will be published alongside articles beginning January 2020. How about a mechanism to evaluate, verify and validate the technology as it rolls out? Is additional oversight needed or will we be dependent on the industry to provide this function? It is reassuring to learn from Thomas Purdie's article that the FDA has taken steps to develop a new, tailored framework for reviewing AI-based software as a medical device. But is that enough?

How does one distinguish between hope and hype? Twenty years ago, radiologists adopted a technology called computer-aided detection (CAD), which was meant to aid them in finding tumors on mammograms. The commercial developers lobbied to have it paid for and convinced Congress this was better for women, and the technology became widespread. A few years ago, Lehman et al. decided to see if CAD was actually beneficial.[2] They compared doctors at centers that used the software with those that didn't. Their conclusion was that CAD does not improve the diagnostic accuracy of mammography and suggested that insurers pay more for it with no established benefit to women. In fact, mammography sensitivity was decreased in the subset of radiologists who interpreted mammograms with and without CAD. This hasn't stopped AI-based models being evaluated in diagnostic radiology; it only heightens the need for high-quality validation. As Julian Hong and John Kang discuss in their residents' perspective, AI's role will proliferate. We are increasingly dealing with large amounts of data and, as one factors in genetic information, diagnostic data and clinical data into clinical decision support systems, they will no longer be able to process this usefully without robust AI. In this connection, the concept of augmented intelligence is significant. As the name implies, this represents AI's supportive role, enhancing human intelligence, not supplanting it. Nevertheless, "High quality validation and continuous quality assurance will be critical," say Hong and Kang.

The future will throw up more questions — resolving bias, liability, data ownership, sharing revenue and profit, workforce disruptions and changing job functions, training, reimbursements, etc. Brian Kavanagh takes a look back and gazes toward what a future patient care ecosystem might look like. It apparently involves "vintage dreampop music in the background." As he states, our future depends on the patient-provider relationship, the relevance of the modality and the value proposition AI brings. The current component coding system in radiation oncology, thanks to the work of pioneers like ASTRO Gold Medalist the late "Bob" Bogardus, has ensured a firm economic foundation for radiation oncology. (See tribute to Bogardus on page 6). AI has the potential to merge those components into a seamless process of care, and while that may be difficult to fit into the current system, it may be incorporated better into an alternative payment model. As for testing for knowledge, experience and skills, Paul Wallner writes that while the ABR does not anticipate inclusion of material related to AI in the near future, data analysis and management enabled by these new tools may be very useful in question development and feedback analysis.

As this issue makes clear, this dialogue is a vital exercise that will intensify over the next few months and years as technology advances. Looking at the just released ASTRO 2019 Annual Meeting program, I am excited to note one of the keynote addresses is on AI and Deep Learning in Medicine (and one of the speakers is Dr. David Magnus, an expert on ethics in AI and deep learning). Popular culture is replete with dystopian tales of machines taking over. Our vision should be different — to arrive at an understanding of artificial intelligence and how it can help us take better care of our patients and distinguish the hype as we pursue hope.

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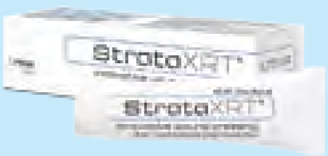

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CHAIR'S*update*

PAUL M. HARARI, MD, FASTRO
CHAIR, BOARD OF DIRECTORS

BLENDING **ARTIFICIAL INTELLIGENCE** AND THE **ART OF MEDICINE**

This issue of *ASTROnews* illuminates current and future considerations regarding Artificial Intelligence (AI) in radiation oncology. As noted by Cardenas and Brock, "AI is threatening or promising, depending on your point of view." Although many talented authors contributing to this issue provide precautionary notes about the application of AI to radiation oncology, the prevailing theme is one of promise and opportunity. Cancer patients yearn for cure, and if cure is not realistic, then effective palliation with attention to quality of life. There is good reason to believe that the judicious application of AI may contribute to these significant objectives.

Despite inherent challenges, we sense the raw power, rationale and potential value to bring deeper and more systematic data to bear in daily radiation oncology practice. Having treated several thousand H&N cancer patients with complex radiation treatment plans over the last 30 years, I am impressed with my inability to compare and contrast even two to three IMRT plans for the same patient. Is a 2 Gy reduction in mean dose to a parotid gland "worth" a small dose increase to a submandibular gland? There are dozens of key structures and dose tradeoffs to consider. We are capable of generating hundreds of treatment plans in less time than ever before. How will the human eye and mind compare and select the "best" for each patient?

Fortunately, radiation oncology is a highly cognitive specialty that blends data with experience. Let's return to H&N cancer, where normal tissue contouring is a natural fit for AI. Tumor contouring however is remarkably more challenging since modern imaging offers only a partial guide. Elective nodal regions harboring risk for cancer display no actual tumor imaging signal, and superficial mucosal tumor extension seen by the naked eye or felt by touch are typically not visible with any imaging modality. It would be naïve to think that imaging alone is a panacea for AI tumor target contouring. How might we best incorporate cognitive parameters that emerge from years of cancer treatment experience and intuition? As noted by Reigel et al., "Algorithms will most likely supplement, not replace, physician discretion."

The articles in this issue highlight compelling reminders that we are just beginning to emerge from an immature state of medical data accumulation, organization and sharing. Generating large, diverse, robust datasets is achievable, although data quality remains a substantial challenge. Unleashing the power of global data sharing holds enormous potential to expand the beneficial impact; however, as noted in the Residents' Perspective, it will be important to "define the right model for the right data for the right problem."

Brian Kavanagh, MD, MPH observes that radiation oncology futures will be significantly influenced by the patient's perception of helpfulness and compassion that they are afforded. **This summons the notion that emotional intelligence and likely other forms of intelligence (including and beyond AI) will continue to play essential roles in cancer medicine.**

Although the availability of robust data and outcomes are clearly valuable, many vital elements of medical practice extend beyond data. Every day, thousands of patients are diagnosed with cancer, live with cancer, die from cancer. They experience and navigate this challenge in distinct ways depending on their individual human psyche, spirituality, culture, family dynamic, aspirations and core beliefs. These elements are not the stuff of algorithms or databases, yet they remain critical to empathetically blend science with the art of medicine.

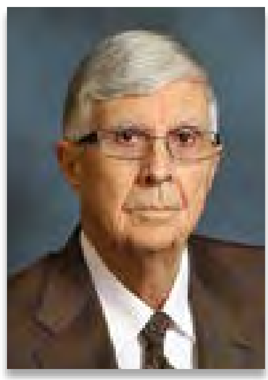
Artificial intelligence will advance radiation oncology practice and make a valuable contribution to the complex puzzle of cancer care. The rigorous application and careful blending of AI with compassionate care will benefit radiation oncology and future generations of cancer patients.

TRIBUTE

Carl Robert Bogardus Jr., MD, FASTRO

BY PAUL E. WALLNER, DO, FASTRO, CHRISTOPHER M. ROSE, MD, FASTRO
AND TIM R. WILLIAMS, MD, FASTRO

CARL ROBERT BOGARDUS JR. was born in Hyden, Kentucky, in 1933 and died in Oklahoma City on February 23, 2019, at the age of 85. Because his father, Carl Sr., was always called "Carl," Carl Jr. was known to relatives, friends and colleagues as "Bob." He came to medicine naturally, following in the footsteps of Carl Sr., a rural family physician. By the age of 15, Bob was assisting at deliveries. After completing a tuition payback period in a small Kentucky coal mining community, Carl Sr. relocated his family to Austin, Indiana, where Bob was raised. He attended Hamilton (IN) College and the University of Louisville Medical School, both of which his father had also attended. At Hamilton, Bob majored in chemistry and physics, but his keen interest in engineering and his physics background directed him to technology-oriented research projects and summer jobs at medical school, and, ultimately, to a residency in therapeutic radiology at Penrose Cancer Hospital in Colorado Springs, Colorado. There he worked under the tutelage of Juan del Regato, one of the pioneers of radiation oncology in the United States. The Penrose training program was an incubator for future leaders of the profession, including J. Frank Wilson, James Cox, Victor Marcial-Vega, Jerome Vaeth and Robert Lindberg, among others. Upon completion of his training at Penrose, Bob spent a year in fellowship at the Mallinckrodt Institute of Radiology in St. Louis, where he divided his time between clinical care and physics research. With his physics colleague Michel Ter-Pogossian, he developed an early computer program for brachytherapy calculations which, until then, had been done painstakingly by hand.[1]



Following completion of training, Bob accepted a faculty post in Oklahoma City, where he would stay for the remainder of his life and career. In 1962, he joined the American Club of Therapeutic Radiologists, and, in 1966, assisting del Regato as secretary, helped establish the American Society for Therapeutic Radiologists (ASTR) at its founding meeting in Scottsdale, Arizona. Shortly after he relocated to Oklahoma, Bob became active in the Oklahoma Radiological Society (ORS) and, in 1979, became an ORS councilor to the American College of Radiology (ACR). At the ACR, his early interest in the socio-economic issues of radiology and radiation oncology became a driving force for the remainder of his career and a fortunate event for the radiology-related disciplines. Beginning in the 1980s, the Health Care Financing Administration (HCFA), forerunner of the Centers for Medicare and Medicaid Services (CMS), became concerned by disparities in charges and descriptions of medical services. Recognizing the direction that events were taking, Bob, along with a small group of like-minded colleagues within the ACR, developed the resource-based relative value structure for radiology (RBRVS) that incented treatment planning and dosimetry for quality radiation therapy and periodic on-treatment management during the course of care. In 1988, funded by a HCFA contract, William Hsaio and colleagues at Harvard completed work on a resource-based relative value system intended for use in all federally-funded health programs.[2] The project was so complex, and the ACR product so inclusive and rational, that the national HCFA RBRVS effectively incorporated the ACR system in its entirety. The significance of their accomplishments in this area cannot be overestimated. The concept of "component coding," the front-loaded medical decision-making paradigm, and the consolidation of the disparate clinical aspects of care into "weekly treatment management" all but assured the financial security of the specialty. Changes in the system through various administrations and policy disagreements would lead to many alterations over the years, but the system developed by Bob and a small group of colleagues would provide a stable payment base for radiation oncology for the next 30 years. He also ensured that their legacy would continue by his generous mentoring of the next generation of ASTRO socio-economic leaders.

Bob left the University of Oklahoma in 1995 for a nine-year stint in private practice but returned in 2004, working there until the end of his life. He was one of the few individuals to serve as president of both the ACR and ASTRO, and, in 2015, was the only person ever to receive the Gold Medal from both societies in the same year. Bob was predeceased by Norma, his wife of 58 years, and is survived by his wife, Carol, two children, their spouses, a granddaughter and generations of grateful colleagues.

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In Memoriam

ASTRO has learned that the following member has passed away. Our thoughts go out to his family and friends.

