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Developing a Research Center for Artificial Intelligence in Medicine

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Abstract

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Artificial intelligence (AI) and machine learning (ML) are driving innovation in biosciences and are already affecting key elements of medical scholarship and clinical care. Many schools of medicine are capitalizing on the promise of these new technologies by establishing academic units to catalyze and grow research and innovation in AI/ML. At Stanford University, we have developed a successful model for an AI/ML research center with support from academic leaders, clinical departments, extramural grants, and industry partners. The Center for Artificial Intelligence in Medicine and Imaging uses the following 4 key tactics to support AI/ML research: project-based learning opportunities that build interdisciplinary collaboration; internal grant programs that catalyze extramural funding; infrastructure that facilitates the rapid creation of large multimodal AI-ready clinical data sets; and educational and open data programs that engage the broader research community. The center is based on the premise that foundational and applied research are not in tension but instead are complementary. Solving important biomedical problems with AI/ML requires high-quality foundational team science that incorporates the knowledge and expertise of clinicians, clinician scientists, computer scientists, and data scientists. As AI/ML becomes an essential component of research and clinical care, multidisciplinary centers of excellence in AI/ML will become a key part of the scholarly portfolio of academic medical centers and will provide a foundation for the responsible, ethical, and fair implementation of AI/ML systems.

Recent advances in artificial intelligence (AI) and machine learning (ML) are transforming medical research, education, and clinical care.[1] Over the past decade, innovative deep learning methods have revolutionized the analysis of medical data, including images, text, structured data, and genomic information.[2] These innovations have led to high interest and rapid growth in the use of AI/ML methods in biomedicine. Many medical institutions have recognized the opportunities and needs in this area, leading to the establishment of centers of excellence in AI, data science, and ML.

Schools of Medicine and their associated health systems are the natural places for innovative work developing AI/ML methods for biomedical sciences and clinical care. Academic medical centers can produce and label the clinical data needed to train and test ML algorithms, a key bottleneck in AI/ML research.[3] In addition, when the medical center is located on a broader university campus, clinicians and clinician scientists can readily collaborate with faculty and students in schools of engineering, who have early awareness and mastery of the latest computer science methods. Campus experts in ethics, business, law, philosophy, and economics can help ensure that innovative AI algorithms are developed in a fair and ethical manner.

As academic health systems grapple with ubiquitous financial pressures while also seeking to innovate in AI, we share our experience establishing an AI center of excellence that bootstrapped a small investment from 3 departments within our school into a strong growing interdisciplinary unit that supports AI/ML research in medicine across our institution.

ESTABLISHING THE CENTER

The value of deep learning methods to the biomedical sciences became apparent in the mid-2010s when neural network approaches first began winning annual image recognition challenges.[4] One challenging task, automated captioning,[5] is directly analogous to the image interpretation tasks performed in radiology, pathology, cardiology, dermatology, ophthalmology, gastroenterology, and many other medical specialties. However, medical data are distinctly different from the data typically used by computer scientists to test their methods. Health data can include high-resolution, 3- and 4-dimensional imaging data, telemetry time-series data, structured laboratory results, and the distinctive terminology and phrasing of narrative medical notes. These disparate data types, together with the need for accurate, high-stakes decision-making from privacy-preserved data, have spurred the development of many AI/ML methods that would not have been developed outside of medicine. These new powerful techniques enable the development of clinical decision support tools in a matter of weeks or months rather than years.

Centers of excellence in AI have been around since the term “artificial intelligence” was first coined in the 1950s. These centers are often located in schools of engineering and have waxed and waned with the boom-and-bust cycles of AI over the past decades. Medicine has not been a major focus of these initiatives in part because AI-ready medical data are scarce outside of repositories secured to assure patient privacy. These sequestered data stores are a marked departure from the open-source software and open data that have spurred the AI/ML revolution outside of medicine.

The unique needs and opportunities posed by applying modern AI/ML methods to biomedical problems led to the recognition that a center within the School of Medicine was necessary to serve as a locus for scientific leadership in this area. In response, the Stanford Center for Artificial Intelligence in Medicine and Imaging (AIMI Center) was established in 2018 with the mission to support the unique needs of medical AI/ML researchers who are optimizing how clinical data are used to improve health. Initial financial support came from the following 3 clinical departments: Radiology, Pathology, and Medicine.

