WINTER 2018-2019 ✦ REPORT 23

THE BLUE RIDGE ACADEMIC HEALTH GROUP

Separating Fact from Fiction:

Recommendations for Academic Health Centers on Artificial and Augmented Intelligence

Members and participants

(June 2018 meeting)

MEETING CO-CHAIRS

Jonathan S. Lewin, MD (current Co-Chair)
Executive VP for Health Affairs, Emory University
Executive Director, Woodruff Health Sciences Center
President, CEO, and Board Chairman, Emory Healthcare

Jeffrey R. Balser, MD, PhD (current Co-Chair)
President and CEO, Vanderbilt University Medical Center
Dean, Vanderbilt University School of Medicine

OTHER MEMBERS

S. Wright Caughman, MD
Professor, Emory School of Medicine and Rollins School of Public Health, Emory University
Emeritus Executive VP for Health Affairs, Emory University

Michael V. Drake, MD
President, Ohio State University

Julie Freischlag, MD (as of September 2018)
Dean, Wake Forest University School of Medicine
CEO, Wake Forest Baptist Medical Center

Michael M.E. Johns, MD
Professor, Emory School of Medicine and Rollins School of Public Health; Emory Emeritus Executive VP for Health Affairs; Emeritus President, CEO, and Board Chairman, Emory Healthcare

Darrell G. Kirch, MD
President, Association of American Medical Colleges

Steven Lipstein
Former President and CEO, BJC Health Care (retired)
Member, Emory University Board of Trustees

Lloyd B. Minor, MD
Dean, Stanford University School of Medicine

Elizabeth G. Nabel, MD (as of September 2018)
President, Brigham Health

Mary D. Naylor, PhD
Marian S. Ware Professor in Gerontology
Director, NewCourtland Center for Transitions & Health
University of Pennsylvania School of Nursing

Daniel K. Podolsky, MD (as of September 2018)
President, University of Texas Southwestern Medical Center

Kenneth S. Polonsky, MD
Executive VP for Medical Affairs; Dean, Biological Sciences Division and School of Medicine, University of Chicago

Claire Pomeroy, MD, MBA
President, Albert and Mary Lasker Foundation

Marschall S. Runge, MD, PhD
Executive VP for Medical Affairs, University of Michigan

Fred Sanfilippo, MD, PhD
Director, Healthcare Innovation Program, Emory University

Richard P. Shannon, MD
Executive VP for Health Affairs
University of Virginia Health System

Irene M. Thompson
Vice Chair, AMC Networks Board of Managers, Vizient, Inc.

SENIOR MEMBERS

William R. Brody, MD, PhD
Professor Emeritus
Salk Institute for Biological Studies

Don E. Detmer, MD, MA
Professor of Medical Education
University of Virginia

Michael A. Geheb, MD
Senior Consulting Director, IBM Watson Health
Board of Directors, Wayne State University Physicians Group

William N. Kelley, MD
Professor of Medicine, Perelman School of Medicine, University of Pennsylvania
Trustee Emeritus, Emory University

Arthur H. Rubenstein, MBBCh
Professor of Medicine, Perelman School of Medicine
University of Pennsylvania

John D. Stobo, MD
Executive VP, UC Health, University of California

Bruce C. Vladeck, PhD
Former CMS Administrator and Health Policy Adviser

FEATURED PRESENTERS

Gari D. Clifford, PhD
Interim Chair, Biomedical Informatics
Emory School of Medicine

Kyu Rhee, MD, MPP
Vice President and Chief Health Officer, IBM Corporation

William B. Rouse, PhD
Chair, Economics of Engineering
Stevens Institute of Technology

Khan Siddiqui, MD
Chief Technology Officer & Chief Medical Officer
higi SH Holdings, Inc.

FACILITATORS

Steve Levin
Director, The Chartis Group

Ryan Bertram
Associate Principal, The Chartis Group

Alexandra Schumm, Principal and VP for Research
The Chartis Group

GUESTS

John G. Rice
Vice Chairman, General Electric (retired)

William W. Stead, MD
Chief Strategy Officer
Vanderbilt University Medical Center

STAFF

Anita Bray
Project Coordinator, Woodruff Health Sciences Center, Emory University

Gary L. Teal
Vice President, Woodruff Health Sciences Center
Emory University

REPORTER AND EDITOR

Alexandra Schumm (See Facilitators)

EDITORIAL AND DESIGN CONSULTANTS

Karon Schindler, Peta Westmaas
Woodruff Health Sciences Center, Emory University

Contents

Report 23. **Separating Fact from Fiction:** Recommendations for Academic Health Centers on Artificial and Augmented Intelligence

Mission *The Blue Ridge Academic Health Group seeks to take a societal view of health and health care needs and to identify recommendations for academic health centers (AHCs) to help create greater value for society. The Blue Ridge Group also recommends public policies to enable AHCs to accomplish these ends.*

Introduction: The Digital Transformation in Health Care

Countless papers, including the Winter 2017-2018 report,[1] of the Blue Ridge Academic Health Group (BRAHG) acknowledge that the promise of electronic health records (EHRs) has yet to be fully realized. While we are learning to use and optimize EHRs, we may be exposed to new hurdles and concerns such as clinician burnout due, in part, to the additional clerical burden associated with most EHRs. However, we need to think much broader than EHRs, as a true digital transformation is under way in health care that goes far beyond this tool.

Today's health care professionals are bombarded by data from multiple sources—diagnostic, claims, financial, psychosocial, epidemiologic, biometric, genomic, consumer-generated—at ever-increasing rates. Each person is estimated to generate enough health data to fill 300 million books in a lifetime[2]—equivalent to filling the Library of Congress nearly 20 times over. In fact, health care data is expected to double every 73 days through 2020. Even if all this data were clean and harmonized, its sheer quantity necessitates new tools to make sense of the ever-expanding data universe. This new requirement goes beyond big data analytics; it requires a fundamental shift in how we generate, curate, clean, and interpret data. Enter artificial intelligence (AI), which can be used to enable human "augmented intelligence." For definitions, see the Definitions sidebar.

The purpose of this report is to clearly define artificial and augmented intelligence, explore its potential impact on health and health care, identify and react to challenges and risks associated with AI-based technologies in health care, and present a call to action for academic health systems (AHSs).

I. Vision of the Future

To help illustrate the transformative power of AI, consider the following vignette in which an AI-powered cognitive assistant plays an important role in a simple primary care visit:

Dr. Edward Cummings, a primary care physician, was wrapping up his clinical day. He sat at his desk, facing a large display connected to his laptop. Millie, Dr. Cummings' cognitive assistant, was on the upper left of the display with a Skype-like visage.

EC: "Pretty routine day, Millie. Do you agree?"

Millie: "Perhaps, except for Mr. Burdell."

George Burdell had presented with symptoms of a sore throat and right ear pain for the last three weeks.

Millie: "You examined and found his ear drums and canal normal but also found an ulcer at the base of the right tonsil."

EC: "Right, and I referred him to a local otolaryngologist—head and neck surgeon—for evaluation."

Millie: "With that constellation of symptoms and signs, this is almost certainly a head and neck cancer."

EC: "Yes, I thought of that, why do you bring it up?"

Millie: "Well, I took the liberty of reviewing the literature on the subject, and it turns out that survival is significantly improved if the patient is treated and evaluated at a major center or an NCI [National Cancer Institute] comprehensive cancer center."

EC: "Well, if that is the case, perhaps we should have him evaluated down in Atlanta—can you set up that referral please?"

Millie: "Yes, I would be happy to. While we are discussing it, did you know Mr. Burdell has been your patient for many years? You last saw him four years ago for what turned out to be a sinus infection."

EC: "I don't recall that, but I am sure you are right."

Millie: "He has never had a routine physical. It seems that he only shows up when he has an obvious health problem."

EC: "Lots of people are like that."

Millie: "Yes, but Mr. Burdell may be facing something serious, and he does not seem like the type of person who takes care of himself."

EC: "Could be. We will worry about that after we see what the folks in Atlanta have to say."

Millie: "OK. I will send you the read-aheads for tomorrow."

EC: "Great. You know how to find me if anything comes up."

Millie: "Of course, good night."

****

Dr. Henry Ramsey is an otolaryngologist (a head and neck surgeon). Ramsey and his cognitive assistant, Peggy, review his day's work, including the examination of Burdell.

Peggy: "As you know, you found a 2.5-cm ulcerated mass at the base of the right tonsil and a 2-cm cervical

Definitions

Artificial and augmented intelligence are often confused or conflated with other related terms. Following are definitions for reference:

- **Artificial intelligence**
  - The ability for a program to make predictions or decisions or take actions based on insights developed by machine learning algorithms.
- **Augmented intelligence**
  - Normal human intelligence is supplemented through the use of artificial intelligence. It is a complement to, not a replacement of, human intelligence.
- **Algorithms**
  - Math formulas and/or programming commands that inform a regular non-intelligent computer on how to solve problems. Algorithms are rules that teach computers how to figure things out on their own.
  - "Care pathways" also can be referred to as algorithms when they include a flow chart format of decisions and actions in cases where a patient with a particular condition or set of conditions is treated in a sequence of steps.
- **Machine learning**
  - A method of data analysis that automates analytical model building, where computers can be supplied with massive amounts of data and can "learn" how to complete a specific task or make a prediction or decision based on patterns it identifies in that data. Traditional machine learning requires labeled data, where humans provide the set of initial rules, data features (individual characteristics or variables—input), and data labels (output), then the computer learns by applying those to a dataset. The resulting algorithm is refined as the computer is provided with and analyzes new datasets. Humans correct any errors the machine makes.
- **Artificial neural network**
  - A computer analysis approach modeled on the layered, dense, and interconnected structure of neurons in a human brain. While the concept of artificial neural networks has been around for some time, increasingly powerful computers and advanced mathematical formulas now enable algorithms to be developed based on many more layers of data in much more complex neural networks than in the past.
- **Deep learning**
  - Deep learning is a form of machine learning, where artificial neural networks are used because of the multiple layers of complex data involved. The computer learns to recognize patterns in the layers of data and make decisions about the data—for example, to analyze an image or sound and determine what it is or means.
- **Supervised and unsupervised learning**
  - Supervised learning: A type of machine learning in which human data labeling and supervision are an integral part of the machine learning process on an ongoing basis. In supervised learning, there is a clear outcome to the machine's data mining, and its target function is to achieve this outcome, nothing more.
  - Unsupervised Learning: A type of machine learning in which human input and supervision are extremely limited or absent altogether throughout the process. In unsupervised learning, the machine is left to identify patterns and draw its own conclusions from the datasets it is given, without a specific outcome identified. The computer does not know if the patterns it identifies will be useful—humans must design experiments to test efficacy or effectiveness of the patterns the machine identifies.
  - In supervised deep learning, the data is labeled by a human. In unsupervised deep learning, the data is unlabeled, and the computer assesses patterns, labels data accordingly, and develops algorithms on its own.
- **Predictive analytics**
  - Often classified as a type of machine learning, predictive analytics uses advanced analytic techniques on large datasets to identify patterns and make predictions about future events.
- **Interrogation of an AI-driven model**
  - The concept of "interrogating" a computer about how it arrived at its conclusions based on its machine learning-derived model. This is particularly relevant in many areas of deep learning, where the neural networks upon which the computer learned are so complicated that it would be difficult to successfully interrogate the model. The incredibly complex models being developed for things such as autonomously driven cars, for example, may not provide transparency or the ability to interrogate. This would be acceptable if the models are always "correct," but less so if the model makes a mistake—one of the cars suddenly drives into a river, for example—and we do not have the ability to understand why.

lymph node in the upper right jugular area."