Paul J. Anderson, MD
Lubbock, Texas

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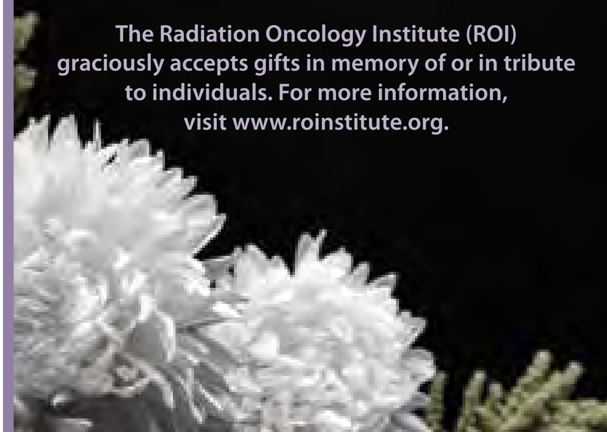

ASTRO Featured in USA Today Supplement on the Future of Cancer Care

CONTINUING OUR EFFORTS TO RAISE THE PROFILE OF RADIATION ONCOLOGY and educate the public about radiation therapy, ASTRO contributed an article by president-elect Thomas Eichler, MD, FASTRO, to the newest USA Today "Future of Cancer Care" campaign. Taking a cue from ASTRO research that found patients want more straightforward discussion about the potential consequences of cancer treatment, the article gives readers an overview of side effects commonly associated with radiation therapy, as well as strategies to manage them. The article was distributed in March as an insert in USA Today to an estimated audience of one million readers, and it was also published online.

ASTRO contributed other radiation therapy-specific articles in past editions of one of the nation's largest newspapers. In addition to Dr. Eichler's piece on managing side effects, other ASTRO articles discuss how advances in radiation therapy benefit patients, from Dr. Brian Kavanagh; how clinical trials advance cancer care, from Dr. Catherine Park; an overview of skin cancer and radiation therapy, from Dr. Anna Likhacheva; dispelling radiation therapy myths, from Dr. Geraldine Jacobson; and harnessing the power of radiation therapy, from Dr. David Beyer.

Excellent Programming Distinguishes the Multidisciplinary Thoracic Cancers Symposium

BY SUE S. YOM, MD, PHD, MAS, UNIVERSITY OF CALIFORNIA, SAN FRANCISCO

EVERY TWO YEARS, the Multidisciplinary Thoracic Cancers Symposium unites the specialties of medicine for the purposes of research, practice and education focused solely on thoracic malignancies. This year's meeting, held March 14-16 in San Diego, was co-sponsored by the American Society of Clinical Oncology, the Society of Thoracic Surgeons and ASTRO. The meeting's content was programmed by co-chairs, a steering committee and a program committee balanced between these co-sponsoring organizations, with additional content advisors provided by the American College of Chest Physicians and the Society of Thoracic Radiology. As a result, this meeting featured an exceptionally broad-based program of multidisciplinary reviews, scientific abstracts, keynote lectures, tumor boards, and career advising and networking sessions.

True to its multidisciplinary nature, the meeting provided extended exposure to important issues pertinent to thoracic malignancies, which may often receive short shrift at a general-interest radiation oncology meeting. For example, lung cancer screening, a critical public health topic not commonly addressed in detail at most radiation oncology meetings, was a major emphasis, featuring interactive discussion among radiologists and pulmonologists and a comprehensive keynote address by Dr. Ella Kazerooni, from the University of Michigan, describing the latest recommendations from the National Lung Cancer Round Table.

Another important focus of the meeting was quality of life, including discussions of the science and strategies underlying end-of-life care and frailty and quality of life assessment in lung cancer patients, as well as a remarkably scientifically dense but practically useful keynote lecture on pain management and opioid use in cancer patients by Dr. Eduardo Bruera from the MD Anderson Cancer Center. This lecture, given the complexity and timeliness of this topic, was worth the price of admission.

A final area of focus was immunotherapy, specifically on newly emerging scientific topics as well as the management of toxicities, topics that carry relevance for all specialists managing lung cancer in the immunotherapy era but which may receive less attention at general meetings. Updates included the latest scientific background on hyperprogression, management of brain metastases, combinations of radiation and immunotherapy, pulmonary toxicities of immunotherapy, safety of immunotherapy in patients with autoimmune disease, and toxicities of immunotherapy combined with targeted therapy. Updates comprised the latest scientific data but highlighted their practical relevance.

Throughout the meeting there were numerous opportunities to discuss the emerging role of stereotactic radiation therapy, especially in the context of oligometastatic disease, as well as the complexities introduced by novel combinations of molecular targeted therapies and chemotherapies with immunotherapy. These larger issues wove continuously through presentations in the oral abstract sessions and were also featured in state-of-the-art review sessions focused on early, locally advanced and advanced-stage lung cancer.

Participants at the meeting commented on the high quality of the educational sessions, which also included reviews of small-cell lung cancer management, thymic tumors, mesothelioma and neuroendocrine tumors. The educational purpose was reinforced by meet-the-expert office hours and a networking luncheon for trainees and early-career practitioners featuring a multidisciplinary panel speaking on experiences and lessons learned from their careers.

This conference provided a comprehensive review of the state-of-the-art management of thoracic cancers, featuring novel but practical content, engaging world-class speakers and genuinely multidisciplinary engagement. If you were not able to attend, consider purchasing the Virtual Meeting, available at www.astro.org/virtualmeeting.

Dr. Yom served as one of the ASTRO representatives on the 2019 Multidisciplinary Thoracic Cancers Symposium Program Committee.

Prior Authorization Remains Greatest Challenge Facing the Field of Radiation Oncology

PRIOR TO ADVOCACY DAY, ASTRO hosted a media briefing to unveil results of our member survey on prior authorization, in which nearly 700 members responded. The survey provided key insights about obstacles that restrictive prior authorization practices create for cancer patient care, including:

- 93% of respondents said their patients experience treatment delays.
- 31% indicated the average delay lasts more than five days.
- 63% said their practice had to hire additional staff to manage prior authorization.
- 62% said the majority of their denials are overturned on appeal.

The survey illuminated other ways prior authorization practices negatively impact patient outcomes, including adding to patient stress and disproportionately impacting patients at community-based clinics. In addition, nearly 1 in 5 respondents said that more than 10% of their time is spent dealing with prior authorization issues instead of patient care. The survey and briefing generated news coverage by U.S. News & World Report, leading health newswire HealthDay, the New Jersey Star-Ledger, Bloomberg, Inside Health Policy and several major medical trade outlets.

ASTRO's Government Relations team continues to work with our Hill champions to address these issues and monitor legislative action. You can listen to the April 2019 press call, which featured leaders from ASTRO, the American Medical Association and the National Coalition for Cancer Survivorship, and review the survey results at www.astro.org/priorauthorization.

2019 Advocacy Day Participants Focus on Prior Authorization, Cancer Research Funding and Stable Medicare Payments

MORE THAN 80 ATTENDEES JOINED US in Washington, D.C., for ASTRO's 2019 Advocacy Day April 29-30. Attendees spent two days meeting with members of Congress and hearing updates on what is happening with current issues on Capitol Hill.

Highlights from the first day included an address from Board of Directors Chair Paul Harari, MD, FASTRO, on ASTRO's recently released prior authorization survey results (see story above for details) and a discussion on federal health policy with Kimberly Brandt, principal deputy administrator for policy and operations at the Centers for Medicare and Medicaid Services (CMS). Participants then heard from Representative Paul D. Tonko, D-N.Y., providing remarks on access to health care and protections for people with pre-existing conditions. He also expressed his ongoing support for access to high-quality radiation therapies for cancer patients. The afternoon continued with lively panel discussions on engaging in advocacy through social media and federal issues effecting radiation oncology, all setting the stage for Day Two's Hill visits.

On the second day, participants visited the offices of approximately 125 members of Congress to discuss key issues, including stable Medicare payments and cancer research funding. In addition, participants talked with policymakers to emphasize the need to remove restrictive prior authorization requirements that unnecessarily delay patient access to cancer treatments.

View our exclusive, online-only recap from the attendees' perspective, plus photos, at www.astro.org/astronews.

BY CARLOS E. CARDENAS, PHD,
AND KRISTY K. BROCK, PHD

A Brief Introduction to ARTIFICIAL INTELLIGENCE for the Radiation Oncologist

Artificial intelligence is threatening or promising, depending on your view, to impact every aspect of our lives including health care. The clinical integration and adoption of artificial intelligence tools are fast approaching, and as stewards for the advancement of the field of radiation oncology, we need to leverage our experience and expertise in safely and effectively using computational power to improve the accuracy and efficacy of radiation therapy. Artificial intelligence is very promising in advancing many related aspects of radiation oncology including normal tissue and tumor segmentation, automation in treatment planning and plan review, and providing clinical decision support and outcome prediction. This article's focus is to introduce and define artificial intelligence, machine learning and deep learning and to describe how these are related.

Artificial intelligence is a subfield in computer science that focuses on the development of intelligent agents that mimic cognitive functions such as learning and problem solving. The goal of an artificial intelligence system is to perceive a problem and take an action that maximizes the likelihood of successfully achieving a desired goal.

Machine learning (Figure 1), or statistical learning, is a subfield of artificial intelligence where mathematical algorithms are able to learn patterns from data, which can then be used to make informed decisions when presented with new observations. Commonly used machine learning algorithms in radiation oncology research are support vector machines, least absolute shrinkage and selection operator (Lasso), decision trees and random forests. In machine learning, a model's inputs are user-defined features that the algorithm uses to develop a prediction model. This is the case in medical imaging where the user has to predefine and calculate imaging features (radiomic features) prior to training and using a model.

Deep learning is a subfield of machine learning, which focuses on the use of deep neural networks, traditionally defined as artificial neural networks that have more than two "hidden" layers between the input and output layers; however, with today's computational power, deep neural networks can have hundreds of hidden layers. When compared with traditional machine learning approaches, deep learning provides the advantage that the previously user-defined features are now "learned" and defined by the deep learning algorithm based on the input data used to train the model. This allows for more robust generalization of the model on unseen data (not used during training). Several factors have promoted the success of deep learning, including: 1) improvements in algorithms driven

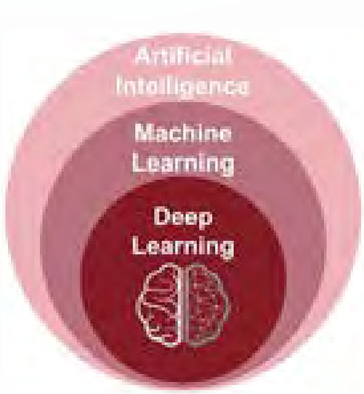

Figure 1. Illustration showing the relationship between artificial intelligence, machine learning and deep learning.

by machine learning and neural network research; 2) improvements in hardware which have allowed for the use of graphical processing units to speed up computations; and 3) the reduced cost in data storage, which has increased the availability of data needed to train these models. Deep convolutional neural networks (CNNs) are widely used in medical imaging analysis due to their ability to provide local connectivity between neurons of adjacent layers exploiting spatially local correlations. This allows the network to learn features both in a global and local scale, making the network more robust to subtle variations in the input data. CNNs can be used for several purposes, with the most popular being image classification and image segmentation, both of which have found applications in radiation oncology.