The AIMI Center aims to bring investigators together in a common academic home, connecting them with researchers using similar methods from other departments and schools, enabling Stanford to pursue pre-eminence, garner extramural support from government and industry, and facilitate the translation of these innovations to the clinical setting. The center draws on key institutional strengths in clinical medicine, biomedical data science, ML, biostatistics, computer vision, and natural language processing:

- Stanford Medicine’s clinical data, occupying over a petabyte of storage, are available in a research repository, enabling rapid assembly of the large data sets needed to train ML algorithms.
- Stanford’s graduate programs in computer science, biomedical informatics, electrical engineering, bioengineering, and computational and mathematical engineering yield highly trained students ready to collaborate on these projects.
- Our school of medicine, our main hospitals (adult and pediatric), our school of engineering, and our other schools are located together on our campus, facilitating interdisciplinary AI/ML research collaborations.

- Because our campus resides in Silicon Valley, we are readily accessible to potential industry partners, both startups and established companies.

The AIMI Center began with a focus on developing and evaluating new AI methods for clinical imaging, leading to an administrative location within the department of radiology. As the field has matured, imaging remains a dominant focus of the health AI/ML industry; 76% of the over 900 radiology AI algorithms cleared by the US Food and Drug Administration (FDA) are focused on radiology.[6] However, it soon became clear that multimodal, multidimensional data, including imaging, clinical narrative, structured data, telemetry, and genomics are necessary to solve many important clinical problems with AI/ML.[2] We therefore broadened our mission to support interdisciplinary ML research that optimizes how *all* biomedical data can be used to promote health. Our goal was to develop, evaluate, and disseminate AI systems that enhance early detection, reduce diagnostic errors, aid in selecting appropriate treatment, and improve the quality and efficiency of medical care.

FOUR ELEMENTS OF THE STANFORD AIMI CENTER SUPPORT MODEL

The Center serves as a locus for faculty collaboration, extramural fundraising, internal seed grants, research seminars, and other academic development activities. The center thus created a positive impact in part through rich scholarly networks and new sources of extramural support. To establish pre-eminence in AI/ML in medicine, we employed the following 4 main tactics:

1. Build an interdisciplinary community.
2. Catalyze extramural funding.
3. Enhance infrastructure for AI/ML research.
4. Engage and educate the community.

In the following sections, we describe our work to support these tactics.

Build an Interdisciplinary Community

Artificial intelligence/ML research in medicine is inherently interdisciplinary. Clinical expertise is required to identify clinically important problems that ML can solve. Data science knowledge is needed to extract, curate, and analyze large medical data sets. Computer science faculty and students are often the first to become aware of the latest ML methods and therefore often lead the development of novel ML architectures appropriate for clinical data. Biomedical scientists often convene these diverse research teams.

At our institution, centers are complementary to departments and generally do not hire their own faculty. We therefore employed a faculty affiliation model. Faculty who had primary appointments in departments across the university could become “affiliated faculty” and take advantage of the center’s services. Over 200 faculty across 20 departments, primarily from the schools of medicine and engineering, are affiliated with our center. About one third of affiliated faculty are active in extramurally funded research projects. Our affiliated faculty and students are drawn from the departments of anesthesia, bioengineering, biomedical data science, cardiothoracic surgery, computer science, computational and mathematical engineering, dermatology, electrical engineering, emergency medicine, management science and engineering, genetics, mechanical engineering, medicine, neurology and neurological sciences, neurosurgery, ophthalmology, otolaryngology, pathology, pediatrics, psychology, psychiatry and behavioral sciences, radiation oncology, radiology, surgery, and urology.

The AIMI Center is based on the proposition that solving important clinical problems requires innovative foundational team science. We reject the dichotomy that often exists between applied and foundational research. Instead, we believe that solving real biomedical problems requires innovative methods, which provide ample scholarly opportunities for both computer scientists and biomedical scientists.