HR: "Yes, and I performed a biopsy in the clinic of the tonsil mass and sent it to pathology."

Peggy: "In reviewing Burdell's history, I noticed that he smokes a pack of cigarettes a day. He also has alcohol challenges."

HR: "Those are certainly major risk factors."

Peggy: "Over the past 10 years, you have seen 12 patients with very similar symptoms and risk factors."

HR: "Anything else common to these patients?"

"They all faced a tough road to recovery."

HR: "How so?"

Peggy: "Many more follow-ups than expected."

HR: "And the results?"

Peggy: "70% recovered, with no recurrence of cancer."

HR: "Good. Let's sustain this batting average."

As Ramsey is driving home, Peggy calls him in his car.

Peggy: "The path report of the biopsy showed a diagnosis of squamous cell carcinoma, moderately differentiated."

HR: "Hmm, interesting. Did they test for p16 as I requested?"

Peggy: "Yes, he was p16+, and as you know the American Joint Commission changed the staging system in late 2017 for oropharyngeal carcinoma that is HPV p16+.

HR: "Yes I am aware of that, and this makes him T2N1Mx Stage I using the new system.

HR: "OK, so please call Mr. Burdell and have him come in for an appointment this week. At the same time please order a PET/CT with contrast to evaluate the extent of disease and if there is any distant metastasis. I would expect there to be none."

Peggy: "Should I provide the usual explanation."

HR: "Yes, of course, please let him know that I will talk with him in the clinic. I want to tell him about the cancer in person."

Peggy: "It looks like his PET/CT scan will be completed in one week. Would you like him added to the tumor board for that following week?"

HR: "Yes, and also please set up appointments with speech pathology and social work along with nutrition. Also please review our clinical trial portfolio, and let me know what is potentially available to Mr. Burdell based on his p16 status."

Peggy: "I assume you want them to see the patient after you have informed him of the cancer."

HR: "Exactly."

Peggy: "By the way, I have found that, over the last two years, more than 100 studies have been published on alternative treatment protocols of squamous cell carcinoma in the oropharynx related to HPV. Do you want a summary of these studies?"

HR: "Is there anything unusual or surprising in this literature?"

Peggy: "No, not really."

HR: "OK, but let's have the summary available for the meeting of the tumor board."

Peggy: "Will do."

HR: "Also, make your usual scan of the SPOHNC website and see if there are national trials that we don't participate in."

Peggy: "Of course. Very familiar with the site, as you know."

HR: "OK. Enough for today."

To continue reading this vignette, please see the appendix on page 23.

The scenario described in the vignette may seem a bit futuristic, but many of the AI applications described therein are already in development or in use today. BRAHG recognizes that AI has significant potential to fundamentally change how patients receive and clinicians provide care, but we do not anticipate a dystopian world some futurists predict wherein robots replace the human workforce. Instead, we expect that AI will augment and enhance a clinician's ability to diagnose and treat patients and will help further personalize the patient experience. Furthermore, we do not pretend to know the speed at which change will occur.

However, it would be myopic to overlook the transformational power these new technologies are likely to have across each component of the AHS tripartite mission. The following framework helps organize the complicated landscape of AI applications across these components:

Clinical domain—including applications for clinical decision support (e.g., diagnosis, treatment options and selection, identification of high-risk patients), apps that help patients and their caregivers prepare for and manage health needs, and operational applications of AI to reduce clerical work and take over and improve back-office functions (e.g., claims submissions and follow-up).

Educational domain—including applications to aid in teaching (e.g., virtual patients, virtual surgery, both of which are not AI themselves but leverage AI and are based on machine learning), as well as changing the type of content to prepare the next generation of health care professionals to incorporate AI-driven tools into their daily practice.

Research and discovery domain—including applications for basic and translational research, clinical trials, voice-based data entry, and cognitive assistant to comb journals/curate and synthesize study findings, as well as find inconsistencies in the evidence.

AI systems and applications that leverage AI and machine learning are expected to improve efficiency, reduce errors, and help proactively manage population and individual health, while also impacting both patient and clinician experience and patient engagement, with the potential to alleviate and reduce clinician burnout, which has reached epidemic proportions.[1]

A recent Accenture study forecast that health care applications of AI will grow to a $6.6 billion market by 2021.[3] In that same vein, a recent Healthcare Information and Management Systems Society survey identified population health and clinical decision support as top areas of potential for AI.[4] Given this aggressive growth and high potential to fundamentally change how clinicians practice and how patients interact with the health care ecosystem, it is imperative that health care professionals, academic health system leaders, and policymakers understand this topic.

Despite this explosive projected growth, the health care delivery system lags in AI adoption relative to other industries, such as finance and manufacturing.[5] Health care's lower adoption rates reflect its greater complexity, including unique moral, ethical, legal, and regulatory issues. These challenges will be explored later in this report.

This year's report explores how AI will transform various dimensions of health care, though perhaps not at the pace at which some pundits have predicted. Furthermore, we share the American Medical Association's position that AI solutions that extend and enhance the work of clinicians are more likely to succeed than solutions that replace them. Academic health center leaders have a responsibility to help their own organizations adapt and to actively shape how the use of AI unfolds across the tripartite mission in an ethical, value-driven manner. Herein, we explore emerging applications of AI across the tripartite mission and the implications for academic medicine and health care more broadly. Finally, we offer a pragmatic call to action for academic medicine leaders to ensure that we are purposeful in our approach to AI.

II. A Principled Approach to Artificial Intelligence

AI presents both great promise and great challenges to AHSs and to health care more broadly. As such, AHSs should arm themselves with a decision-making framework for selection and deployment of AI to prepare for and manage the transformation. As a starting point, it is helpful to recognize where humans excel compared with machines.[6]

Humans excel at:

- Consciousness
- Planning and executive functions
- Creativity and imagination
- Emotion and empathy
- Complex problem solving and dilemmas
- Morals
- Abstract thinking

Computers excel at:

- Input and output
- Information processing, capacity, and memory
- Pattern identification and inconsistency identification

Humans and computers each excel at:

- Vision
- Language
- Complex movement
- Structured problem solving

Understanding these differences is useful in helping identify situations where AI applications may be more effective in creating value. If we don't control for the aforementioned human factors, AI applications may fall short of our needs, or worse yet, cause harm. AHSs are best positioned to advance AI because of our large numbers of clinician scientists and our access to expertise in other needed fields in most of our universities. However, for many AHSs this is fairly or entirely new and uncharted territory. As such, we recommend that AHSs adopt a set of four core principles to drive decisions:

PRINCIPLES TO ADVANCE AI IN ACADEMIC MEDICINE

1. Adopt an ethical framework to ensure societal benefit in areas of scientific exploration and application of new knowledge. Note that various organizations have explored these issues, providing AHSs a starting point if desired (e.g., the Institute of Electrical and Electronic Engineers Global Initiative on Ethics of Autonomous and Intelligent Systems).[7] A legal approach—and potentially a new law or set of laws—will likely need to be formed to handle the instances when a clinician does not agree with an AI-driven diagnosis or treatment, or when a mistake or bad outcome occurs in part because of the recommendations of an AI-powered tool. These will take place outside of the domain of AHSs, but AHSs should stay abreast of such legal advancements and make adjustments to their own policies and procedures as necessary.
2. Focus on solving real health care problems (i.e., use cases) rather than on the technology, and then start with the problems where improvements would be of highest value.
3. Promote human-centered design as you re-imagine workflows that will incorporate AI.
4. Promote data literacy—develop mechanisms to collaborate across different domains of knowledge, which often come from other schools within the university or other organizations.

Incorporating these principles into future institutional planning activities should help ensure that AHSs help participate in shaping how AI affects health care, as opposed to passively experiencing the change and being ill-prepared for its impact.

III. The Promise of AI/Machine Learning: Applications Across the Tripartite Mission

There are many promising health care AI applications that could positively impact all three elements of an AHSs tripartite mission:

- Improving health care quality, health outcomes, efficiency, and patients', family caregivers', and clinicians' experience—and reducing the cost of care;
- Augmenting research capabilities and shortening clinical trial timelines; and
- Enhancing educational tools and resources, while also expanding educational curricula and skill requirements for health care professionals.

Many AI-based applications are being explored, developed, piloted, and in some cases rolled out by AHSs, health profession schools, and other institutions. We believe AI applications described herein warrant discussion and consideration for investment, with recognition of the very real hurdles in their continued development and adoption.