In addition to the layers that make up the CNN, the two main components include the weights (how important is this layer) and the loss function (how accurate is the model). The output of each layer in the CNN is weighted by its importance to the overall model on achieving accurate results, which is measured by the loss function. The goal of any machine learning model is to generalize well to unseen data. During deep learning model training, data is fed through the network to train the model's weights such that the network learns "optimal" weights until no substantial improvement in performance is achieved. While this is the goal of the training process, it could lead to overfitting of the training data, leading to poor generalization. A cross-validation data set is commonly used as a regularization method to prevent this type of overfitting. While training, the model's performance can be checked on the cross-validation data giving a hint as to how the model would behave on unseen data.

Only once the model's parameters have been optimized and the model's weights have been trained should one use the model to check the results on a final test set data. It's important for users of any machine learning or deep learning algorithm to know the accuracy of the model on this final, independent test set, as it is the best estimation of how well the model will do on new data. In addition, it is very important to know the variation in the type of data that is used in the training, validation and independent test set. For example, if an algorithm is trained and validated to segment the liver on CT, and all training, validation and test datasets are CT scans of the abdomen, it is possible that the model will also find a "liver" to segment if presented with a head CT, since it never "learned" that there are some images without a liver.

Machine learning and deep learning algorithms are rapidly being integrated into our clinical workflows and as clinicians we must have an understanding about how these tools work and how to assess their accuracy. This will help us better evaluate and commission new artificial intelligence tools as they are being rolled out into our own clinics and it will help us identify cases in which these methods may not be appropriate. There are many available resources online to learn machine and deep learning in more detail. In addition, ASTRO, the Radiological Society of North America (RSNA) and the American Association of Physicists in Medicine (AAPM) have devoted special sessions at their annual meetings with relevant information to our field. Many of these sessions are video recorded and available through the organizations' websites. We encourage all readers to use these resources as they touch on specific subjects in more detail.

This is an exciting time for our field as we see a new wave of technological advances reaching every aspect of what we do in the clinic. As we move forward, we should welcome these advances but remain cautious as any undetected mistakes by these novel predictive tools could have significant impact on patient care and safety.

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Dr. Carlos E. Cardenas

Dr. Kristy K. Brock

FROM SCIENCE FICTION TO REALITY:

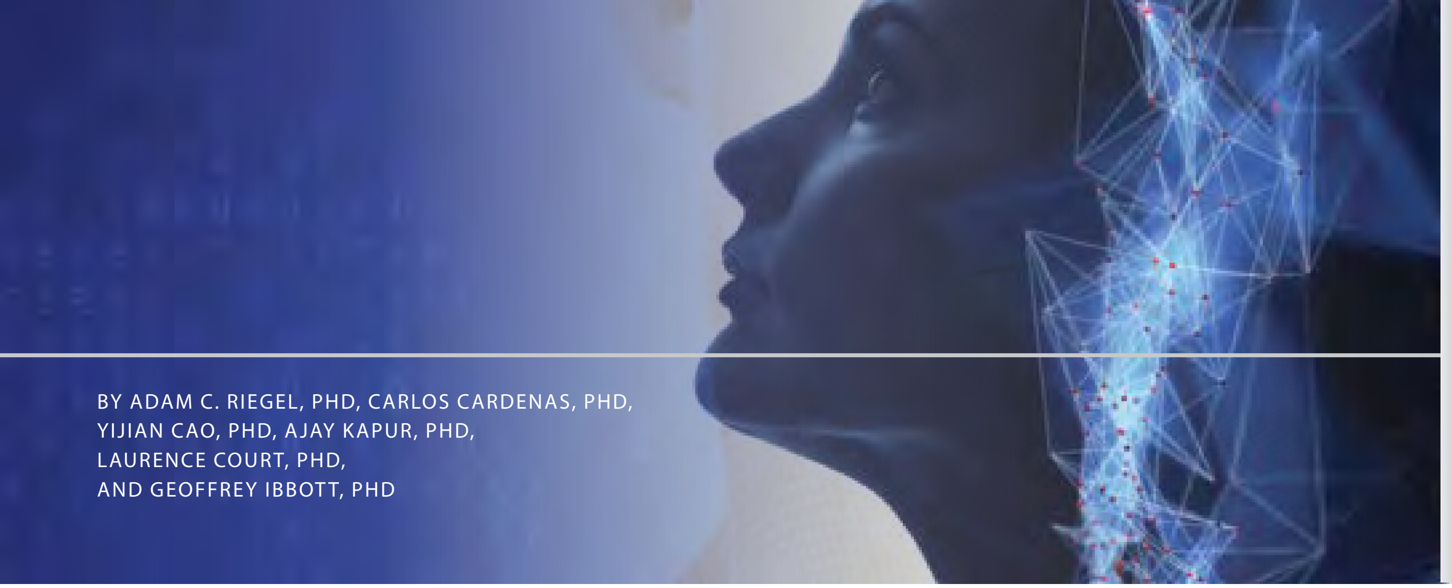
THE NASCENT RISE OF AI IN RADIATION ONCOLOGY PHYSICS

ARTIFICIAL INTELLIGENCE (AI) IS A CONCEPT THAT, UNTIL RECENTLY, was the province of science fiction, a technology that promised human-like robots and conversational computers. Although the wildest dreams of science fiction writers have not yet been realized, we are moving rapidly toward harnessing AI in a variety of medical fields. The technologically-intense nature of radiation oncology makes it an ideal discipline to pioneer AI technology for other potential applications in medicine. Through advances in machine learning (ML) and deep learning, commercial products are already available for tissue segmentation, knowledge-based treatment planning, dose optimization and plan review. The purpose of this article is to explore the present and discuss the future of these technologies.

Tissue segmentation can be split into two categories: normal tissue delineation and target delineation. The former category was one of the earliest applications of AI in radiation oncology, utilizing classic image processing and segmentation techniques such as region-growing algorithms and gradient-based segmentation. Normal tissue contouring is the lowest hanging fruit and will most likely be mastered first. Currently, most commercial treatment planning software includes some atlas-based segmentation algorithm which utilizes a library of prior contours from which the algorithm can pull likely matches to the current case. Though widely available, these atlas-based algorithms lack robustness; they work very well in some cases but not in others. This shortcoming may be overcome soon, though, with applications of deep learning algorithms, a specialized case of ML that leverages large amounts of unstructured data to provide a more robust algorithm.

Target delineation is a trickier problem than normal tissue segmentation. By definition, the target anatomy is abnormal and highly patient-specific, which makes atlas-based methods less effective. In addition to gross tumor, radiotherapy targets often include prophylactic regions such as nodal chains that do not display any discernible disease on some imaging modalities like CT. These regions are often treated at multiple dose levels that require discretion to separate high-risk and low-risk areas. Again, deep learning algorithms may assist in this area, but target delineation requires much more discretion by the attending physician, which both clouds the data pool of previous cases from which the algorithm is learning and may create conflicts with the physician treating the current patient. Though advances in radiomics (the ability to identify disease in diagnostic radiology) and multi-modality segmentation (including additional imaging modalities such as MR and PET) may hone target delineation algorithms, it is unlikely that the role of the radiation oncologist will diminish in the near term, as substantial judgment in target definition is still required. These algorithms will most likely supplement, not replace, physician discretion.

Artificial intelligence has also been applied to the next step in the treatment planning process: plan design and optimization. Plan quality in treatment planning is very dependent on the individual planner. Knowledge-based treatment planning extrapolates the achievable dosimetry of the current plan from a regression model derived from the structure geometry and previously achieved dosimetry in a library of clinical treatment plans. Already commercially available, some algorithms also provide parameter recommendations such as gantry and collimator angles, as well as intensity-modulation optimization goals and weighting. Initial experience with knowledge-based planning has yielded promising results, including increased plan homogeneity across multiple planners and decreased planning time, but, like automated normal tissue contouring, the results vary with treatment site and technique. Furthermore, there



BY ADAM C. RIEGEL, PHD, CARLOS CARDENAS, PHD,
YIJIAN CAO, PHD, AJAY KAPUR, PHD,
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AND GEOFFREY IBBOTT, PHD

is concern that automated planning techniques like knowledge-based planning may increase the disconnect between physicians, physicists, dosimetrists and the technology that is generating the plans. This could lead to a lack of understanding of what's going on "under the hood" and lax oversight of plan results. If applied correctly, however, AI and ML with a high-quality treatment plan database, appropriately sophisticated models and ample transparency between vendors and the professional community have the potential to substantially increase plan quality and homogeneity among academic and community centers. Furthermore, there is a potential for automating more aspects of the treatment planning process, which may have applications in community centers without access to comprehensive training.

Plan review is another venue for AI and ML. Development of quality assurance tools in verifying plan accuracy and deliverability are one potential application. For example, one could characterize the variability of individual dosimetric parameters versus the history of plans for a similar diagnosis. Comparing planning parameters, such as number of monitor units, number of beams or leaf positions, to the history of plans could help identify and investigate outliers to ensure deliverability of the plan. Modeling patient-specific, intensity-modulated radiation therapy quality assurance may yield targeted cases that are at risk for failure, thereby reducing the measurement workload in the department. Ultimately, linking treatment plan quality with specific clinical endpoints such as local control, disease-free survival, toxicity and quality of life for specific disease sites, may aid in the generation of predictive models of treatment efficacy that could play a role in physician decision support.

In conclusion, artificial intelligence is no longer science fiction: It is science coming to a clinic near you. Though initial applications of artificial intelligence and machine learning have yielded limited success at this early stage, the potential for these technologies to improve standardization and increase quality of care across the community is tremendous.

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Artificial Intelligence in Patient Care:

Promises and Pitfalls

BY SEWIT TECKIE, MD

THE CLINICAL PRACTICE OF MEDICINE TODAY IS COMPLEX AND RAPIDLY ADVANCING, with both satisfactory and unsatisfactory experiences among patients and clinicians alike. Artificial Intelligence (AI)-driven tools are attempting to ease the burdens and shortcomings of modern clinical practice, for both clinicians and patients. While clinical care AI is still in its early stages, it holds much promise. AI can reduce administrative burdens for clinicians in meaningful ways, connect clinicians and caregivers and improve clinical workflows. For patients, AI's potential is even greater, as it can inform and engage patients more effectively to achieve better health outcomes.