The center fosters team science through its project-based learning program, also known as the Healthcare AI Bootcamp. Led by a postdoctoral scholar and advised by several core faculty, selected students with AI/ML skills receive course credit to collaborate with faculty from the Schools of Medicine and Engineering. On the first day of class, clinician scientists present their clinical problems and the data sets that can be employed to address them with AI/ML. Students form teams to approach these problems over the subsequent one or two quarters. These project-based learning programs are attractive to research scientists in the school of medicine because they supply computer science expertise at no additional cost. The resulting projects enable clinical faculty interested in AI/ML to participate as clinical experts, data labelers, and leaders of clinical trials to evaluate the resulting algorithms.[7] Engineering students are attracted to a project-based learning experience that solves problems that they believe have societal significance. Our project-based learning programs have mentored over 100 students and have become a strong engine for rigorous scientific research and innovation.

Catalyze Extramural Funding

Artificial intelligence/ML methods are sometimes insufficient to solve a specific clinical problem. Thus, preliminary work showing the promise of a particular approach is essential to the success of extramural grant applications. To address this need, the AIMI Center established an internal seed grant program. In 2019, this program supported 7 one-year $75,000 AI/ML research projects, primarily focused on imaging. Five of these 7 projects subsequently received National Institutes of Health R-grants: 2 R01 grants, 2 R21 grants, and 1 K99R00 grant garnered $7.2 million in total costs for a 15:1 return on investment (not including subsequent venture investments in the developed technologies).

In 2021, after consultation with prospective applicants and our executive committee, we increased the size of these grants to $100,000 per year for 2 years. We sought and received matching funds from our university-wide AI institute, the Human Centered AI Institute (HAI), and the department of pathology, resulting in a $1.2 million internal grant program that supported 6 projects. We offered a similar program again in 2023. A complementary cloud computing grant program developed through industry partnerships supports 15 compute-intensive ML research projects, including many of the seed grant projects.

As a result of these internal grant programs, the AIMI Center has attracted extramural support from a variety of other sources. They are as follows:

- Millions in additional extramural sponsored research funds, primarily from the National Institutes of Health, have been received through the AIMI Center since 2018.
- The AIMI Center has received sponsored research support and gifts from 3 foundations—the Gordon and Betty Moore Foundation, the Lowenstein Foundation, and the Paustenbach Fund.
- A 5-year research partnership with a large health care information technology vendor, established in 2019, supports 20 faculty and students working on 4 clinical AI research projects focused on computed tomography (CT) and magnetic resonance image enhancement, imaging workflow, and AI/ML computing infrastructure.
- Our faculty and trainees have received several career development awards for AI-related research.
- The AIMI Center attracts numerous self-funded visiting postdoctoral scholars and faculty who contribute to ongoing AI/ML research across Stanford laboratories.

Enhance Research Infrastructure

One of the most important bottlenecks in ML research is the availability of AI-ready labeled data sets. To address this need, we collaborated with the research technology unit in our school of medicine to make petabyte-scale biomedical data readily accessible in digital form for ML experiments. We have assisted with the migration of all radiology data since 2011 (millions of imaging studies) from our hospital's vendor-neutral archive to the Stanford Research Repository (STARR),[8] where they are linked to Stanford's electronic health record (EHR) data. We helped develop tools for data migration, cohort selection, and image and text deidentification within STARR, which now serves as a searchable petabyte-scale repository of AI-ready clinical data. We licensed image labeling software for all Stanford investigators and developed an open-source clinical text deidentification algorithm[9] that has been used by other laboratories over 10 million times. Over time, other forms of digital data will be migrated to STARR, including pathology images and genomic information.

We are using these multimodal data to create foundation models for both EHR data and medical imaging data to improve the accuracy and function of a wide variety of ML models in medicine.[10-14]

In parallel, we have created a realistic information technology simulation of a radiology reading room. A research instance of our picture archiving and communication system is connected to an image router, the STARR data archive, a test version of our EHR, and a second instance of our radiology speech recognition documentation system. This simulation of a radiology reading room serves as a model for other specialties to create clinical simulation environments that support reader studies, algorithm evaluations, and complex data-labeling tasks.