CLINICAL DOMAIN EXAMPLES

While the use of AI in the clinical setting is at the leading edge or experimental—few tools are yet deployed broadly for everyday practice—there are numerous opportunities to leverage AI to transform health care delivery and improve value, defined as improving quality, safety, and outcomes efficiency. Illustrative opportunities include the following:

Clinical decision support and predictive analytics tools based on AI algorithms

Augmented clinical support tools driven by predictive analytics will enable health professionals to do less "hunting and searching" for information, helping them find clinical analogs to an individual patient's condition and health history, best practices, and clinical trials to aid in making a precise, accurate diagnosis and decide on the best course of treatment. Clinicians will have more time to evaluate and interpret the available relevant data, synthesize results, and design a personalized course forward for a patient. Patient outcomes will improve as their conditions can be monitored, flagged, and addressed earlier and most appropriately. Examples of these types of tools and applications include the following:

Diagnosis support—

- Medical imaging is arguably the most promising clinical area for AI-powered applications to be put into practice and to make an impact. Such applications can help radiologists and other clinicians make diagnoses and prioritize patients by reading images and comparing them with hundreds of thousands of medical images while also taking into consideration other medical data related to the patient. The American College of Radiology (ACR) is in the process of developing ACRassist, a tool that combines raw clinical content and a communication framework that facilitates content delivery. It uses natural language processing developed through deep learning and brings evidence-based guidelines for recommendations and reporting into a radiologist's workflow, providing guidance during interpretation and incorporating structured data elements into free-form reporting.[8,9] In April 2018, the FDA approved the first autonomous diagnostic tool to diagnose diabetic retinopathy. For more detail on this example, see the IDx-DR sidebar.
- Pathology is another area where AI can help clinicians reach a diagnosis more efficiently and accurately. In a 2017 study, researchers at Case Western Reserve University developed a deep learning algorithm based on 400 biopsy images from multiple hospitals and 200 images from the Cancer Genome Atlas and University Hospitals Cleveland Medical Center. In a study with 600 participants, the algorithm was able to accurately identify the presence of invasive types of breast cancer based on pathology images 100% of the time.[10]
- Cardiology is another clinical area that may benefit from AI-driven diagnosis tools. Completing the typical testing required to inform a diagnosis of coronary artery disease can often take a patient weeks or months because of scheduling restraints and common "re-tests" requested by physicians, particularly if the patient is accessing a health system that isn't coordinated across departments or is relying on third party testing entities. Emerging AI-powered testing devices, such as a scanning tool created by Analytics 4 Life Inc., can take a minutes-

Clinical AI Application Case Study: IDx-DR

- **Problem**
  Diabetic retinopathy is one of the leading causes of blindness in adult, working-age men and women in the United States, and the CDC estimates that between 2010 and 2015 the number of adults with diabetic retinopathy is expected to double—from 7.7 million people to 14.6 million.[11] If diabetics regularly receive eye exams, early detection is more likely and vision loss/blindness rates can be reduced.[12] However, like the general population in the U.S., less than half of diabetic patients receive annual eye exams.[13, 14]
- **Solution**
  A tool was developed by the IDx company to autonomously detect the presence of diabetic retinopathy. The tool detects lesion characteristics indicative of diabetic retinopathy from images of a patient's eye and brings its findings together into a diagnosis using an algorithm developed through machine learning.[15] After a clinical trial showed that the tool outperformed pre-set sensitivity and specificity thresholds, the FDA approved the use of this tool in a clinical setting in April 2018.[16] This is one of the first AI-powered autonomous medical diagnostic systems to be approved by the agency.
- **Impact**
  Because of the "autonomous" nature of the IDx-DR tool, diagnosis can be reached without a human clinician trained in reading retinal images. The system can therefore be used in the primary care setting, or potentially a retail setting, with simple usage training provided by IDx to staff. While it is too early to know how fast the use of this autonomous diagnostic tool will spread, if it is brought into a wide variety of settings it has enormous potential to reach more diabetic patients, diagnose more diabetic retinopathy cases earlier, and ultimately reduce vision loss and blindness in diabetic patients.
- **Caveat**
  While this example is an interesting one with substantial potential to positively impact many patients' health, we do not anticipate that most diagnostic imaging tools supported by AI will be autonomous. Rather, they will provide information and clinical support to augment the information available to clinicians, improving their diagnostic capabilities. At least for the foreseeable future, these tools will still require human interpretation or human "approval" of a diagnosis recommendation.

long recording of a patient's heart function and collect more than 10 million data points.[17] The data can be analyzed through special software, and a three-dimensional image of the patient's heart along with a detailed report can then be sent to the clinician. The patient can receive a diagnosis after just one test, saving time, reducing costs, and potentially introducing an intervention or treatment sooner and avoiding an adverse event. Analytics 4 Life is in the process of conducting a two-stage study with 12 clinical partners, including Ochsner Health System, Rochester Regional Health, and Sentara Heart Hospital. The first stage consists of a prospective, non-randomized trial to develop a machine-learning algorithm to detect and assess significant coronary artery disease. The second stage consists of a prospective, blinded, non-randomized, paired comparison trial to test the machine learning algorithm.[18]

- It is important to note that AI-driven diagnostic recommendations are not always better or faster. Contrary to the previous example, some algorithms will recommend or require many tests and datapoints before a diagnosis recommendation can be made by the machine, whereas the human doctor would arrive at the diagnosis without needing some of those tests. This gap may be reduced as algorithms improve, but for now it is important to note that not all emerging AI-driven diagnosis tools are "better" or more efficient than humans alone.

Tailoring treatment and precision medicine—

- Precision medicine is defined by the National Institutes of Health as "an emerging approach for disease treatment and prevention that takes into account individual variability in genes, environment, and lifestyle for each person."[19] Clinicians can use this information with the help of AI-powered tools to predict more accurately which medications, treatments, health management, and prevention approaches will work best for a particular patient. In one example, clinicians at Holston Medical Group in northeast Tennessee and southwest Virginia are utilizing a clinical-genomic application called 2bPrecise, embedded in their EHR. The application analyzes drug-to-gene interaction and applies pharmacogenomics patterns—identified through machine learning during the development of the application—to determine the most effective drug regimen for each patient. The group is using this tool to help improve behavioral health care and tailor treatment plans for opioid patients. The tool was initially tested and adopted by experts at the NIH, including those at the National Human Genome Research Institute, the National Cancer Institute, and the NIH Clinical Center.[20]
- Another growing area of precision medicine is precision oncology, where molecularly targeted drug therapies are prescribed based on the genomic status of the drug target in order to maximize efficacy. However, the more commonly prescribed early treatment chemotherapy drugs—those that are "nonspecific"—do not have biomarkers and therefore the genomic-based precision oncology approach does not apply. Recognizing this limitation, a team of researchers recently applied deep learning techniques to identify features within genome-scale omics data to develop a model that predicts the effectiveness of drugs in the treatment of various cancer cell lines, regardless of whether the drugs are molecularly targeted or nonspecific. While the results were promising—the new model significantly outperformed the precision oncology approaches that use the genomic status of drug targets as therapeutic indicators—the researchers acknowledged that further refinements will be needed before they bring their model to the clinical environment. Still, the team emphasized that some version of their approach could "significantly broaden the scope of precision oncology beyond targeted therapies, benefiting an expanded proportion of cancer patients."[21]

Identifying high-risk individuals and managing population health—

- Research has shown that sepsis contributes to up to half of hospital deaths in the U.S.[22] and that mortality rates increase by 8% every hour a sepsis patient goes untreated.[23] Therefore, identifying sepsis as early as possible could lead to a reduction in mortality. At the University of Pennsylvania (Penn), clinician-scientists developed an AI-powered tool to predict sepsis using machine learning and EHR data from more than 162,000 patients. The algorithm is based on dozens of factors that human clinicians would not be able to research, track, process, and synthesize themselves in a reasonable amount of time. The algorithm was piloted on more than 10,000 patients, and the Penn researchers found that it was able to continuously sample real-time EHR data to prospectively identify patients at risk for developing sepsis so that monitoring and treatment could begin. The next step for this pilot is to examine outcomes to determine whether the tool actually leads to a reduction in mortality and morbidity, or simply identifies those on the path toward high mortality and morbidity.[24] At Emory University, clinician-scientists and bioinformatics colleagues developed an algorithm to predict sepsis onset four, eight, and 12 hours before human clinicians would detect it. While there were some false-positives, "no predictor is going to be perfect," said the lead researcher, Shamim Nemati, and any lead-time in identifying potential sepsis patients is valuable.[25] The next step for these researchers is to design a prospective trial to assess the clinical utility of deploying this sepsis prediction model.
- Nearly 300,000 cases of *Clostridium difficile,* a common hospital-acquired infection, occur annually in the U.S. To date, the industry has lacked an effective clinical tool to accurately measure patient risk. As part of a collaborative effort among University of Michigan (UM), Massachusetts Institute of Technology, Harvard Medical School, and affiliated hospitals, a machine learning model has been developed to address this issue. The team evaluated EHR data from 191,014 adult admissions to UM Hospitals and 65,718 admissions at Massachusetts General Hospital (MGH), extracting thousands of features, including patient demographics, admission details, patient history, vital signs, and daily hospitalization information. The model developed shows promise, with at least half of cases predicted correctly at least 5 days in advance of sample collection within both study populations.[26] One important outcome of this partnership study: the algorithm developed at UM did not work on patients at MGH, and vice-versa. There are an increasing number of examples of this phenomenon, underscoring that the data underlying algorithms and the environments in which those algorithms learn and are given input significantly impact how they operate and on which populations they will be effective.[27]
- Increasingly, social determinants of health (SDOH) are being recognized as significant contributors to health and health outcomes. The CDC acknowledges that "by applying what we know about SDOH, we can not only improve individual and population health but also advance health equity."[28] A team from the University of Tennessee Health Science Center recently studied whether they could use a combination of biological and social conditions to predict the likelihood of a hospital re-visit for pediatric asthma patients after an initial visit. They developed the concept of "sociomarkers," measurable indicators of social surroundings and conditions for a given person. The team applied machine learning to an integrated dataset containing individual-level biomarker patient information and zip code-level sociomarkers. Their resulting algorithm could predict an asthma re-visit for pediatric patients accurately 66% of the time, a percentage the team said could potentially be improved with more and better data—they only used a 12-month time period and did not have data for pediatric patients who went to hospitals outside of their network. Still, their findings demonstrate the promise of advanced risk prediction tools that could be used to assist in population health management efforts.[29]
- Suicide rates in the U.S. have risen more than 25% since 1999, with some states like North Dakota seeing increases of more than 50%.[30] While suicide is often linked to mental illness, only half of those who die by suicide have a known diagnosed mental health condition,[31] and suicide is often attributed to a multitude of factors, making it difficult to predict. Researchers at Vanderbilt University Medical Center (VUMC) developed an algorithm based on EHR

data to predict the likelihood that a particular patient would attempt suicide in the next week and in the next two years. As lead researcher Colin Walsh stated, "If an AI [tool] with an 80% prediction success rate is used to assess risk of suicide every time a patient comes into contact with medical care, then, in theory, we would be able to predict, treat, and hopefully prevent far more suicide attempts."[32] In a trial using data from 5,000 patients who were admitted to VUMC for a suicide attempt or self-harm, the algorithm was 85% accurate in predicting the likelihood of suicide attempt within a week and 80% accurate in the two-year prediction.