While clinician-facing AI may require complex software systems, most patient-facing AI use smartphones as the bridge to the patient. With 95% of Americans now owning a cellphone of some kind, and 77% owning a smartphone,[1] the ability to reach patients in any setting, not just in the clinic or hospital, is now possible.

Before we delve into real-world examples of health care AI, it would be useful to define the relevant concepts. "Digital health" is a catch-all term that refers to the use of digital technology in clinical aspects of health care. Digital health tools include patient-facing websites and applications, clinical decision support tools for practitioners and diagnostic aids. Many digital health tools do not need to use AI; instead, they are driven by algorithms, which are automated instructions, such as "If X, then Y." Machine learning (ML), on the other hand, is a set of algorithms that uses structured data in order to complete a task or detect a pattern. One example of ML is credit card fraud detection technology, which uses structured data about your credit card use and determines if that behavior seems unusual. AI takes it a step further than ML: AI can use unstructured data to reach conclusions.

Clinician-directed AI

Clinician-directed AI is largely attempting to achieve four goals: extend care to virtual visits; provide clinical decision support (CDS); reduce administrative burden; and improve in-hospital communication. As other articles in this issue focus on CDS and outcome prediction, it will not be repeated here.

One exciting use of AI coming our way is in real-world evidence collection to assist clinicians in making treatment decisions. The term "real-world evidence" can be defined as a new model of evidence collection that uses real-world, often unstructured data and attempts to make sense of the data using AI. Health care technology tools are constantly collecting patient data. With AI advances, we can begin to categorize and make sense of this data to see patterns in care and generate hypotheses for future study and possible implementation into clinical practice. Real-world evidence AI is currently in development by private start-ups, the pharmaceutical industry, and national and international disease registries.

Patient-facing AI

Patient-facing AI is a rapidly developing field that is here to stay. AI's current use in the patient realm can be subdivided into three broad goals: reduce unnecessary face-to-face visits; improve patient education about treatment and health choices; and empower patients toward self-management.

1) **Virtual Health Assistants**
Virtual care delivery that leverages algorithms or AI has led to the proliferation of Virtual Health Assistants (VHAs). When physicians first meet new patients in clinic, we often deliver a wealth of information, including printed handouts, and expect patients to refer to that conversation and those materials for the remainder of their treatment and beyond into survivorship. VHAs are interfaces such as chatbots or voicebots (think Amazon's Alexa) that are designed with specific information in order to supplement the need for human interaction. AI enables the conversational element of VHAs. For example, chatbots are being used in clinical practice to check in with patients and collect their health data and symptoms in a variety of settings, including elderly care, disease management, medication adherence and patient triage. VHAs hold particular promise in improving patient access to areas of medicine with provider shortages, including primary care and mental health.

How are VHAs making a difference in clinical practice? Current selected use cases of chatbots include chronic disease management, such as diabetes, head and neck cancer radiation treatment management and follow up (a pilot study being conducted at my institution, Northwell Health, to be presented at ASTRO's Annual Meeting), cognitive behavior therapy for patients with depression and anxiety (studies conducted at Stanford and in Europe), and post-surgical management for joint replacements. In all these settings, patients interact with a chatbot or voicebot interface that acts as a bridge to their care team. When VHAs are integrated into clinical practice, patient input into the program can be seen remotely by clinicians, who can then choose to act on relevant data and potentially prevent adverse events including hospitalization, illness or even death.

As with any new clinical tool or program, we must prove utility, efficacy and value before integrating into routine clinical care. VHA-developers and clinicians will have to collaborate on feasibility and efficacy studies if we are to incorporate these tools into our everyday practices.

2) **Patient-reported Outcome (PRO) and Symptom Trackers**
PRO measurement has proven to be more useful than clinician report, especially in advanced cancer patients. As a result, government regulators have encouraged researchers to implement PROs as a standard part of all clinical trials.[2] Pharmaceutical and medical device companies are investing in and using PRO measurement tools via patient-facing apps and websites.[3] Current PRO measurement does not quite qualify as AI; however, it tends to use algorithmic workflows and branching logic to engage with patients and provide feedback, instead of machine-learning or true AI.

3) **Patient Preferences and Shared Decision-making**
Another emerging use of digital health and VHAs is the measurement of patient preferences and facilitation of shared decision-making. Much of this work has been done in academic and research settings. It will likely expand to the commercial world as the value of shared decision-making is understood.

Despite the promise of patient-facing AI, there are pitfalls that can limit wider adoption. First, patients may not trust the tech-enabled interface for interaction, although market research data has shown that many patients do not mind interacting with technology for their health care needs. Second, there can be high rates of "app fatigue" or ignoring of texts and notification that leads to high rates of tech abandonment. Lastly, programs must integrate seamlessly into clinical workflows in order to be useful and efficient for clinicians in busy practices.

Patients and clinicians alike know there are many shortcomings in our current delivery of health care. The system needs to adapt to modern times and move clinical care out of high-cost, low-access, cumbersome clinical settings to the patient's and clinician's fingertips. If done correctly, artificial intelligence has the potential to achieve these goals and improve the health care experience.

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MEDomics:

A FRAMEWORK FOR ARTIFICIAL INTELLIGENCE IN RADIATION ONCOLOGY

BY OLIVIER MORIN, PHD, WITH CONTRIBUTIONS FROM STEVE BRAUNSTEIN, MD, PHD, TIMOTHY SOLBERG, PHD, AND CATHERINE PARK, MD

EXPANSION OF SCIENTIFIC DATA IN CANCER HAS CREATED ENORMOUS OPPORTUNITY IN PERSONALIZING CHOICES FOR PATIENTS WITH CANCER. However, given that humans can process only about five to eight variables at any given time,[1,2,3] the amount of data challenges our ability to discern and direct the most appropriate treatment choices. Examples include the use of genetic panels to help screen patients for specific treatments or clinical trials. Furthermore, data from electronic health records (EHRs) have been shown to increase opportunities to enhance and optimize decision making. With the emergence of statistical learning, artificial intelligence oncology tasks such as workflow optimization, clinical trial eligibility detection and risk stratification can be developed to provide decision support using historical data.[4,5] Fewer than 3% of cancer patients enroll in clinical trials, the gold standard of testing medical hypotheses.[6,7,8] Better utilization of digital health records will enable us to significantly expand the learning pool while simultaneously reducing confounding factors such as selection bias.

Although predictive modeling using data from EHRs and medical images has the potential to drive personalized medicine and improve health care outcomes,[1,2,9,10] we face a number of challenges for the broad development of data science and artificial intelligence in the treatment of cancer.

Specifically, EHR data suffer from the following:

- **Poor standardization:** Inconsistent data storage and variability across hospitals.
- **Siloed structured and unstructured data:** Some medical information to EHR, images in Picture Archiving and Communication System (PACS), most radiation data in a separate Oncology Information System (OIS), and histopathology and molecular testing are often stored in different systems.
- **Incomplete patient treatment outcome records:** No improvement can be made if important pieces are not documented, organized and accessible.

Because of these challenges, current prognostic models are created with significant manual effort, often missing key information, leading to models that may not generalize well. Additionally, modern EHRs and OISs have no feedback mechanism present to learn from past experience and update for real-time changes in cancer management. EHR/OIS have become the attic of medical data.

We believe a change of paradigm in how medical data is managed and prepared for the development of powerful algorithms is needed to realize the potential for the digital era of medical care. Successful clinical implementation of statistical learning algorithms in oncology will depend on large, diverse and complete datasets to predict cancer treatment outcomes.

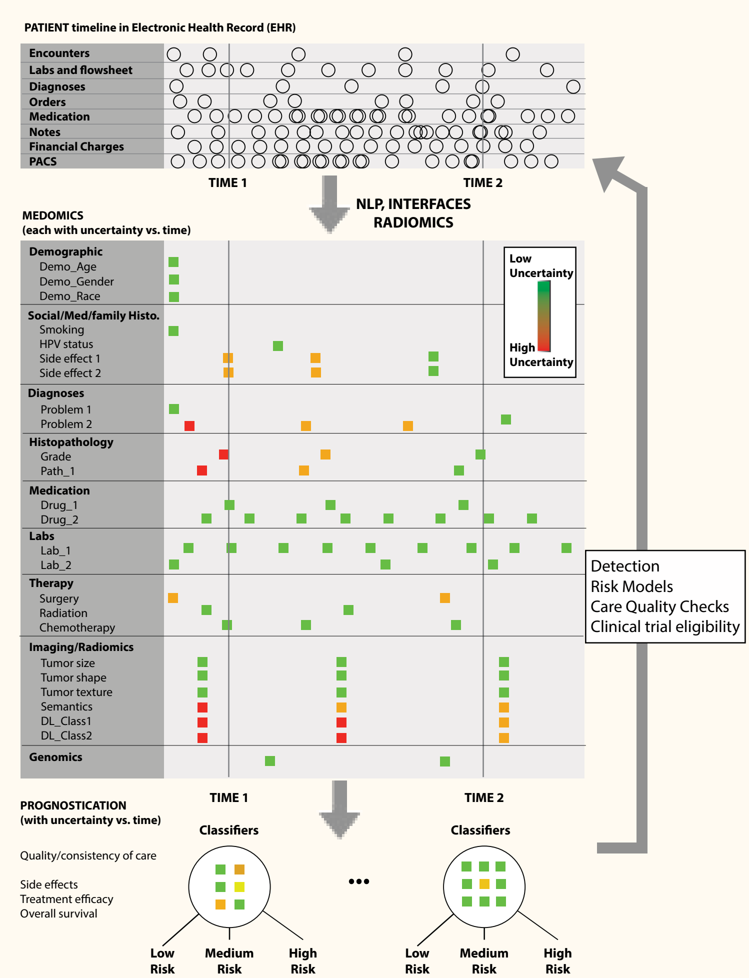

Figure 1. Patient MEDomic profile constructed for diverse prognostications.

Although standardization and ontologies are instrumental[11] in facilitating the global comprehension of a patient health profile, they are also not sufficient. Standardization involves medical processes and internal policy changes, which can be difficult and time consuming to implement. If a significantly large pool of comprehensive oncology training data were available, novel machine learning algorithms could be developed to complement and augment the efforts of standardization, leading to a wide range of global decision support tools for patients and physicians.

We are developing the MEDomics concept, presented in Figure 1, as a possible solution to these important problems. MEDomics are smart elements of medicine used for the creation of precision medicine tools, such as prediction models and dashboards to aid physicians. A MEDomics profile is a comprehensive temporal representation of the key medical factors that are important for optimal cancer treatment. Important parts of the MEDomics profile include medical and family history, diagnoses, laboratory tests, medications, therapies received, imaging, tumor size, lymph node involvement, molecular subtypes, side effects and treatment outcomes. MEDomics elements have a name, value (numerical or categorical), date and uncertainty.

Over the past three years, our department has developed a comprehensive cancer data pipeline to develop artificial intelligence applications in oncology. The resulting database consists of roughly 160,000 cancer patients treated at a single institution from January 2010 to December 2018.