Engage and Educate the Community

We share the unique resources and expertise available in our center through education, tools, and data that are useful to other laboratories. Artificial Intelligence in Medicine and Imaging faculty developed an AI in health care specialization, in partnership with the Stanford Center for Health Education, on an online education platform (Coursera), which has attracted over 17,000 learners. In partnership with HAI, our university-wide AI/ML institute, AIMI cosponsors an annual AI + health virtual CME meeting, which recently attracted over 1000 registrants who heard from over 100 speakers in 4 tracks. Our annual AIMI symposium garners a hybrid audience of thousands each year. The center hosts monthly research seminars, journal clubs, and panel discussions that educate the community and provide speaking opportunities for center affiliates. We have also engaged dozens of high school students through our summer internship program, which this year received over 2000 applicants for 50 positions.

Our open data program is a key point of engagement with the broader research community. In partnership with the Stanford Health Care Privacy Office, the University Privacy Office, and our Research Technology Office, the AIMI Center makes AI-ready Stanford clinical data widely available for noncommercial use. On the basis of partnership with a cloud vendor (Microsoft), this program has released over 384,000 images in 20 AI-ready imaging data sets, many with associated code on GitHub and AI models on Hugging Face. Our seminal work on chest radiographs included the release of 223,000 labeled chest radiographs and reports and has garnered thousands of citations.[15-17] These data sets are released under a data sharing program that requires both electronic deidentification and human review of each released data point. We frequently share private data securely with other academic organizations and with industry partners under data use agreements that support collaborative projects.

We view industry as a key element of our learning ecosystem. Industry partners often know more about the needs of users than academic researchers. They have core competence in bringing innovations through regulatory approval to the point of care, making them ideal partners for the collaborative development and dissemination of AI/ML models. The AIMI Center Industry Affiliates program is one of more than 80 such programs at Stanford University, which is designed to provide mechanisms for faculty and industry partners to discuss and explore broad research topics in a precompetitive environment. The center's industry affiliate program has garnered support from 16 affiliates, enabling research collaborations and sustaining our internal grant programs. The program enables faculty and students to learn about industry perspectives and priorities while corporate members are exposed to new ideas and research directions. Artificial Intelligence in Medicine and Imaging-affiliated faculty and students have spun off 10 health AI companies, some of which have become AIMI industry affiliates.

Our center partners with HAI to provide evidence-based AI policy recommendations for legislators and policymakers. Since the inception of our policy work in 2021, we have disseminated 6 AI health policy briefs to congressional staff and other policymakers and have funded policy projects clarifying tort liability for health AI, reporting on the dangers of dual use of health AI technologies, and supporting an AI Health Policy Scholars program for individuals who are underrepresented in medicine. Already, health AI regulators are proposing novel frameworks to accommodate the specific risks and benefits of AI/ML tools.[18]

Rapid recent progress in AI/ML research is beginning to outstrip our ability to design and implement health AI/ML systems fairly, ethically, and responsibly. One of the center's engagement goals was to develop policy recommendations and showcase concrete examples of responsible AI/ML implementation in medicine. To this end, we joined the founding team for the Coalition for Health AI, which is a community of academic health systems, organizations, and expert practitioners of AI/ML whose mission is to provide guidelines for the use of health AI tools to ensure high-quality care and increase credibility among users. In a recent review of responsible adoption of AI, we found limited guidance on how to assess fairness or utility.[19] To address the need for thoughtful consideration of ethics and fairness, Stanford recently established Responsible AI for Safe and Equitable Health (RAISE Health), a joint initiative between Stanford Medicine and the Stanford Institute for HAI that brings together scholars from our center and across campus to guide the responsible use of AI/ML in biomedical research, education, and patient care. For example, we have devised a framework to estimate algorithm usefulness[20] and made it broadly available.[21] We developed a method to assess fairness[22] and found its application in a fairness audit.[23] We have collaborated with ethicists to publish a framework for using and sharing clinical imaging data[24] and proposed governance models for AI/ML in clinical imaging.[25] When relevant, we include patients on AI research teams. The team that developed a coronary calcium detection algorithm included a patient who was instrumental in designing the notification message for patients.