- End-of-life conversations are best had before death is imminent and when introduced by an experienced clinician such as one specializing in palliative care. But predicting the timing of death is difficult when it isn't looming in the next few days. At Stanford Medicine, Nigam Shah, an associate professor of biomedical informatics, developed an algorithm that predicts the likelihood of patients dying within the next three to 12 months. Palliative care clinicians at Stanford University Medical Center now receive an email every morning with patient record numbers for those whom the algorithm has identified as having a 90% or higher probability of dying within the next three to 12 months, and the clinicians decide which patients on the list will receive a visit from their team. The palliative care staff also respond to clinician referrals over the course of the day but can now identify patients with longer-range mortality likelihood so that appropriate end-of-life conversations can be planned and conducted. The patients identified by the algorithm and selected by the palliative care team are flagged and monitored by Shah's team so that the algorithm's accuracy can be tracked over time, and so that tweaks may be made to further improve the model.[33]

Population health, health management, and wellness—

- Patients and their families are also crucial in achieving positive outcomes and preventing disease. Machine learning has been incorporated into the development of many Internet and mobile-based apps that help patients and their caregivers with pre-procedure preparation, recovery from an acute episode or surgery, medication adherence, and general health management. One example is an app which Arkansas Surgical Hospital recently began offering as an option to help patients before and after joint replacement surgery. The system, called PeerWell, includes hundreds of patient programs that are personalized using machine learning and are proven to improve surgery results and accelerate the recovery process.[34]
- Another example in the health management and wellness space is higi, the largest network of consumer-centric health-assessment and biometric stations in the U.S., with more than 11,000 FDA-cleared stations in drugstores and other retail and corporate settings, as well as more than 80 integrated health devices and applications. Consumers can measure key health metrics at physical kiosks and track their progress via kiosk, a secure website, or smartphone app over time, promoting increased patient engagement. Connected health care clinicians can also monitor a patient's biometric data and progress. In 2017, higi announced a partnership with Interpreta. Biometric and patient-reported data from higi will be combined with claims, clinical, and genomics data from Interpreta. Machine learning techniques will be applied to identify patterns in patient data and outcomes. While it is still in development, the goal is to use the identified patterns to develop a personalized "roadmap" or care plan, to be created and delivered in real time to consumers and their connected clinician(s).[35]

AI-powered support tools to reduce repetitive clerical work

Health professionals spend hours every day entering or verifying data in EHR systems and other technology platforms. Some of these clerical tasks occur at night and on the weekend, resulting in them being not-so-fondly referred to as "EHR pajama time"; the burden this after-hours work places on clinicians has been linked to burnout.[36] New tools are being embedded in EHRs and other hospital tech platforms that reduce or eliminate the time required for clerical tasks. These tools allow clinicians to spend more time with patients, pursue other professional endeavors, and pursue other personal interests, contributing to greater fulfillment and satisfaction. These tools also improve the accuracy of data entry and reduce clerical work for office staff so they can provide better "customer service" with each patient interaction. Examples of these types of tools and applications include the following:

Improved EHR data and dictation entry—

- Platforms are now available that are powered by automated speech recognition (ASR) capabilities, largely developed with use of machine learning techniques, enabling faster and more accurate data entry and dictation in EHRs, with the potential to also reduce errors and omissions. Examples being used in hospitals today include Nuance Dragon Medical, Dolbey, and Entrada, among others. For a detailed example, see the Nebraska Medicine case study in the sidebar.

Scheduling—

- Optimizing clinical scheduling and ensuring that patients show up for their appointments has long been a major challenge for most health care organizations. Some are using machine learning-based tools to optimize scheduling. Boston's Beth Israel Deaconess Medical Center (BIDMC) used machine learning to analyze and optimize the hospital's operating room schedule, using the results of the analysis to adjust the schedules of 15 surgeons and thereby freeing 30% of the total operating room capacity. A team at BIDMC also developed a tool using machine learning that would identify patients at highest risk for appointment cancellation or no-show and then targeted those patients with reminders, transportation services, or other support to increase the likelihood they would arrive for their appointment.[37]

Automation tools for back-office functions

Business functions that include repetitive and error-prone tasks are ripe for improvement using AI-powered automation tools. The impact has already been demonstrated in health care institutions and in other industries, with proven

Nebraska Medicine

- **Problem**
  Nebraska Medicine implemented the Epic EHR in 2009. Physicians became increasingly dissatisfied with the amount of time required to complete the physician notes section in Epic.
- **Solution**
  The health system investigated voice-recognition software, powered by AI, as a potential solution. Their search identified available technologies that also allowed physicians to use ASR apps on mobile devices for dictation and offered features that would analyze physician notes in real time and alert the physician when the notes suggested that more information was needed for compliance, or when the physician should consider ruling out something or taking a particular action that would potentially improve a patient's outcome. In the end they implemented Nuance Dragon Medical One.
- **Impact**
  A physician survey conducted after the new tool had been implemented showed that 94% of physicians believed the tool helped them do their job better; 70% of physicians felt that the quality of documentation had improved; and 50% saved more than 30 minutes per day on physician notes.
- **Caveat**
  While voice recognition tools have made vast improvements in notes entry, the organization of the information and data integrity issues remain to be solved. Another question is whether EHR systems will allow new technologies and software to be embedded in or connected to their platforms, which would affect their potential value and impact.

cost savings and return on investment, error reduction, and improvement in an organization's capabilities and the ability to repurpose humans formerly performing those often-detested repetitive tasks. Examples include the following:

Claims processing—

- Robotic process automation (RPA), also known as intelligent process automation, applies software to complete repetitive tasks quickly, accurately, and tirelessly. While RPA has been around for decades, its capabilities are expanding as machine learning techniques are applied to develop the software—particularly in the banking, retail, telecommunications, and insurance sectors.[38] In a growing number of hospitals and health systems, revenue cycle "bots" (in actuality, an algorithm), are being used for front-end EHR assessment to ensure that patient information entered into the EHR and coding for each claim reflects the clinical assessment; this enables submission of accurate claims that are more likely to be approved and paid at the correct reimbursement level. Similar bots are used to respond to back-end claims denials, resubmission, and follow-up. For a detailed example, see the Ascension Health Agilify sidebar.

Data security and compliance—

- Hospitals and health care organizations are ideal targets for cyber criminals and hackers because they house "immutable data"—data that doesn't change regularly like an email address or phone number might. Immutable data is particularly valuable for identity theft and insurance reimbursement fraud. AI-based data security and compliance tools can automate complex processes to detect data security violations and react to breaches. These algorithms can track and learn user behavior, identify atypical use patterns, and flag a potential breach. Daniel Nigrin, CIO at Boston Children's Hospital, underscores the importance of transitioning from legacy data security systems and incorporating AI-driven systems: "If we continue to use our approach…of being reactive and only addressing attacks once we have seen them, then we're always going to be one step behind the bad guys… so I think [by] using AI, we can do a better job at being more prospective… starting to be able to detect that anomalous behavior or activity as it's happening… and shut down those attacks before they become a problem."[39]

CLINICAL DOMAIN IMPLICATIONS

AI has promising applications for clinicians, health care organizations, and patients. However, there are many issues AHSs should consider when exploring the development or rollout of AI-powered tools.

First, AHSs must acknowledge the potential risks of increasing reliance on technology in clinical decision-making, intervention, and documentation. Examples include the following:

- **Bias**—AI algorithms perpetuate biases in training datasets, e.g., demographics, practice norms, care setting. The algorithms may not replicate in patient populations and settings with differing characteristics, such as race or ethnicity. In addition, there is a risk that as we augment our own work and thinking with AI-powered machines we may bias what we "know." If we do not recognize how the machines arrive at their conclusions or where biases exist, those may permeate our own thinking and be difficult to remove.
- **Capabilities**—Some overhyped technologies won't deliver their promised capabilities. If too many examples fall short, there is a risk that clinicians and health care professionals will discount or dismiss technologies that do have real potential.
- **Complacency**—There is a risk that reliance on new tools will become dependence, leading to skill erosion, as clinicians no longer repeatedly exercise their full set of clinical abilities. For an analog in the transportation industry, see the Pilot Automation sidebar.
- **Control**—There is a risk of losing control of critical health care processes, as ownership of some care decisions shifts from clinicians (though we do not foresee clinicians being removed entirely). Some of the tools will produce recommendations without transparency regarding the underlying logic because of deep learning methodology applied (see definitions on page 3.
- **Compliance**—With few exceptions, no clear, consistent framework for legal and ethical compliance and security exists for some of these AI tools.