Custom reports are generated in EHR/OIS and translated using PostgreSQL and HL7 Fast Healthcare Interoperability Resource (FHIR) format to ensure future integration with clinical practice. All new patients are automatically added to this retrospective database. In total, 17 medical data tables are generated in SQL to capture information on demographics, medical history, family history, social history, allergy, medication, problem list, imaging, surgery, pathology, radiation, encounters, labs, micro, procedures and notes — including over 15 million medical notes that can be used for training. Additionally, the University of California, San Francisco (UCSF) cancer registry tables are also integrated to these data elements to provide strong labels for MEDomics training and for prediction of patient outcomes.

We propose to use this comprehensive database to develop automatic text and image feature extraction pipelines. A complete oncology medical language model is being created using the millions of records available in our database. Once the language model is created, the group will address a wide range of text classification problems, such as exposures, molecular markers, staging information and binary outcomes at specific times from point of diagnosis. Our preliminary results indicate that cancer diagnosis associated with medical notes can be recovered with an accuracy of 97%. In selected cancer types, patient survival at five years from diagnosis can be predicted with an 85% accuracy using only the first year of medical notes. The high accuracy and transparency of inputs in prediction models further facilitate interpretability of results. MEDomics' long-term goal is to facilitate the creation of powerful prediction models and tools to assist physicians and other medical staff for the treatment of cancer.

MEDomics' advantages include that it is structured, diverse, portable and secure. Because of these features, MEDomics could also help facilitate the concept of distributed learning in which patient profiles stay within the institution while optimizing prediction models globally, thus ensuring patient data privacy.

Given the size of the database accumulated in the department, MEDomics will allow for the testing of new hypotheses from real-world data outside conventional clinical trials, such as the impact of new biomarkers, new imaging agents, molecular tests, integrative approaches and more.

Ultimately, we believe MEDomics will help create robust artificial intelligence applications, risk models and dashboards for more responsive EHRs and may serve as a crucial practical concept towards personalized medicine.

Olivier Morin, PhD, is the principal investigator of the MEDomics Medical Informatics Laboratory at the University of California, San Francisco. His group's efforts focus on developing data pipelines, feature extraction and AI algorithms for dynamic and optimal cancer care.

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Using AI for Clinical Decision Support through the Community in Oncology for RApid Learning (CORAL)

BY ANDRE DEKKER, PHD

PHYSICIANS, INCLUDING RADIATION ONCOLOGISTS, find it hard to predict expected outcomes of treatments in individual patients.[1] Given the biases and limits in human cognitive capacity in a multifactorial disease such as cancer, artificial intelligence (AI) might provide patients and physicians with more objective and validated clinical decision support.[2] For our field and patients to really benefit from the AI revolution seen in many other sectors, we need to come together and share data, methods and infrastructure to learn from each other's data.

The Community in Oncology for RApid Learning (CORAL) aims to leverage existing initiatives to share routine clinical cancer data and use AI methods to gain new knowledge from the data. This community consists of more than 35 cancer centers from all continents and uses a unique distributed learning infrastructure.[3]

The metaphor for the CORAL infrastructure is the "Personal Health Train." Data are made Findable, Accessible, Interoperable and Reusable (FAIR)[4] and put into FAIR data "stations" inside the cancer center. Then questions ("trains"), such as learning an AI for predicting survival in lung cancer patients, are sent to each cancer center and their data station rather than moving the actual data. These trains are tightly secured, monitored and controlled by the "track."

The Personal Health Train infrastructure allows learning from data in a privacy-preserving manner and under full control of the cancer center. CORAL has shown to scale toward multiple countries and thousands of patients and, for that, it received the ESTRO Varian award in 2019. ASTRO initiatives, such as the Minimal Data Element guideline, as well as AAPM-driven and ESTRO/ASTRO-supported standardization and ontology efforts are expected to greatly synergize the CORAL effort.

In our experience, efforts to make sure we note the same data elements in the same way as well as establishing an infrastructure to use each other's FAIR data without losing control or breaching privacy are crucial elements to advance the field and are a breakthrough to address ethical, legal and societal concerns. Challenges do exist — including varying data quality and biases between countries and institutions in the ways patients are treated and data is recorded — but by establishing trust, building a community like CORAL and providing access to our data, these challenges can be, and are being, addressed.

In the near future, these joint efforts will make it possible to ask radiotherapy driven questions on a global scale, leveraging the long-standing willingness for collaboration and openness that exists in our community. The ultimate goal is to create value from big data in a responsible and equitable manner and develop and use AI to provide value through clinical decision support for our cancer patients.

Andre Dekker, PhD, is a professor of Clinical Data Science and a board certified medical physicist at MAASTRO Clinic at Netherlands' Maastricht University.

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How We Use Watson for Oncology in Everyday Practice

BY MARISA KOLLMEIER, MD

WATSON FOR ONCOLOGY (WFO) IS A CLINICAL DECISION SUPPORT TOOL designed via a cross-institutional collaboration between Memorial Sloan Kettering (MSK) and IBM for the purpose of providing clinicians on a global scale with treatment recommendations derived by harnessing the evidence-based expertise of MSK's multidisciplinary disease management teams. The initiative at MSK began in 2012 with breast, lung and colorectal cancers and has since expanded to include many other malignancies. Currently, the program is being utilized in several countries, with the greatest concentration of users in China, India and Korea.

When we first set out to develop the tool for use in genitourinary cancers, it was very clear that a multidimensional approach would be required to provide the most useful and balanced decision-making support. As such, we gathered physician representatives from radiation oncology, medical oncology and surgery to collate clinical trial data, physician experience, programmatic standards and national guideline standard algorithms (e.g., National Comprehensive Cancer Network and subspecialty guidelines). Clinical disease states were scrutinized for essential prognostic factors, which would impact decision-making.

For the prostate cancer module, prognostic elements beyond Gleason score — such as the percentage of core positivity, high-risk pathologic details, and/or prostate MRI findings, which could impact preferred radiotherapeutic regimens — were integrated into input data. Additionally, integration of a patient's relevant history, including prior prostate interventions, comorbidities and baseline urinary symptoms could be considered when generating output recommendations.

For the bladder cancer module, integration of prior treatment, comorbidities and relevant lab values were incorporated into the input data that will impact treatment recommendations. Treatment regimens are ranked where the most favored choices of the MSK disease management team and most supported by the available medical evidence appear as "Recommended," and less favored although reasonable approaches appear as "For consideration." Treatments that would not be recommended are also delineated in the output.

Providing clinicians with immediate and more personalized treatment recommendations for individual patients has clear advantages. First, this tool provides a more granular approach than is allowed using consensus-panel generated guidelines. Unique patient scenarios and feedback during data input provide context to the user based on curated key attributes. Second, as the volume of clinical research inundates oncologists with new information, it becomes increasingly difficult for physicians in community-based practices to analyze the depth of information available across each oncologic subspecialty. Tools such as Watson for Oncology provide a resource to communicate information to patients without direct access to a tertiary cancer center. By providing a range of potential choices in treatment, the tool allows flexibility; centers with more limited resources can optimize what is available or guide community-based practices as to which preferred modalities to bolster. One example of such a potential is strengthening of community-based brachytherapy programs.

Designing this tool was a challenge. Determining and agreeing upon key attributes was difficult, particularly in settings where these are more nuanced or where controversy exists. Once the attributes were set, we set out to dissect and rank recommendations in various patient scenarios during regular meetings — imagine your busiest and most challenging day at the clinic condensed into 90 minutes!

While we aimed to be inclusive of and consistent with information from published guidelines, we were not bound by this structure. All recommendations were considered as if the patient were an MSK patient; however, unlike a real-life clinic, subtleties such as patient quality of life goals and psychosocial factors could not be incorporated, although clearly elemental in decision-making. As such, we do not intend Watson for Oncology to replace the doctor-patient relationship, which is so critical to optimal patient care, but rather to serve as another tool that can assist oncologists as they care for their patients.

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**Dr. Kollmeier is an employee of MSK. MSK has an institutional collaboration agreement with IBM for Watson for Oncology and receives royalties from IBM.*

Preparing for the Future

Hype or Reality: The Residents' Perspective

BY JULIAN HONG, MD, MS @JULIAN_HONG, AND JOHN KANG, MD, PHD @DRJOHNKANG

THIS IS AN EXCITING TIME FOR A RADIATION ONCOLOGY RESIDENT TO BE INTERESTED IN ARTIFICIAL INTELLIGENCE (AI). The continued integration of computational tools and, more specifically, AI has created both enthusiasm and reservation across many fields — medicine not excepted — by advancing the ability to analyze the increasingly large amounts of data collected.

As AI becomes more broadly adopted in clinical settings, physicians will need to be both involved in and comfortable with its development and implementation. AI will touch a variety of domains: physics and imaging, biology, clinical informatics and emerging data, such as wearables and virtual assistants. A number of examples have demonstrated the importance of a clinical understanding of data used for training AI. AI can offer strength in both assessing complex causal relationships and improving the accuracy of predictions, but domain knowledge will be needed to identify both appropriate problems and potential shortcomings of AI.

In one classic clinical example, a high-performing model determined that asthma was favorable for survival from pneumonia when, in fact, asthma was a surrogate for improved access to health care.[1] In an imaging scenario, AI models trained on chest X-rays used watermarks (such as "PORTABLE") to diagnose pneumonia.[2] In essence, the models exploited confounding variables to improve predictive performance, which may impact real-world generalizability.

Below, we provide a few perspectives for trainees to separate hype from reality regarding medical AI.

AI will not replace humans, but understanding the strengths and limitations will become important for clinical practice.

A number of commercial products will soon reach clinics, spanning diagnosis, risk stratification and treatment planning. Clinicians will require a baseline understanding of their functions and limitations. In some cases, their contribution will be transparent, such as in treatment planning, where automatic segmentation or treatment plans are verifiable. In others, such as risk stratification, being cognizant about how the model was validated will be important. AI could serve in an "augmented intelligence" role, and studies have suggested that physicians with AI assistance exceed the performance of either alone. Unlike other technical advances, AI decision tools will require close physician involvement.

There are a variety of domains where computational techniques may be relevant, and education in these domains is just as important.

AI tools, like traditional statistical methods, are leveraged in a variety of areas where domain knowledge and understanding of data sources are critical. Bioinformatics has leveraged AI tools for some time but still demands exploration of mechanistic understanding. Analogs of understanding source data are profound in imaging analytics (variation in scanner models) and clinical informatics (informative data incompleteness or systematic data variations).