EXAMPLES OF SCIENTIFIC WORK

A guiding principle of our center is that high-quality scholarship serves as the foundation for the other goals of the center. Below are examples of the scholarly work being conducted by the center:

1. Our first interdisciplinary AI Bootcamp project produced a collection of algorithms that identify patients at high risk for mortality within 1 year. These algorithms were prospectively validated and are now deployed across 3 care settings to enable team-based advanced care planning. They have improved the care of about 6000 patients across 8 clinical disciplines and increased our institution's advance care planning rate—a key quality metric—from 3% to over 25%.[26,27]

2. Our infrastructure work produced a state-of-the-art clinical text deidentification algorithm that is not only widely used by our own laboratories but also has been used over 10 million times by other laboratories.[9,28]

3. Our industry partnerships have resulted in several publications including a practical toolkit for user-centered design to configure AI/ML models in a clinically actionable way and mitigation strategies for improving model stability.[29,30]

4. Our open data program has produced a chest radiograph data set that is widely used as a benchmark and testbed for AI/ML computer vision algorithms[15] and an entity and relation extraction algorithm that produces knowledge graphs from clinical text.[31]

5. A pneumonia detection algorithm we developed is deployed at over a dozen urgent care sites at Intermountain Health as part of a prospective trial to measure the effect on treatment decisions, adherence to antibiotic guidelines, and mortality.[32,33] We have received a grant to support a clinical trial at a second hospital system.

6. Researchers in our center developed an AI algorithm that quantifies coronary calcium on a routine (non-gated) CT of the chest, enabling opportunistic screening of patients who undergo chest CT for any reason.[34] This creates the potential for coronary risk screening to reach an additional 18 million patients per year at little additional cost. We have received NIH funding to test how knowledge of this information might affect clinical decision-making. A clinical trial reported that notifying the patient and primary care clinician increased the rate of statin use from 7% to more than 50%[35] The algorithm has been licensed to a startup spun off from the center, was recently cleared by the FDA, and is now in use at major hospital systems throughout the United States.

7. Center faculty have developed AI algorithms that synthesize high-quality images suitable for diagnostic use from noisy, abbreviated, and low-dose images.[36-38] These technologies enable the reduction of radiation dose, contrast dose, and imaging times and ultimately facilitate the production of less expensive imaging devices. This technology has been cleared by the FDA, licensed to a startup, and is being used at hospitals throughout the United States.

These examples showcase the interdisciplinary and translational nature of our work and highlight the importance of our relationships with industry.

CENTER GOVERNANCE

The center is led by a faculty director and codirector. Funded staff include an executive director, an IT program manager, a project manager, and a half-time administrative assistant. A group of volunteer associate directors takes leadership responsibility for thematic areas, such as research and education, ethics and policy, and data science. An executive committee comprising associate directors and core faculty meets monthly to review progress, share information, and ensure that the center’s activities are aligned with the interests of the center’s stakeholders.

The center is guided by an internal advisory committee that meets 2-3 times per year, composed of the chairs of the departments of radiology, pathology, medicine, and biomedical data science, as well as key collaborators from the school of engineering, a hospital vice president, the chief data scientist at our adult hospital, and the chief medical information officer at our pediatric hospital.

Individuals from industry and from academic institutions other than Stanford who engage actively with the center can become affiliate fellows and affiliate scholars, respectively.

NEXT STEPS

Our cross-department, cross-school model of engaging researchers, together with specific initiatives to encourage cross-disciplinary team science, has been successful in developing a vibrant and collaborative research center. We have accomplished the goals we set for the center 5 years ago and have enhanced Stanford's reputation as a pre-eminent institution in AI/ML and health research. Our funding programs and the data science infrastructure we have helped build have catalyzed extramural funding in AI/ML. We have also fostered a larger community of AI/ML scholars outside Stanford who utilize the public data, code, and other research resources we produce.

As we celebrate our fifth anniversary, we intend to expand our current focus from clinical decision support to both scientific discovery in biosciences and clinical implementation in care delivery settings.

Labs focusing on scientific discovery are increasingly capitalizing on AI/ML methods, including drug discovery, protein structure determination, genome sequencing, and interpretation of multiplex cellular imaging. These investigators would benefit from the programs we have developed for clinical decision support research.