Second, AHSs must redesign care models and business processes to unlock and optimize the value potential that accompany these AI tools. As precision medicine approaches are further tested and evidence-based protocols are developed, care processes should be redesigned to consistently incorporate the new tools, and educational materials should be developed for clinicians and patients. The new care processes should be human-centered, with workflows designed to incorporate the new tool(s) in a way that will be understandable, executable, and comfortable for a clinician. When an AHS decides to use augmented intel-

Ascension Health Agilify

- **Problem**
  Many necessary business processes involve mundane, repetitive, time-consuming tasks for employees. These processes can be prone to errors because of the potential number of repeated steps involved and the dull nature of the tasks. These tasks include claims processing—a key function that can materially impact the financial health of the hospital if performed incorrectly.
- **Solution**
  Ascension Health's Ministry Service Center subsidiary provides shared services to its member hospitals and also sells these services to others. The Ministry Service Center noticed that RPA use was growing in other industries and began testing and piloting AI-powered automation software, eventually launching Agilify, an intelligent automation solutions company.
- **Result**
  Ascension's use of Agilify has produced a 10% year-over-year reduction in costs over the first five years of its use. Ascension has since begun marketing Agilify to other health systems and companies in other industries who might benefit from intelligent process automation.[40]

Pilot Automation

- **Problem**
  As airplanes have become increasingly advanced, with digital technology and an increasing number of functions that can be controlled by a computer (advanced autopilot), we are running the risk of pilots' skills eroding as computers take the wheel more and more often. In one tragic example in 2009, Air France's Flight 447 crashed after a thunderstorm struck while in flight, ice crystals formed on the wings, an airspeed censor stopped functioning, and the autopilot disconnected. The human pilots, fatigued and disengaged from the details of the flight and not having actively piloted the plane in the time leading up to the thunderstorm, were unable to quickly identify the set of problems and correct them. While the stall alarm sounded more than 75 times, the least experienced pilot continued to pull up on his "sidestick"—the opposite of what he should have been doing—but couldn't seem to explain this to either of the other captains. Because of a difference in the design of this particular plan of which they were unaware, the other captains couldn't figure out what was happening. One exclaimed, "What the hell is happening. I don't understand what's happening… We've totally lost control of the plane, we don't understand at all."[41]
- **Result**
  The plane tragically crashed, killing all 228 souls aboard. It was concluded that automation made it more likely that pilots would not face a true crisis while in flight and learn how to handle it. The U.S. Federal Aviation Administration tasked researchers to design a new methodology so pilots could experience, study, and practice examples of aerodynamic stall, as well as other in-flight complications.
- **Solution**
  New pilot training programs and continuing education programs have been rolled out and new content will continue to be introduced in 2019.[42]

ligence to aid in clinical decision-making, there should be clear protocols around when and how to use it, and what to do if a clinician (or patient) disagrees or distrusts the algorithm's output. If automatic process automation tools work well in one business function, the implementation of those tools in other similar areas should be explored.

Third, AHSs should rethink capital deployment in light of a digitally enabled workforce and digitally enabled consumers. AHSs should consider investing in research and development of new technologies as well as acquisition of existing products and applications. AHSs should also understand that patients' and family caregivers' expectations for access to cost/quality/service information are changing, making it increasingly important that clinical services and patient-facing business processes (e.g., billing) are as consumer-friendly, personalized, and digitally supported as possible.

Fourth, AHSs (and industry players developing AI-driven tools for health care) must learn from past examples—both positive and negative—in order to follow emerging best practices and avoid demonstrated pitfalls. For example, in the development of IBM's Watson for Oncology, the computers were being trained on a small amount of "synthetic data" with only one or two Memorial Sloan Kettering Cancer Center (MSKCC) physicians providing recommendations for each type of cancer included in the tool. Using synthetic data is not uncommon in machine learning, but it is likely to be more problematic when it comes to patient data and connecting data to recommendations based on anything other than evidence-based, peer-reviewed, clinically accepted findings. Consequently, when other hospitals tried to use the MSKCC-trained Watson, the software was making treatment recommendations guided by the treatment patterns and preferences of the MSKCC physicians instead of a true AI-based interpretation of actual patient data.[43]

Finally, the BRAHG strongly believes that AI-based tools in the clinical setting will not replace clinicians but rather augment and supplement available information and enable more efficient care delivery. There is much buzz in the popular press about AI causing drastic changes in health care, such as the elimination of radiologists, but we believe that such a complete "replacement" is unlikely.

EDUCATION DOMAIN EXAMPLES

The digitization of health care and increasing incorporation of AI-based applications in health care settings necessitate new educational curricula and skill requirements for health care professionals. Additionally, AI will introduce improved ways of educating the current and especially the next generation of health care professionals through applications such as AI-driven virtual patient avatars, virtual reality platforms, and AI-driven testing of surgical skills and performance.

Virtual patient avatars

Virtual patients can be programmed through AI-based software to present signs, symptoms, test results, physical emotion and expression, physical exam findings, and diagnostic and therapeutic algorithms, based on thousands of real patient records. Health care professional students can use these virtual patients to practice patient interactions and diagnosis. The overall cost is significantly less than using real patients or actors, and students can access the tool at their convenience.

Similar to advanced flight simulation software that is being implemented in pilot training to avoid potential disasters like the one described in the sidebar on page 13, health professional schools are increasingly incorporating simulated virtual patients for training purposes, presenting health professionals with virtual patient encounters based on extensive real patient data and guiding students through the patient encounter, diagnosis, and treatment recommendation. As AI-based tools become more present in clinical practice, innovative tools such as those described earlier—some of which are still in the experimental phase—could also be incorporated into such training. This will help clinicians stay on top of their "traditional" training that they would apply without any AI-powered tools, as well as train them to incorporate those tools into their practice without losing their human-based decision-making capabilities.[44]

ImmersiveTouch

- **Problem**
  Traditional medical education, in particular surgery, relies on human patient examples and is hampered by biased sets of examples by design.
- **Solution**
  Surgical simulation company ImmersiveTouch, founded in 2005, uses head-mounted displays as well as patient-specific anatomy and tactile feedback, analyzed by AI-driven algorithms, to train surgeons. The company currently offers modules for neurosurgery, ophthalmology, orthopedic surgery, and otolaryngology (ENT) as well as minimally invasive surgeries.
- **Results**
  In a recent study, ImmersiveTouch training reduced surgical errors by 54%, compared with a control group using current [traditional] training methods. Dozens of academic medical centers are currently using ImmersiveTouch training, including Johns Hopkins and the University of Chicago.[45]

Virtual reality training platforms

Similar to gaming platforms, surgeons-in-training can practice procedures and learn how to work well with a surgical team using a virtual reality platform. Simulation technology has been in practice for years; the newer AI-based training tools are more detailed, more precise, and more human-like. These tools require fewer resources and less time from both educators and learners and allow educators to adjust and normalize the case study examples. The global market for virtual reality in health care is forecast to reach $3.8 billion by 2020.[46] For more detail, see the ImmersiveTouch example in the sidebar.

New methods of testing health care professional performance

Much of current health care professional skill evaluation—outside of written tests—relies on human observation and assessment, which always has a subjective element, often resulting in inconsistency. Newer AI-based testing applications ensure more consistent testing requirements and thresholds, increased ability to track subtle behaviors or mistakes, and reduced subjectivity.

- A team at Wayne State University recently used machine learning models to automatically distinguish between "expert" and "novice" performance of surgeons performing robotic-assisted surgery. They found that the tool "effectively, objectively, and automatically" evaluated surgeons' performance and were able to design the tool to provide more personalized feedback, available for surgeons' to review online.[47]

EDUCATION DOMAIN IMPLICATIONS

First, AHSs should embrace and leverage the new AI-powered tools such as those described herein to enhance health professional education programs. Students will have the opportunity to learn at their own pace in an interactive manner using potentially lower-cost, evidence-based tools. They also will be able to be tested in a more objective way and receive more personalized feedback.

Second, AHSs will need to teach students how to use emerging AI-based tools that are being introduced into clinical practice, such as those described in the Clinical Domain section of this report. While some tools may be experimental at this stage, many have the potential to become part of the recommended "normal" practice, and students will be ill prepared if they have not been exposed to them before beginning their professional practice.

Third, health care professionals should also understand how AI-based tools work. AHSs will need to develop health care-literate data scientists and data-literate health care professionals. AHSs should consider adjusting the curricula and/or adding new courses and requirements to teach students the basics of machine learning and how to work with large datasets. AHSs should also help trainees understand the evolving role AI-driven technologies will play in the care of their patients, arming them with information to help them make their own choices and helping them consider the legal, moral, and ethical issues that accompany the incorporation of algorithm-based tools into clinical practice.

Finally, it may be prudent to rethink the selection criteria for health professional students. The new Carle Clinic College of Medicine holds itself out as the "world's first engineering-based college of medicine," with every entering student in the inaugural class having an undergraduate engineering background. While we don't foresee every health professions school mimicking Carle Clinic's engineering-based curriculum, we do believe that there should be an emphasis on data science literacy within medical education and that the proportion of students with engineering and data science backgrounds should increase. Health professions schools may also want to explore partnerships, cross-discipline courses, or credit requirements with other schools within or external to their own university. Many engineering schools are building out courses on artificial intelligence, machine learning, and advanced data manipulation. One school—Massachusetts Institute of Technology—is creating an entirely new college for artificial intelligence, with a planned $1 billion investment, including a $350 million commitment from Stephen Schwarzman of the Blackstone Group.[48]

RESEARCH AND DISCOVERY DOMAIN EXAMPLES

Machine learning and augmented intelligence present new opportunities for discovery and innovation, often with enhanced capabilities and reduction of costs. Harnessing these new tools will help AHSs remain research and discovery leaders who are able to accelerate innovations and trials that improve patients' health.

Basic research

Basic research can be materially augmented with advanced analytic tools and AI-driven algorithms that can help analyze vast datasets and translate patterns into findings to explore further. Examples of these types of tools and applications include the following:

- Data sharing, modeling, and informatics—AI-supported algorithms can connect many currently separate research databases, help identify patterns in the data, and lead to accelerated research findings. An example is My Intelligent Machines, which helps scientists find, share, and analyze their "omic" data.[49]
- Accelerated drug discovery—Pharma companies are using AI algorithms, such as Atomwise and IBM Watson Health, to analyze enormous datasets to identify new compounds, which could be translated into potential drugs. The algorithms can also predict how well potential drugs will do in testing, uncover combinations of drugs that might work well together, and find new uses for previously tested compounds.[50]
- AI-based research assistant—A virtual research assistant can comb journal articles based on a set of criteria, curate the most relevant articles, and/or synthesize study findings, helping health care professionals stay on top of current medical literature and best practices with limited amounts of available time and focus their attention on the journal articles most relevant to them.[51]

Translational research

Algorithms that offer a promising clinical application may be identified in research and then replicated and tested/validated for targeted subpopulations and settings. Then a clinical or operational intervention trial may be designed to further test and demonstrate the feasibility of using the algorithm, with process changes, decision support, and education. Finally, studies can be designed to measure the effectiveness of introducing the algorithm into clinical care or processes and rolled out as a standard of care if shown to be effective and/or more efficient.

Clinical trials

Finding and securing participants is one of the most time-consuming and expensive parts of a clinical trial. Approximately 2 million patients participate in ~3,000 clinical trials in the U.S. every year. But 6 million patients are needed to reach study recruitment requirements, a factor that delays study timelines and hinders ability to draw conclusions and bring new therapies into practice. AI-driven models can help accelerate the clinical trials process. For a more detailed example, see the sidebar.