Acknowledging this need, the new Accreditation Council for Graduate Medical Education draft curriculum for radiation oncology mandates that intradepartmental conferences address a number of topics, among them, clinical informatics. The Agency for Healthcare Research and Quality recommends that accrediting bodies require training of health care workers to achieve levels of competency in health informatics.[3] A 2017 ASTRO survey revealed that 76% of trainees believed bioinformatics training could "definitely or probably" advance their career, and 84% were able to identify a relevant project.[4] Education and collaboration opportunities include the Practical Big Data Workshop, the Radiation Oncology Education Collaborative Study Group, and ad hoc workshops by the National Institutes of Health and National Cancer Institute.

Physicians should play a role in development of AI tools.

Clinicians have valuable insight for quantitative collaborators. In order for AI to be useful, developers will need guidance regarding the clinical objective, the state of the data when a model is run (imperative to be reflected in training data) and interventional strategies. For instance, a model to predict acute events is useful only if it provides sufficient lead time for an effective intervention. Additionally, clinicians understand the workflow to integrate tools into daily operations.

Not yet "intelligence."

Equally important, clinicians should be thoughtful of the questions they pursue because — despite its name — AI has not reached human intelligence in generating knowledge and causal reasoning. Computer scientists largely view AI as being able to find high-dimensional correlations. It can be tempting (and easy) to blindly run prediction models without considering objectives and context, but this is prone to false results from overfitting or sources of bias, increasing the burden of validation. We suggest defining the right model for the right data for the right problem. Deep learning is an AI framework that excels in finding complex patterns in unstructured data, such as imaging and natural language. However, deep learning has less interpretability, causing problems such as in the previous X-ray example. In a number of situations, more interpretable techniques may be equally accurate (if not more so). High quality validation and continuous quality assurance will be critical.

AI will play a growing role in medicine and specifically in radiation oncology. Several opportunities for engagement and education are available where one can contribute existing domain knowledge. In the coming years, it will be important for the field to be engaged and thoughtful to ensure that these tools offer the best care to our patients.

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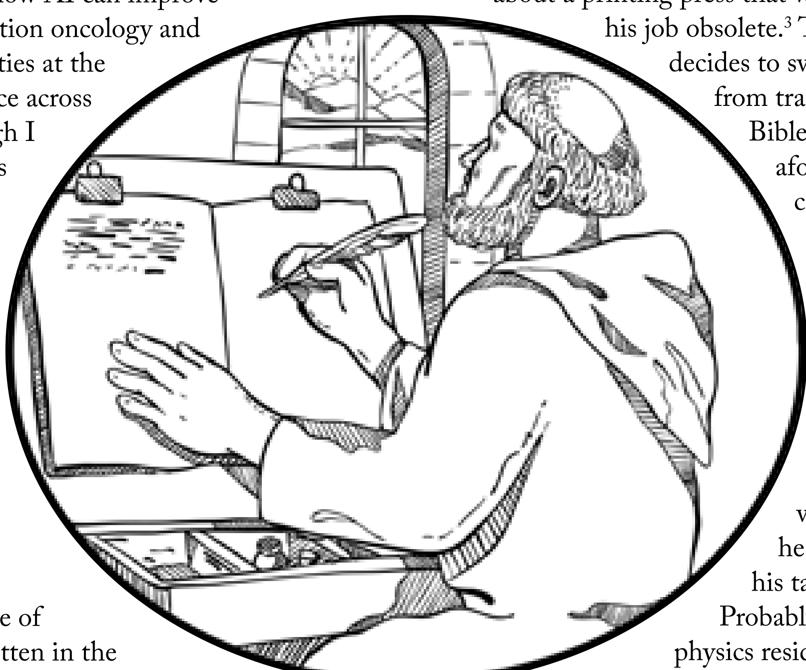
Julian Hong, MD, MS, is a radiation oncology resident at Duke University and will be joining the faculty at UCSF in Fall 2019. His research interest is in the development and deployment of clinically actionable computational tools, combining clinical and imaging informatics, natural language processing and machine learning.

John Kang, MD, PhD, is a radiation oncology resident at the University of Rochester (2020 graduate) with research interests at the intersection of machine learning, genomics, education and interpretability. He hopes to help clinicians better understand the ins and outs of AI applications in oncology.

FROM THE SCRIPTORIUM TO THE GPU AND BEYOND

BY BRIAN D. KAVANAGH, MD, MPH, FASTRO

THIS ISSUE OF *ASTRONEWS* CHALLENGES US to consider the potential impact of artificial intelligence (AI) in all of its protean forms on the field of radiation oncology. The authors of the individual pieces offer thoughtful insights on how AI can improve technology within radiation oncology and yield broader opportunities at the patient-provider interface across all of medicine. Although I have commented on this topic once before,[1] here is a quick backward and forward look with a more kaleidoscopic lens.



The use of computers to think faster for us is not new in radiation oncology

Consider the process of IMRT planning and one of the countless papers written in the past 20 years addressing ways to improve computational speed. A team from San Diego compares the performance of a graphics processing unit (GPU) to conventional computer processors.[2] In the test case of a nine field IMRT plan involving 5x5mm beamlets calculated over voxels measuring 2.5x2.5x2.5mm, each optimization iteration would include the summation of 43,266,357 individual dose contributions from the 6,453 beamlets. Thus, for 50 iterations, over 216,000,000 dose inputs would need to be determined and summed.

Suppose a Benedictine monk named Dom Pierre Perignon in a scriptorium in 1438 AD heard rumors about a printing press that was about to make his job obsolete.[3] The visionary Pierre decides to switch his attention from transcribing the Bible to performing the aforementioned set of calculations for 10 hours a day, six days a week. If each beamlet input to each voxel is checked in three seconds using a lookup table, and Pierre adds up 6,453 numbers in sixty seconds (he is good with an abacus), then he would be completing his task right about now. Probably a kindly medical physics resident named Taylor would be willing to do the plan quality assurance for him as an act of mercy.[4] The GPU did the calculations in less than three seconds.

How AI impacts our value proposition remains to be seen

A business might articulate a “value proposition” that describes the benefits its customers enjoy and how their products are better than the competition’s. There has been discussion of a putative value proposition for radiation oncology, but primarily the focus has been on the issue of characterizing value per se using the now-familiar rubric of quality divided by costs.[5]

The prospect of alternative payment models in radiation oncology is looming on the horizon. Exactly how those version 1.0 efforts play out remains to be seen. In principle, AI in some form or another (auto-contouring target volumes, auto-selection from a library of plans for a given indication, etc.) might reduce the person hours required for certain tasks, thus lowering expenditures, thus rendering it possible to provide services for bundled reimbursement rates that are lower than comparator historical precedents.

But what if the health care environment evolves further to something more closely resembling a free market? Currently, purchasers of radiation oncology services are faceless, monolithic federal and private payers. Imagine, though, that we arrive at a place where a patient diagnosed with cancer receives a monthly stipend to cover expenses, though he or she can still choose to spend a bit extra out of pocket for deluxe services, perceived as adding value.

Imagine in that exotic futurescape, would a radiation therapy center with the RoboRadThink package of mistake-free auto-contouring and treatment planning, entirely void of the risk of human error, be seen by a patient or referring physician as more attractive than the competition across the street? Because the competition has the Radomatic AdaptoKnife, an integrated planning/delivery system in which the patient is never touched by human hands and simply walks into a white room with an International Klein Blue rectangular canvas on one wall — vintage dreampop music in the background — and lies down on a padded table before sliding into and out of a high-gloss plastic cylinder. Au Revoir Simone finish playing "Shadows" just as the entire image guidance/plan adjustment/delivery is completed. The University of Colorado will be buying both systems to hedge their bets.[6]

Our future hinges on the patient-provider relationship and relevance of the modality itself

Patients will always appreciate personal interactions of the type that never goes out of style. As AI enhances the performance capacity of radiation treatment systems, replacing various technical tasks, it will be even more important for our entire clinic teams to perform their patient-facing roles at the highest level. Physicians in particular will need a deep fund of cancer knowledge and correspondingly strong levels of empathy and emotional intelligence.

Ultimately, the overall longevity and profile of radiation oncology as a field will not be driven by how many silicon chips we use but, rather whether what we do for our patients is considered by them to be helpful and whether they are treated with compassion. This latter condition includes the ethical and scientifically valid use of radiotherapy within multi-disciplinary cancer care. Figuring out how and when best to apply our favorite modality of therapy enough, but not excessively, in the care of patients is a challenge that will call for real intelligence for generations to come.

International Klein Blue rectangular canvas; IKB 191, painted in 1962 by Yves Klein.

Brian Kavanagh, MD, MPH, is a professor and chair of radiation oncology at the University of Colorado School of Medicine and immediate past chair of the ASTRO Board of Directors.

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3. No, not the guy who invented champagne. True, he was a Benedictine monk, but he lived in France in the 17th century. Our Pierre here is a fictional character.
4. Taylor Patton is a real-life medical physics resident, and I know him to be a kind person.
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6. We have returned to the world of science fiction. The RoboRadThink and Radomatix AdaptoKnife are not yet trademarked, FDA-approved devices. And I don't think my own university could afford both, anyway.

From the ABR

BY PAUL E. WALLNER, DO, AND ANTHONY M. GERDEMAN, PHD

ARTIFICIAL INTELLIGENCE AND BEYOND: ROLE OF THE AMERICAN BOARD OF RADIOLOGY

AS DESCRIBED IN SEVERAL ARTICLES IN THIS EDITION, there is widespread interest and research into the potential utilization of the ever increasing relational and computational abilities of computers to aid in all aspects of medical decision-making. These rapidly emerging disciplines, such as artificial intelligence (AI) — sometimes called machine intelligence (MI), informatics and artificial neural networks (ANN), will become increasingly important in medicine, including radiation oncology (RO).

Even with minimal success, the near-term implications of these advances are significant, and the potential for long-term changes in the practice of medicine are astounding. Obvious questions that arise in the face of these novel developments are how medical specialties will teach their trainees and practicing members the requisite skills to understand and utilize the advances, and to what extent they will be assessed by member boards of the American Board of Medical Specialties (ABMS) of which the American Board of Radiology (ABR) is one.

The Accreditation Council for Graduate Medical Education (ACGME) Radiation Oncology Review Committee (RO RC) is responsible for promulgating requirements for graduate medical education in radiation oncology. Many of the requirements for training are left purposefully vague and open-ended. The current requirements for the emerging decision-support (or decision-making) systems noted above are such. Under its core competency section of Practice-based Learning and Improvement, the RO RC includes a requirement for training in "using information technology to optimize learning."[1] This lack of specificity provides little guidance to the ABR in its exam development process.

Medical informatics has long been associated with the practice of RO. The specialty was an early adopter of electronic health records (EHRs) now effectively universal in health care, and record and verify (R & V) software was in widespread use in RO as early as the 1970s. In keeping with the ACGME requirements, a small number of questions related to medical informatics will soon be added to the ABR initial certification (IC) qualifying (computer-based) exams and the ABR maintenance of certification (MOC) online longitudinal assessment (OLA) tool to roll out for RO in 2020. The material to be covered will be described in detail in the web-based study guides that are now in the process of being updated to include the new content.