Accelerating the Clinical Trials Process

- **Problem**
  The problem: In 2017, more than 1.7 million people in the U.S. will be diagnosed with cancer (first time), and there are an estimated ~10,000 cancer clinical trials in progress. But our health care system has a limited ability to link these patients with the relevant trials in an efficient and comprehensive way. This is detrimental to patients wanting to access the most cutting-edge care and extends clinical trials by extending the time required to recruit appropriate trial participants. And it is costly—it is estimated that more than 90% of clinical trials are delayed or over budget. Researchers have suggested that 25%-50% of cancer patients should be enrolled in trials. But fewer than 5% of cancer patients, on average, enroll in a clinical trial, often because patients and doctors don't know what trials are available.
- **Solution**
  AI-powered algorithms that analyze patient data and match with databases of clinical trials can identify eligible patients for clinical trials in minutes.
- **Results**
  In an early comparison participant search, a principal investigator used a traditional recruitment method to identify and validate 23 eligible patients for a biomarker/non-small cell lung cancer trial over the course of six months. An AI-powered software tool, Deep 6, found and validated 58 eligible matches in less than 10 minutes. The key to making this application work is data sharing among health care institutions.[52]

RESEARCH AND DISCOVERY DOMAIN IMPLICATIONS

First, AHSs must invest in core resources required to support AI-powered tools that will augment their research and discovery efforts. That includes advanced data storage and manipulation software, tools that enable secure data sharing, clinical trial subject sourcing tools, and personnel who have advanced skills in health care data informatics and a thorough knowledge of machine learning.

Second, AHSs should evolve their approach to collaboration and data sharing. We believe many of the next big discoveries will be based on very large datasets, which no single institution owns. Pharmaceutical companies have and use AI-based tools on enormous datasets—we don't need to reinvent the wheel; we can form partnerships to access these capabilities. That being said, although partnerships and collaboration will be important, relationships should be structured carefully to protect the data, preserve patient interests, and ensure that proper recognition (if relevant) of any commercialization rights is appropriately assigned.

Finally, the funding for research may shift. Currently, the NIH and the pharmaceutical industry dominate the research funding pipeline at most AHSs. As AI-powered innovations continue to develop, advocacy efforts toward the government may need to emphasize AI as a worthy area of investment. Furthermore, as patient data is increasingly available through more public (but secure) channels, AHSs and other health care research institutions may be able to pursue research endeavors with data from non-traditional channels.

IV. A Call to Action for Academic Health Systems

Several overarching implications emerged as BRAHG explored examples of AI applications associated with the AHS's tripartite mission as described earlier. For AHSs, there will be an increasing need to do the following:

- Invest in infrastructure and new competencies;
- Promote data literacy and cross-disciplinary collaboration;
- Pursue and embrace partnerships with other AHSs, health systems, and industry leaders in AI to share data, coordinate data integrity, launch research and development efforts, and disseminate findings and new solutions; and,
- Assure that the interests and welfare of patients and their caregivers are at the forefront.

To that end, we recommend that AHS leaders take the following actions to help deliberately advance the development and deployment of AI at their institutions and beyond. We also suggest that leaders prepare their governing boards for these priorities and investments and present a clear rationale behind them.

- Become knowledgeable about this topic to help bridge the gap between reality and hype. It is incumbent on AHS leaders to do so, as faculty and learners are increasingly knowledgeable about this topic.
- Invest time to understand where AI is headed and what may already be occurring at your own institution, so you can help shape its development and direct resources appropriately. Develop a thoughtful AI strategy to align resources and optimize investments based on your institution's strategic priorities, competencies, and risk profile. Investments in this area—particularly in development—come at a high cost. Some investments will likely come to fruition, but others will not be as successful. In this developing area, due diligence and careful examination of forecasted return on investment and potential risks are imperative.
- Invest in the researchers, data scientists, and biomedical informatics scientists as well as the governance infrastructure to support this growing domain of science. Many AHSs have already launched new centers for data science to find/develop scholars needed for this activity, which is different from the mechanics of running IT infrastructure and operations.
- Promote data literacy across disciplines and foster collaboration across domains of knowledge to identify opportunities, evaluate the applicability of those opportunities, and effectively conduct research and development. A faculty member at a leading academic medical center observed that there are not enough "bilingual" innovators who both understand the practice of medicine and are experts in engineering/data science. He feels that without a deep understanding of each language, collaboration efforts sometimes fall short or move too slowly.
- Ensure that educational programs embed data literacy to prepare current and future health care professionals for digitally enabled care models.
- Develop your own institutional framework for pursuing partnerships that focus on value creation. Given the scale of data required to develop AI technologies, AHSs will most certainly require partnerships to succeed—both across AHSs and with industry. When working with pharmaceutical companies and device manufacturers, understand that many AI/ML tools contain intellectual property and/or have a for-profit entity involved. Careful diligence is required to pursue relationships that will make strategic sense and to identify those that are most likely to succeed. In collaboration with profit-oriented businesses, educating those involved in the partnership about potential conflicts in decision-making around patient care is also crucial.
- Come together with other AHSs to create mechanisms and guidelines for data sharing, data aggregation, testing, and best practices. Approach data sharing and "crowd-sourcing" of data carefully—many large datasets, including the data contained in most of our EHRs, is not curated. Developing algorithms using poor data will only result in poor algorithms and ineffective or potentially harmful tools. Coming together in some way to promote data curation will be paramount in our progress toward the development of effective AI-driven clinical tools.
- Work collaboratively with other AHSs to develop industry partnerships in a principled manner: AHSs should lead the charge in educating the industry on what we need and on standardizing approaches to ensure fair participation in value creation.
- Uphold the standards AHSs have applied to all new treatments and clinical process: those of the human clinical trial. Amidst the hype around the potential that AI/ML brings to health care, many AI/ML solutions are being rushed to implementation through in silico testing (testing by computer). These tools merit prospective, randomized clinical trials to ensure efficacy and identify risks. It is important to remember that insurers may be inclined to push the deployment of these new tools, as they are familiar with the efficiency benefits and savings that come from AI-driven back-office tools. In clinical settings, we should require reasonable evidence that an AI/ML tool brings clinical and not just financial advantages.
- Adopt and advance an ethical framework to guide this transformation to the benefit of all. Known ethical challenges already exist. As AI technology advances, we will likely uncover new issues. As leaders in the field, we will have to be alert to thoughtfully address these issues as they arise.

AHSs have always played an important role in leading the transformation of health care. Our strength is biomedical research, and the associated resources required do not necessarily change the care delivery paradigm. Artificial and augmented intelligence requires completely new skill sets and technologies, which can and will impact the way that we conduct research, partner on research, source funding, teach, and deliver care. It therefore will be difficult to embrace this new area, and it isn't guaranteed that we will be leaders, though the opportunity certainly exists. Given our shared tripartite mission—discovery and innovation, learning labs for future clinicians and health care leaders, and provision of care to communities across the country and world—it is incumbent upon AHS leaders to be thoughtful in helping shape this next transformation in health care.

References

1. Blue Ridge Academic Health Group. *The Hidden Epidemic: The Moral Imperative for Academic Health Centers to Address Health Professionals' Well-Being.* Atlanta: Emory University; 2018. Available at http://whsc.emory.edu/blueridge/publications/archive/blue-ridge-winter2017-2018.pdf. Accessed January 2, 2019.
2. Ahmed M, Toor A, O'Neil K, Friedland D. Cognitive computing and the future of health care. *IEEE Pulse.* May/June 2017. Available at https://pulse.embs.org/may-2017/cognitive-computing-and-the-future-of-health-care/. Accessed January 2, 2018.
3. Collier M, Fu R, Yin L. Artificial intelligence: Healthcare's new nervous system. Accenture. December 15, 2017. Available at https://www.accenture.com/t20171215T032059Z__w__/us-en/_acnmedia/PDF-49/Accenture-Health-Artificial-Intelligence.pdf. Accessed January 17, 2019.
4. Sullivan T. Half of hospitals to adopt artificial intelligence within 5 years. *Healthcare IT News.* April 11, 2017. Available at https://www.healthcareitnews.com/news/half-hospitals-adopt-artificial-intelligence-within-5-years. Accessed January 2, 2018.
5. Chui M, Manyika J, Miremadi M. What AI can and can't do (yet) for your business. *McKinsey Quarterly.* January 2018. Available at https://www.mckinsey.com/business-functions/mckinsey-analytics/our-insights/what-ai-can-and-cant-do-yet-for-your-business. Accessed January 4, 2019.
6. RodriguezRamos J. Brains vs. computers. Medium. March 12, 2018. Available at https://becominghuman.ai/brains-vs-computers-f769548010f1. Accessed December 4, 2018.
7. Institute of Electrical and Electronic Engineers. Available at https://standards.ieee.org/industry-connections/ec/autonomous-systems.html. Accessed January 9, 2019.
8. ACRassist. ACR Informatics. Available at http://www.acrinformatics.org/acr-assist. Accessed December 4, 2018.
9. ACR Assist empowers radiologists to efficiently provide value-based imaging. *Imaging Technology News.* November 25, 2015. Available at https://www.itnonline.com/content/acr-assist-empowers-radiologists-efficiently-provide-value-based-imaging. Accessed December 4, 2018.
10. Cruz-Roa A, Gilmore H, Basavanhally A, Feldman M, Ganesan S, Shih N, Tomaszewski J, Ganzalez F, Madabhushi A. Accurate and reproducible invasive breast cancer detection in whole-slide images: A deep learning approach for quantifying tumor extent. *Scientific Report (Nature).* 2017;7:46450. Available at https://www.semanticscholar.

org/paper/Accurate-and-reproducible-invasive-breast-cancer-in-Cruz-Roa-Gilmore/d5b91f292c611dea61f6e95b007ae53c2766a5f9. Accessed January 4, 2019.

11. Watch out for diabetic retinopathy. *CDC Features*. Centers for Disease Control and Prevention. Available at https://www.cdc.gov/features/diabetic-retinopathy/index.html. Accessed December 4, 2018.

12. People with diabetes can prevent vision loss. National Eye Health Education Program, National Eye Institute. 2016. Available at https://nei.nih.gov/sites/default/files/nehep-pdfs/2016_NDM_Article_FINAL_508.pdf. Accessed December 4, 2018.

13. Murchison A, Hark L, Pizzi L, Dai Y, Mayro E, Storey P, Leiby B, Haller J. Non-adherence to eye care in people with diabetes. *BMJ Open Diabetes Research & Care.* 2017;5(1):3000333. Available at https://www.ncbi.nlm.nih.gov/pubmed/28878930. Accessed January 4, 2019.

14. Sixty percent of Americans with diabetes skip annual sight-saving exams. American Academy of Ophthalmology. October 20, 2016. https://www.aao.org/newsroom/news-releases/detail/sixty-percent-americans-with-diabetes-skip-exams. Accessed January 16, 2019.

15. Quellec G. Abramoff M. Estimating maximal measurable performance for automated decision systems from the characteristics of the reference standard application to diabetic retinopathy screening. *Conference Proceedings, IEEE Engineering in Medicine and Biology Society.* August 2014. Available at https://www.researchgate.net/publication/270659182_Estimating_maximal_measurable_performance_for_automated_decision_systems_from_the_characteristics_of_the_reference_standard_application_to_diabetic_retinopathy_screening. Accessed January 4, 2019.

16. Abramoff M, Lavin P, Birch M, Shah N, Folk J. Pivotal trial of an autonomous AI-based diagnostic system for detection of diabetic retinopathy in primary care offices. *npj Digital Medicine (Nature).* 2018;1:39. Available at https://www.researchgate.net/publication/327271235_Pivotal_trial_of_an_autonomous_AI-based_diagnostic_system_for_detection_of_diabetic_retinopathy_in_primary_care_offices. Accessed January 4, 2019.

17. Johne M. Artificial intelligence launches a new era in cardiac care. *Peter Munk Cardiac Center Magazine (The Globe and Mail).* November 2017. Available at https://www.uhn.ca/PMCC/media/Globe_Mail/Pages/artificial-intelligence-launches-new-era-in-cardiac-care-2017.aspx. Accessed January 4, 2019.

18. Coronary artery disease learning and algorithm development (CADLAD) clinical study. Analytics 4 Life. Available at https://www.analytics4life.com/clinical-study/. Accessed December 4, 2018.

19. What is precision medicine? National Institutes of Health, U.S. National Library of Medicine. Available at https://ghr.nlm.nih.gov/primer/precisionmedicine/definition. Accessed December 4, 2018.

20. 2bPrecise, an Allscripts company, launches a genomics and precision medicine Initiative at National Institutes of Health. Allscripts. August 8, 2016. Available at https://2bprecisehealth.com/wp-content/uploads/2017/01/News-Release_Allscripts-NIH-Genomics-Initiative_FINAL.pdf. Accessed December 4, 2018.

21. Ding M, Chen L, Cooper G, Young J, Lu X. Precision oncology beyond targeted therapy: Combining omics data with machine learning matches the majority of cancer cells to effective therapeutics. *Molecular Cancer Research.* 2018;16(2):269-278. Available at https://www.ncbi.nlm.nih.gov/pubmed/29133589. Accessed January 4. 2019.

22. Liu V, Escobar G, Greene J, Soule J, Whippy A, Angus D, Iwashyna T. Hospital deaths in patients with sepsis from 2 independent cohorts. *JAMA*, 2014;312(1):90-92. Available at https://pdfs.semanticscholar.org/2e7c/f2c7ae32c88dc14838991e1570d3fa4be0da.pdf?_ga=2.231972058.41750408.1546632281-1989338097.1546632281. Accessed January 4, 2019.

23. Kumar A, Roberts D, Wood K, Light B, Parrillo J, Sharma S, Suppes R, Feinstein D, Zanotti S, Tailberg L, Gurka D, Kumar A, Cheang M. Duration of hypotension before initiation of effective antimicrobial therapy is the critical determinant of survival in human septic shock. *Crit Care Med*, 2006;34(6):1589-96. Available at http://www.ccmpitt.com/ebm/sepsis/Kumar%20A,%20et%20al.%20%20Duration%20of%20hypotension%20before%20initiation%20o.pdf. Accessed January 4, 2019.

24. Giannini H, Chivers C, Draugelis M, Hanish A, Fuchs B, Donnelly P, Lynch M, Meadows L, Parker SJ, Schweikert WD, Mikkelsen, ME, Fishman N, Hansen CW, Umscheid C. Development and implementation of a machine-learning algorithm for early identification of sepsis in a multi-hospital academic healthcare system. Abstracts from the American Thoracic Society International Conference. May 2017. Available at https://www.atsjournals.org/doi/abs/10.1164/ajrccm-conference.2017.195.1_MeetingAbstracts.A7015. Accessed January 4, 2019.

25. Nemati S, Holder A, Razmi R, Stanley M, Clifford G, Buchman T. An interpretable machine learning model for accurate prediction of sepsis in the ICU. *Crit Care Med.* 2018;46(4):547-553. Available at https://www.ncbi.nlm.nih.gov/pubmed/29286945. Accessed January 10, 2019.

26. Oh J, Makar M, Fusco C, McCaffrey R, Rao K, Ryan EE, Washer L, West LR, Young VB, Guttag J, Hooper DC, Shenoy ES, Wiens JA. A generalizable, data-driven approach to predict daily risk of *Clostridium difficile* infection at two large academic health centers. *Infection Control & Hospital Epidemiology.* 2018;39(4):425-4333. Available at https://www.ncbi.nlm.nih.gov/pubmed/29576042. Accessed January 9, 2019.

27. Weins J, Shenoy E. Machine learning for healthcare: On the verge of a major shift in healthcare epidemiology. *Clinical Infectious Diseases*. 2018;66(1):149-153. Available at https://www.ncbi.nlm.nih.gov/pubmed/29020316. Accessed January 10, 2019.

28. Social determinants of health: Know what affects health. Social Determinants of Health, Centers for Disease Control and Prevention. Available at https://www.cdc.gov/socialdeterminants/. Accessed December 4, 2018.

29. Shin EK, Mahajan R, Akbilgic O, Shaban-Nejad A. Sociomarkers and biomarkers: predictive modeling in identifying pediatric asthma patients at risk of hospital revisits. *npj Digital Medicine (Nature)*. 2018;1:50 (2018). Available at https://www.researchgate.net/publication/328028243_Sociomarkers_and_biomarkers_predictive_modeling_in_identifying_pediatric_asthma_patients_at_risk_of_hospital_revisits. Accessed January 10, 2019.

30. Suicide rising across the US. *Vital Signs*. Centers for Disease Control and Prevention. Available at https://www.cdc.gov/vitalsigns/suicide/infographic.html. Accessed December 4, 2018.

31. Suicide rates rising across the U.S. CDC Newsroom. Centers for Disease Control and Prevention. Available at https://www.cdc.gov/media/releases/2018/p0607-suicide-prevention.html. Accessed December 4, 2018.

32. Goldhill O. Prescription AI: Machines know when someone's about to attempt suicide. How should we use that information? Quartz. September 5, 2018. Available at https://qz.com/1367197/machines-know-when-someones-about-to-attempt-suicide-how-should-we-use-that-information/. Accessed December 4, 2018.

33. Newby K. Compassionate intelligence: Can machine learning bring more humanity to healthcare? *Stanford Medicine.* Summer 2018. Available at http://stanmed.stanford.edu/2018summer/artificial-intelligence-puts-humanity-health-care.html. Accessed December 4, 2018.

34. Top Arkansas joint replacement center invests in technology to engage patients. OrthoFeed. April 20, 2017. Available at https://orthofeed.com/2017/04/20/top-arkansas-joint-replacement-center-invests-in-technology-to-engage-patients/. Accessed December 4, 2018.

35. Philippidis A. Interpreta and higi eye healthcare 'roadmaps' using patient data collected at grocers, pharmacies. *Clinical OMICS.* September 28, 2017. Available at https://www.clinicalomics.com/articles/interpreta-and-higi-eye-healthcare-roadmaps-using-patient-data-collected-at-grocers-pharmacies/1262. Accessed December 4, 2018.

36. Arndt B, Beasley J, Watkinson M, Temte J, Tuan WJ, Sinsky C, Gilchrist V. Tethered to the EHR: Primary care physician workload assessment using EHR event log data and time-motion observations. *Annals of Family Medicine.* 2017;15(5):419-426. Available at http://www.annfammed.org/content/15/5/419.full. Accessed January 10, 2019.