The ABR does not anticipate inclusion of material related to AI, MI or ANN in assessment instrument content in the near future, but other potential uses of the processes for internal ABR use are apparent. Data analysis and management enabled by these new tools may be adaptable to development of new IC and MOC questions. For example, a future test development system may be capable of producing new, high-quality exam questions by supplying the system with enough pre-existing, high-quality content. With enough input, the intelligent system could conceivably learn both the known and unknown rules that embody high-quality questions and produce new questions for exams based on those learned rules. In addition, continuous updating of existing questions, dynamic updating of referenced sources, assessment instrument grading and performance analysis, more detailed reporting of candidate and diplomate performance and more comprehensive candidate feedback analysis may be possible. For instance, when the ABR is provided with hundreds of candidate comments on hundreds of exam questions, an intelligent system may be the most efficient method of condensing the comments into summaries that could be useful for future question development. Along with its stakeholder organizations, trainees and diplomates, the ABR will be watching these developments carefully.

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Encouraging FAIR Data in ASTRO Journals

A perspective on data discoverability for humans and machines

BY DAWIT TEGBARU, MANAGING EDITOR, *PRACTICAL RADIATION ONCOLOGY* AND *ADVANCES IN RADIATION ONCOLOGY*

"We must continue to embrace and invest in data interoperability standards, data sharing, data equity, education and training, research funding, and impact studies. Otherwise, future AI tools could be constrained in scope and value, and we could be vulnerable to the dictates of external stakeholders, with unanticipated consequences."
— *The Future of Artificial Intelligence in Radiation Oncology*[1]

ARTIFICIAL INTELLIGENCE (AI) SHOWS PROMISE FOR REVOLUTIONIZING HEALTH CARE. However, the principles of FAIR (findable, accessible, interoperable, reusable) data should not be overlooked. FAIR data underpins the successful deployment of AI — it enables practical applications, by making it easy for machines and individuals to use data.

Imagine a user-friendly web tool that provides survival estimates within seconds. With immediate access to multi-institutional clinical data, physicians simply select the patient, tumor and treatment variables they want to test and, after a few clicks, a learned model is generated. This is already on the horizon in the Distributed Rapid Learning Dashboard being developed by the Community of Oncology RApid Learning (CORAL) and Varian Medical Systems.[2] For proof of concept, CORAL launched their 20K challenge to machine learn a predictive model using data from 20,000 non-small cell lung cancer (NSLC) patients from several health care providers spanning beyond five countries.[3] In just two-and-a-half months, they gathered data on more than 37,000 NSLC patients and, shortly thereafter reported a successful distributed learning system that generated survival prediction models with good accuracy. For the project to be viable, participating institutions were required to conform to FAIR data principles. [2-3] (See page 18 for more on CORAL.)

Data Sharing Landscape in Scientific Publishing

ASTRO publishes three prestigious peer reviewed journals that report the latest radiation oncology research affecting its members and society at large.[4] The *International Journal of Radiation Oncology • Biology • Physics*, also known as the Red Journal, focuses on cutting-edge prospective clinical research. *Practical Radiation Oncology*, ASTRO's practice-based journal, publishes research focusing on patient safety, quality improvement and clinical practice statements. *Advances in Radiation Oncology*, ASTRO's open-access journal, focuses on original clinical research and multidisciplinary studies, such as disparities in care, immunotherapy, digital health care innovations and clinical investigations of data sciences that may change future practices of radiation oncology.

FAIR data sharing initiatives are an increasingly discussed topic among funders, patient advocates, researchers, publishers and societies seeking to advance their disciplines more efficiently and inclusively.[5] The propagation of editorial policies that discuss data sharing signal it as a normative practice necessary for evaluating and building upon scientific research (Table 1). Indeed, conversations throughout the scholarly publishing community have evolved from declaring crude data sharing policies toward support of FAIR data.[6-9] Two major impetuses for the shifting landscape are researchers' ability to analyze big data and society's recognition of open science and research integrity.

Journal	Data Sharing Policy
The New England Journal of Medicine	Data sharing statement required for clinical trial results per ICMJE.
The Lancet	Data sharing statement required for clinical trials results, encouraged for non-clinical trial research reports.
Cell	Data deposition in public repository mandatory for certain types (e.g., protein, DNA/RNA sequences); encouraged for other research data types.
Proceedings of the National Academy of Sciences	Data sharing statement required for all submitted research.
JAMA	Data sharing statement required for clinical trial results per ICMJE.

Table 1. Top five ranked medical journals according to Google Scholar and their data sharing policies.

Researcher Survey on Data Sharing

In 2018, academic publishing company Springer Nature published one of the largest surveys on data sharing with over 7,700 researchers responding. Their survey found widespread data sharing associated with publications and a desire from researchers to make their data discoverable.[10] The survey also reaffirmed findings about data sharing attitudes and challenges that were published in The State of Open Data 2017 report from Digital Science.[11]

Springer Nature's anonymized survey dataset has been made publicly available under a Creative Commons license[10] and was further analyzed to highlight data sharing norms and challenges, particularly in the medical sciences.

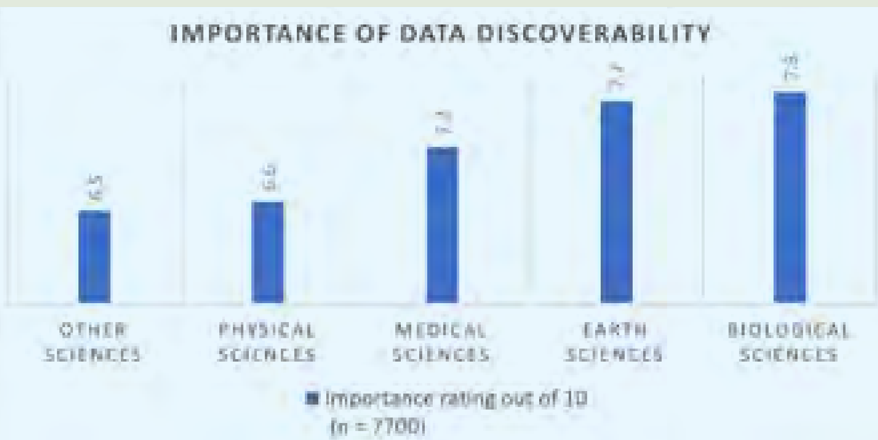
Out of 7,700 researchers surveyed, 2,670 said they perform investigations that generate data related to human research participants. When asked about the importance of data discoverability, researchers representing the medical sciences reported an average rating of 7.2 (Figure 1).

When medical science researchers were asked how their data were being shared, the majority (60%) suggested they share data through some medium (Figure 2).

When evaluating obstacles to data sharing, such as time, lack of knowledge and money, lack of knowledge (or awareness) emerged as the primary challenge for researchers in medical science (Figure 3).

Continued on following page

Figure 1. Data discoverability is rated most important to the biological sciences, followed by earth sciences, medical sciences, physical sciences and other.



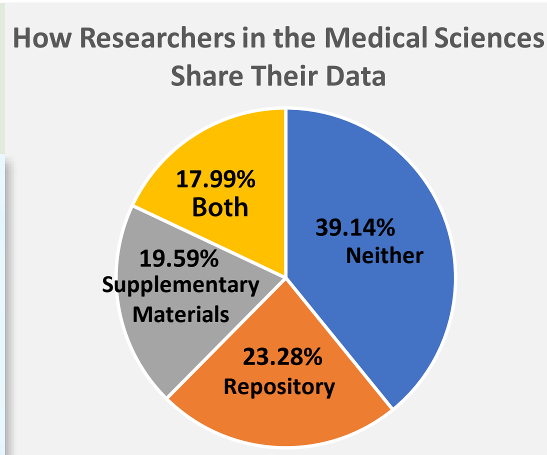
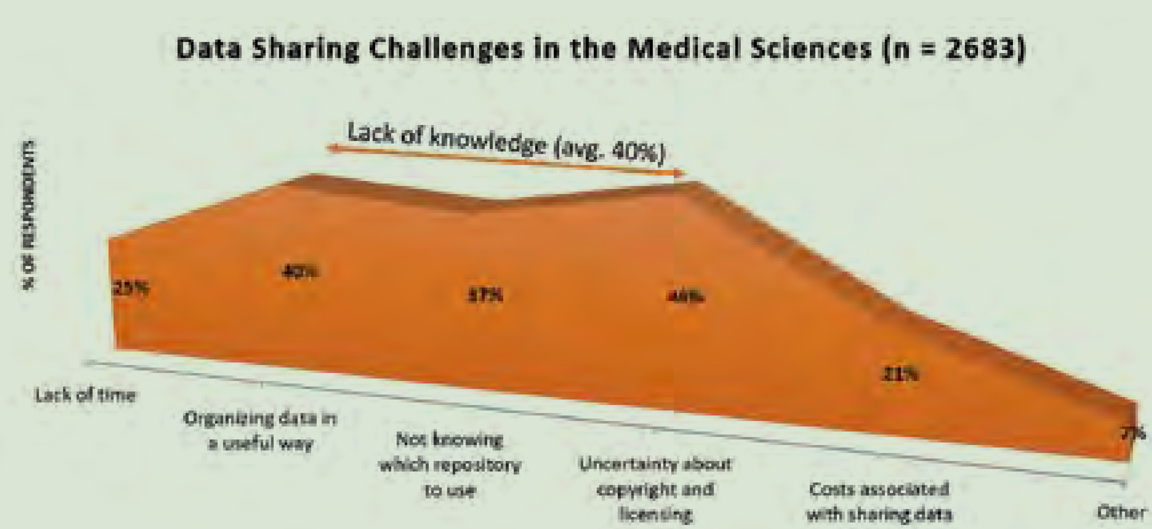


Figure 2. 60% of respondents in the medical sciences stated that they submitted data files through a repository, as supplementary materials or both. Repository (n = 624), supplementary materials (n = 525), both (n= 482), neither (n = 1049).

Figure 3. The highest proportion of researchers in the medical sciences reported lack of knowledge as an obstacle to sharing data. Uncertainties were attributed to organizing data, selecting a data repository, copyright and licensing. The "Other" 7% consisted of responses related to privacy and ethics issues with clinical data.



Encouraging FAIR Data in ASTRO Journals

ASTRO journals are committed to raising awareness of data sharing best practices. Following health information privacy standards[12] and scholarly publishing community guidance around data deposition and citation,[13] ASTRO produced a data sharing policy and best practice guide for authors submitting to its journals.

ASTRO's data sharing policy: *Authors should indicate, in data availability statements, if the data are being shared and, if so, how the data may be accessed.* Data availability statements will be published alongside articles beginning in January 2020.

To facilitate broad dissemination and increased awareness, a data sharing best practices article has been submitted for publication to *Advances in Radiation Oncology*. A self-assessment CME accredited activity based on the article will also be made available through ASTRO Academy, free to members and non-members. Some of the topics covered include choosing a data repository and how to write a data availability statement.

ASTRO journals encourage researchers to incorporate FAIR data into the earliest stages of an investigation, as doing so advances scientific discovery and increases opportunities for collaboration.

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How will AI/ML research impact clinical practice and change patient care in radiation oncology?

BY THOMAS PURDIE, PHD, MCCPM

ARTIFICIAL INTELLIGENCE (AI) AND MACHINE LEARNING (ML) ARE PROMISING to dramatically disrupt how we work and care for our patients.

As in other fields of medicine, AI has some clear use cases, and radiation oncology is no exception. Two main areas of use could be summarized as 1) extracting insights from data that would not otherwise be possible (outcomes prediction and treatment selection using radiomics methods), and 2) automation to simplify and standardize tasks (automated image segmentation). These are also the areas getting the most attention from the radiation oncology research community, and we have seen good representation from these areas in the published literature.

The more recent popularity in ML is not new and is based on research from decades ago but has become more relevant to our field with increases in computing power, the availability of vast data, and access to ML frameworks leveraging state-of-the-art open source algorithms. The availability of ML algorithms is a game changer, as it has made it possible for researchers to explore problems using tools with unprecedented power that are more specialized for the tasks in radiation oncology.

However, there are many implications in trying to transition AI technology from research to clinical practice which must be thoughtfully considered both in terms of what AI can actually achieve to improve patient care, and also in terms of the limitations of AI. From a research perspective, the current focus in AI/ML in radiation oncology is demonstrating value for using AI/ML under a specific, limited scope, although for clinical implementation we will need to have a better understanding of what the algorithms we are using are actually telling us (or not telling us).

For example, just like we would need to be aware that an ML classifier trained on identifying cats and dogs in images will never be able to properly classify a giraffe, since it is not trained to know what a giraffe is, we must understand the limitations of the algorithms we are using and the data that was used to train these algorithms. We will then understand the biases in the data, which may or may not be desired, and understand where biases may exist that were not intended.

Similarly, when AI "fails," the output it provides is essential to the clinical end user of the technology. In our example above, an undesirable algorithm may say that the giraffe is either a dog or a cat (because that is all it knows about). A better algorithm may say that it cannot actually classify it, which solves one problem but is unsatisfying if the majority of responses from the classifier cannot classify it. The best we can expect would be to have the output as probabilities as to what the AI thinks the image is representing. In this way, we have a better understanding of what the algorithms are capable of, and in this case, understand that giraffes were never even considered in the prediction.

The next step is how well the model is generalizable. That is, how tuned is the algorithm to get good results for the data it has, and is it so well fitted to that data that it might not be able to provide insights into anything, even a small deviation, from this?

These considerations prompted the commissioner of the U.S. Food and Drug Administration (FDA) to detail the FDA's new initiatives in the digital health space, of which AI was a focus. The FDA has taken steps to develop a new, tailored framework for reviewing AI/ML-based software as a medical device (SaMD), and this is being facilitated through a discussion paper and request for feedback.

We will continue to examine the fundamental promises of AI/ML methods that can potentially provide the relevant recommendations on a per patient basis. Similarly, ML models codifying recommendations may be a future dissemination strategy for practicing clinicians to keep up with clinical advances and translate it to treating patients.

Thomas G. Purdie, PhD, is a medical physicist at Princess Margaret Cancer Centre and associate professor at the University of Toronto, in Toronto, Ontario, Canada. He serves as the AI editor for the Red Journal.

HIGHLIGHTS FROM *INTERNATIONAL JOURNAL OF RADIATION ONCOLOGY•BIOLOGY•PHYSICS*

March 15, 2019

Early Changes in Cardiovascular Biomarkers with Contemporary Thoracic Radiation Therapy for Breast Cancer, Lung Cancer and Lymphoma

Demissei et al.

The authors report results from a prospective longitudinal study of patients treated with thoracic radiation therapy. They measured the changes in conventional and newer cardiovascular biomarkers pre- and post-radiation and the relationship between biomarker levels and echocardiography-derived measures of cardiovascular function. The authors note that their findings suggest the newer PIGF and GDF-15 biomarkers may be helpful to predict for subclinical cardiac toxicity.

Chest Wall Toxicity After Stereotactic Body Radiation Therapy: A Pooled Analysis of 57 Studies

Ma et al.

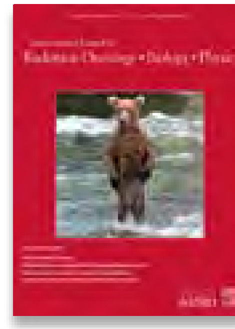
This meta-analysis examines the incidence of chest wall pain and rib fracture in patients who received SBRT for non-small cell lung cancer. The authors found that 11% of patients across all studies experienced some degree of chest wall pain and 6.3% experienced rib fracture. Female patients were more likely to experience chest wall toxicity, though the authors suggest considering factors identified in other studies, such as the distance from the tumor to the chest wall or the chest wall volume receiving equal or greater than 30 Gy.

April 1, 2019

Long-term Follow-up on NRG Oncology RTOG 0915 (NCCTG N0927): A Randomized Phase 2 Study Comparing Two Stereotactic Body Radiation Therapy Schedules for Medically Inoperable Patients with Stage I Peripheral Non-Small Cell Lung Cancer

Videtic et al.

This article provides updated results of a randomized phase 2 study comparing two different fractionation schemes; 34 Gy in one fraction and 48 Gy across four fractions. The authors found the arm receiving the 34 Gy in one fraction continued to experience less toxicity while the treatment shows similar efficacy. They note that median overall survival (OS) was comparable between the two arms at four years post-treatment, though at six years the 34 Gy arm showed 12% lower OS. OS was not the primary endpoint of the study, and this difference may be due to the low number of patients remaining in follow-up.



May 1, 2019

SABR in High-risk Prostate Cancer: Outcomes From 2 Prospective Clinical Trials With and Without Elective Nodal Irradiation

Alayed et al.

This article examines the outcomes of two phase 2 trials exploring the use of stereotactic ablative radiation therapy (SABR) for high-risk prostate cancer patients with or without elective nodal irradiation (ENI). The authors report that after 5.6 and 4.0 years of follow-up for the two studies, biochemical control rates for SABR appeared comparable to external beam radiation therapy with a brachytherapy boost. In one study, ENI was found to reduce the probability of biochemical failure without increasing toxicity. The authors conclude that the comparison generates interesting hypotheses, but phase 3 trials will be necessary to establish the use of SABR and ENI in high-risk prostate cancer treatment.

A Phase 2 Clinical Trial of SABR Followed by Immediate Vertebroplasty for Spine Metastases

Wardak et al.

These authors present a study comparing stereotactic ablative radiation therapy followed by vertebroplasty to a historical control of external beam radiation therapy for osseous spine metastases (RTOG 9714). The study primarily compares pain response at three months. In this study, 95% of patients experienced complete or partial pain response, indicating a significant improvement over the control, where only 51% experienced a complete or partial response. Measuring vertebroplasty effectiveness was limited by a change in the initial technique and low numbers of patients who underwent the procedure.

HIGHLIGHTS FROM *PRACTICAL RADIATION ONCOLOGY*

Articles in Press

Lessons Learned from Hurricane Maria in Puerto Rico: Practical Measures to Mitigate the Impact of a Catastrophic Natural Disaster on Radiation Oncology Patients

Gay et al.

This article addresses the impact of Hurricane Maria on patients receiving radiation therapy in Puerto Rico. The authors explain their PCOC (Prepare, Communicate, Operate, Compensate) plan and share the obstacles faced and the solutions found. The authors emphasize the importance of an emergency operations plan and summarize strategies and procedures that can be adapted by radiation therapy clinics globally.

Why Smart Oncology Clinicians do Dumb Things: A Review of Cognitive Bias in Radiation Oncology

Evans et al.

The authors discuss how cognitive bias affects radiation oncologists and their patients. The article provides examples of common biases, factors that increase the likelihood of succumbing to these biases and strategies for identifying and overcoming them. The authors also shed light on how cognitive bias may affect the validity of interviews, chart rounds and other established practices.

Practical Radiation Oncology has published a podcast further exploring this topic with a few of the authors. The article and podcast are available at https://doi.org/10.1016/j.prro.2019.03.001.

A Burnout Reduction and Wellness Strategy: Personal Financial Health for the Medical Trainee and Early Career Radiation Oncologist

Royce, Davenport and Dahle

This review addresses how low financial independence, especially related to loan debt, can be related to burnout in early career radiation oncologists. The authors identify tenets of strong financial health and several strategies to reduce debt and begin investing. The review concludes that a decreased financial burden can lead to greater personal and professional freedom and reduces burnout by improving quality of life.

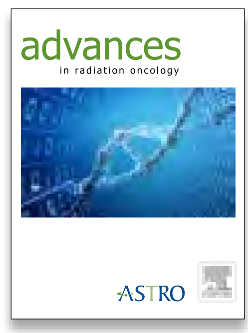
This article has been made open-access to facilitate broad dissemination and is available at https://doi.org/10.1016/j.prro.2019.02.015.

Lessons Learned from the First Human Low-field MRI-guided Radiation Therapy of the Heart in the Presence of an Implantable Cardiac Defibrillator

Gach et al.

This article reports the method used to treat a patient with an unresectable cardiac fibroma and a cardiac implantable electronic device (CIED). The patient was not device-dependent, and the device and leads were MR-conditional. MR-IGRT allowed for real-time imaging and beam gating; however, the CIED created challenges with artifacts and latency during imaging. The authors suggest that MR-IGRT may become more common as MR-conditional CIEDs and MR-LINACs become more accessible.

HIGHLIGHTS FROM *ADVANCES IN RADIATION ONCOLOGY*



April-June 2019

MRI Radiomic Features Are Independently Associated with Overall Survival in Soft Tissue Sarcoma

Spraker et al.

These authors report results of an effort to use radiomic features to predict survival in patients with soft tissue sarcoma. Using MRI-based radiomic features is a promising avenue for soft tissue sarcoma, as they are acquired from nearly all patients. The authors found that radiomic features extracted from pretherapy T1 MR images were independently predictive of overall survival, and that a model combining radiomic and clinical features performed best of the models tested.

First Reported Case of Pediatric Radiation Treatment with Magnetic Resonance Image-guided Radiation Therapy

Henke et al.

This article presents the first use of magnetic resonance image-guided radiation therapy (MRgRT) in a pediatric cancer patient. MRgRT was used to maximize the soft-tissue visualization and account for motion management as the tumor was diaphragmatic. The authors document how they overcame obstacles in this treatment, including the magnetic field's effect on dose distribution and the necessity for anesthesia monitoring equipment. The use of MRgRT provided greater sparing of normal tissue and provides an alternative to breath-hold techniques that are often limited by patient age.