37. Raths D. One CIO's view of the path to precision medicine. *Healthcare Informatics* blog. May 10, 2018. Available at https://www.healthcare-informatics.com/blogs/david-raths/innovation/one-cio-s-view-path-precision-medicine. Accessed December 4, 2018.
38. Kumar S. Robotic process automation across industries. *Digitalist.* March 8, 2018. Available at https://www.digitalistmag.com/digital-economy/2018/03/08/robotic-process-automation-across-industries-05955888. Accessed December 4, 2018.
39. Faggella D. AI in healthcare IT security—Why hospitals are targets. emerj. October 8, 2017. Available at https://emerj.com/ai-podcast-interviews/ai-healthcare-security-hospitals-targets/. Accessed December 4, 2018.
40. Ascension debuts subsidiary to help other companies succeed through process automation. *Business Wire.* June 18, 2018. Available at https://www.businesswire.com/news/home/20180618006054/en/Ascension-Debuts-Subsidiary-Companies-Succeed-Process-Automation. Accessed December 4, 2018.
41. Air France Flight 447's lessons—four years later. CBS News Online. June 1, 2013. Available at https://www.cbsnews.com/news/air-france-flight-447s-lessons-four-years-later/. Accessed December 4, 2018.
42. Preventing a plane crash—Research helps pilots train for aerodynamic stalls. *Phys Org.* June 8, 2018. Available at https://phys.org/news/2018-06-plane-crashresearch-aerodynamic-stalls.html. Accessed December 4, 2018.
43. Ross C, Swetlitz I. IBM's Watson supercomputer recommended 'unsafe and incorrect' cancer treatments, internal documents show. *STAT*. July 25, 2018. Available at https://www.statnews.com/2018/07/25/ibm-watson-recommended-unsafe-incorrect-treatments/?utm_source=STAT+Newsletters&utm_campaign=beb06f048d-MR_COPY_08&utm_medium=email&utm_term=0_8cab1d7961-beb06f048d-150085821. Accessed December 4, 2018.
44. Wu N. Simulation improves medical education—one case at a time. *Healthcare Innovation News*. 2015;2(1):1-2. Available at https://www.i-human.com/wp-content/uploads/2015/01/Healthcare-Innovation-News-Jan-2015-Wu.pdf. Accessed January 10, 2019.
45. Fink C. How VR saves lives in the OR. Immersive Touch. April 23, 2018. Available at https://www.immersivetouch.com/press-archive/2018/4/23/how-vr-saves-lives-in-the-or. Accessed December 4, 2018.
46. The Top 7 virtual reality digital health companies. Medtech Boston. February 26, 2018. Available at https://medtechboston.medstro.com/blog/2018/02/26/the-top-6-virtual-reality-digital-health-companies/. Accessed December 4, 2018.
47. Fard M, Ameri S, Chinnam R, Pandya A, Klein M, Ellis RD. Machine learning approach for skill evaluation in robotic-assisted surgery. *Proceedings of the World Congress on Engineering and Computer Science.* October 2016. Available at https://arxiv.org/pdf/1611.05136.pdf. Accessed January 10, 2019.
48. Lohr S. M.I.T. plans college for artificial intelligence, backed by $1 billion. *The New York Times,* October 15, 2018. Available at https://www.nytimes.com/2018/10/15/technology/mit-college-artificial-intelligence.html. Accessed December 4, 2018.
49. Jenna S. How artificial intelligence will make basic research self-sustainable. TEDx Concordia. December 19, 2017. Available at https://www.youtube.com/watch?reload=9&v=tPb_IqoKNDY. Accessed December 4, 2018.
50. Accelerating research with AI & Watson for drug discovery. IBM. Available at https://www.ibm.com/blogs/insights-on-business/healthcare/accelerating-research-ai-watson-drug-discovery/. Accessed December 4, 2018.
51. Milmo C. AI system will trawl through millions of academic journals to find links missed by scientists. *Independent.* November 3, 2015. Available at https://www.independent.co.uk/news/science/ai-system-will-trawl-through-millions-of-academic-journals-to-find-links-missed-by-scientists-a6719876.html. Accessed December 4, 2018.
52. Bookbinder M. The Intelligent trial: AI comes to clinical trials. *Clinical Informatics News.* September 29, 2017. Available at http://www.clinicalinformaticsnews.com/2017/09/29/the-intelligent-trial-ai-comes-to-clinical-trials.aspx. Accessed December 4, 2018.

Appendix

Opening vignette, *continued from page 4*

The tumor board is convened, including Dr. Henry Ramsey in otolaryngology, Dr. Maria Moreau in medical oncology, and Dr. Steven Wilson in radiation oncology, as well as several other clinicians.

HR: "This is a stage 1 T2N1M0 p16 positive squamous cell carcinoma of the tonsil."

The case is reviewed by all present, and a therapeutic approach is recommended based on the clinical picture, as well as on Peggy's summary of the relevant scientific literature and her review of available clinical trials that might be relevant.

HR: "The treatment options include transoral robotic resection of the tumor with neck dissection followed by post-operative radiation therapy or concurrent chemotherapy/radiation therapy to standard dosing. Mr. Burdell has expressed interest in proceeding with surgery and if possible would like to avoid chemotherapy."

Various comments and gestures of agreement come from members of the tumor board.

Most of those present have their laptops open during this discussion. It is easy to spot their cognitive assistant icons on the upper left of their screens. Etiquette for interactions of clinicians and cognitive assistants has emerged over the few years that this technology has been available.

First, during meetings clinicians can query their assistants by typing but not by talking. Second, assistants cannot communicate with each other during meetings. Before adopting these rules, meetings had become rather chaotic, with everybody talking at once but not to each other. Communications among assistants often resulted in a second meeting being conducted below the surface.

The meeting concludes by all agreeing on a summary of the tumor board recommendations, which are sent to primary care physician, Dr. Edward Cummings.

****

Drs. Ramsey, Moreau, and Wilson meet with the patient, Mr. George Burdell and his older sister, Agnes Hunsinger. They walk through the treatment options, i.e., transoral robotic surgery versus concurrent chemoradiation.

GB: "What is the surgical procedure?"

HR: "We use a "robot" to remove the tumor in the tonsil. We have to remove the enlarged cancer lymph node from your neck, including the surrounding lymph nodes as well."

GB: "Is there a name for the procedure?"

HR: "It's is called TORS with selective neck dissection."

GB: "Dissection! Sounds terrible. Like high school biology."

HR: "I know, but, medically speaking, it just means the surgical removal of tissues which are diseased."

AH: "I am going to be helping George with the practical issues associated with all this. What will that include?"

HR: "Well, for the surgery we would perform the neck dissection and then one week later return to the OR and remove the tumor using the robot."

He hands Ms. Hunsinger a summary sheet.

SW: "We would then wait at least four to six weeks and then start your post-operative radiation."

GB: "Well, what about the other options?"

MM: "Well, instead of surgery we would give you a higher dose of radiation and also a dose of chemotherapy to make the tumor respond better. "

GB: "Why would I choose one over the other?"

AH: "This seems complicated, and George has never been that good at being organized."

GB: "You always say that Agnes. I am not that bad."

HR: "Do you have a cell phone, Mr. Burdell?"

GB: "Sure, an iPhone actually."

HR: "Great, we are going to provide you an app called HealthHelp that will assist you with all this."

GB: "Like the app that keeps track of how much I walk?"

HR: "Something like that. It will know about all your appointments and prescriptions. It will send you text messages to remind you. It can review what we discuss today to help you make a decision or understand the treatment options better. You can ask it questions. You can even give it a name."

GB: "I think Agnes would be a good name."

HR: "You can provide your sister Agnes with access to HealthHelp so she can keep track of things with you and provide help when you need it."

GB: "Then I think I will change the name to Ruth, who was our mother. I wouldn't want to be confused by two Agneses."

The conversation then switches back to the benefits and risks of the various treatment options. Mr. Burdell ultimately decides to proceed with TORS with neck dissection followed by radiation.

GB: "Do you interact with HealthHelp as well?"

SW: "Yes, we all do. You will receive communications from your whole cancer team, including Drs. Ramsey, Moreau, and me, as well as several other people you will meet along the way, including your speech pathologist, nutritionist, and social worker."

GB: "And, I can ask questions of anybody?"

SW: "Yes, of course. You might find it interesting that we keep track of all questions that patients ask, as well as all the answers. This has enabled us to continually improve patients' experiences."

GB: "I guess that I better be careful of what I ask."

SW: "We don't keep track of who asked what questions. Your privacy is assured."

GB: "That's nice to know."

****

Following the completion of all planned therapy, Drs. Ramsey, Moreau, and Wilson follow Mr. Burdell on a three-month basis for signs and symptoms of recurrence. Dr. Cummings sees Mr. Burdell for routine checkups for any other chronic disease.

Millie: "Mr. Burdell has become a model patient. He schedules checkups and takes his prescriptions, quite unlike his previous behaviors."

EC: "Seems like HealthHelp changed his life. His sister, Agnes, even sent me an email about that."

Millie: "I wonder if it isn't the combination of a serious health scare and the availability of HealthHelp?"

EC: "Well, Millie, why don't you research that question and let me know what you find?"

Millie: "I already have. That's why I brought it up."

About the Blue Ridge Academic Health Group

The Blue Ridge Academic Health Group studies and reports on issues of fundamental importance to improving the health of the nation and its health care system and enhancing the ability of the academic health center (AHC) to sustain progress in health and health care through research—both basic and applied—and health professional education. In 22 previous reports, the Blue Ridge Group has sought to provide guidance to AHCs on a range of critical issues. (See titles, page 26.)

For more information and to download free copies of these reports, please visit www.whsc.emory.edu/blueridge.

Previous Blue Ridge Reports

See http://whsc.emory.edu/blueridge/publications/reports.html.

Report 22: *The Hidden Epidemic: The Moral Imperative for Academic Health Centers to Address Health Professionals' Well-Being.* 2018.

Report 21: *The Academic Health Center: Delivery System Design in the Chnging Health Care Ecosystem—Sizing the Clinical Enterprise to Support the Academic Mission.* 2017.

Report 20: *Synchronizing the Academic Health Center Clinical Enterprise and Education Mission in Changing Environments.* 2016.

Report 19: *Refocusing the Research Enterprise in a Changing Health Ecosystem.* 2015

Report 18: *A Call to Lead: The Case for Accelerating Academic Health Center Transformation.* 2014

Report 17: *Health Professions Education: Accelerating Innovation Through Technology.* 2013.

Report 16: *Academic Health Center Change and Innovation Management in the Era of Accountable Care.* 2012.

Report 15: *The Affordable Care Act of 2010: The Challenge for Academic Health Centers in Driving and Implementing Health Care Reform.* 2012.

Report 14: *The Role of Academic Health Centers in Addressing the Social Determinants of Health.* 2010.

Report 13: *Policy Proposal: A United States Health Board.* 2008.

Report 12: Advancing Value in Health Care: *The Emerging Transformational Role of Informatics.* 2008.

Report 11: *Health Care Quality and Safety in the Academic Health Center.* 2007.

Report 10: *Managing Conflict of Interest in AHCs to Assure Healthy Industrial and Societal Relationships.* 2006.

Report 9: *Getting the Physician Right: Exceptional Health Professionalism for a New Era.* 2005.

Report 8: *Converging on Consensus? Planning the Future of Health and Health Care.* 2004.

Report 7: *Reforming Medical Education: Urgent Priority for the Academic Health Center in the New Century.* 2003.

Report 6: *Creating a Value-driven Culture and Organization in the Academic Health Center.* 2001.

Report 5: *e-Health and the Academic Health Center in a Value-Driven Health Care System*. 2001.

Report 4: *In Pursuit of Greater Value: Stronger Leadership in and by Academic Health Centers.* 2000.

Report 3. *Into the 21st Century: Academic Health Centers as Knowledge Leaders.* 2000.

Report 2: *Academic Health Centers: Good Health Is Good Business.* 1998.

Report 1: *Academic Health Centers: Getting Down to Business*, 1998.

EMORY UNIVERSITY

Woodruff Health Sciences Center