Clinical implementation suffers from a resource gap: extramural sources of funding (eg, NIH and industry) are focused on the development of novel methods to address major public health problems and are reluctant to fund the substantial costs of converting novel algorithms into clinically usable systems. Hospitals often view these translational activities as outside their purview because their infrastructure is designed to support finished products. Our chief data scientist has been charged to test a growing portfolio of AI/ML models in our health system, starting with 3-5 during the first year, supported by investments from the health system, dean's office, and department of medicine.

DISCUSSION

Development of interdisciplinary academic units to support progress and innovation in medical AI/ML are critical to the success of the research enterprise. Many other medical institutions have established academic units focused on this area. The Alliance for Centers for Artificial Intelligence in Medicine currently has more than 50 members (personal communication, Dr Anthony Chang), many of which focus on interdisciplinary work, team science, and collaboration between clinicians and computer scientists. We have described an approach to the design and implementation of one such center of excellence. By sharing the principles behind the establishment of our new unit, we hope to provide other academic medical schools with a guide to the formation of such centers.

Several local strengths have led to the success of this model at our institution. Our well-established laboratories in bioscience, data science, and computer science continue to innovate in areas that lead to breakthroughs in AI/ML in medicine. We have a long history of clinician scientists working in AI dating back to the 1970s. Our clinical care enterprise is located on campus and has embraced the use of these tools to support clinical care. Our privacy offices recognize the value of open science and open data and have allowed us to make many of our AI-ready data sets available to the research community. All these strengths are located within a few blocks of one another on campus. Finally, our location in Silicon Valley and the entrepreneurial culture at our institution have facilitated our relationships with industry partners.

Although we have leveraged a small investment to build a successful center over 5 years, our center, like many academic units that support research, is not yet financially self-sustaining. Some of the AI algorithms developed in our center have been licensed to commercial vendors and will bring licensing revenues to the institution. Our partnership with HAI, our university-wide AI institute, provides economies of scale and matching funds for some activities. We are planning to extend our open data program to enable commercial entities to license data sets for a fee that would help defray the costs of the program. We have received additional investments from clinical departments and are also seeking additional sources of industrial, foundation, and philanthropic support that would sustain our center. Extramural program grants and synergies with our existing clinical and translational science award can also support our work.

CONCLUSION

As progress in AI/ML is accelerating, it is difficult to predict the innovative breakthroughs that may occur in the next 2 years, let alone the next 5 or 10 years. However, a massive investment in AI/ML algorithm development is occurring in biosciences, with the release and rapid adoption of large language models and other powerful tools to solve important biomedical problems. We have described an example of how an AI research center can support academic investigators pursuing ML research projects in medicine. Because academic health systems can partner with consenting patients to produce vast stores of biomedical data, they are uniquely positioned to lead the development, demonstrate the benefits, and capitalize on the innovations in AI/ML for health care. Their location on a broader university campus uniquely positions them to address ethics and fairness to ensure the responsible development and use of AI/ML systems.

Rigorous evaluation of a research center must ultimately rest on explicit comparisons between the structure we have described and alternative models that exist at other institutions. The success of these AI research centers will help accelerate and guide these breakthroughs, which should be measured by their effects on the quality, efficiency, and cost of care and ultimately by their impact on public health.

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POTENTIAL COMPETING INTERESTS

Dr Langlotz reports grants/gifts paid to institution from Carestream, Clairity, GE Healthcare, Google Cloud, IBM, IDEXX, Hospital Israelita Albert Einstein, Kheiron, Lambda, Lunit, Microsoft, Nightingale Open Science, Philips, Subtle Medical, VinBrain, Visiana, Whiterabbit.ai, Lowenstein Foundation, Gordon and Betty Moore Foundation, and Paustenbach Fund; consulting fees from Sixth Street and Singapore Ministry of Health; support for attending meetings and/or travel from Singapore Ministry of Health and Radiological Society of North America; patents planned, issued or pending—GE Healthcare; leadership or fiduciary role in Bunkerhill Health, Board of Directors and Radiological Society of North America, President and Board of Directors; stock or stock options holder at Bunkerhill Health and whiterabbit.ai; and advisor and option holder in GalileoCDS, Sirona Medical, Adra, and Kheiron. Dr Shah reports as primary employer at Stanford Health Care and Stanford University; royalties or licenses in Coursera (artificial intelligence in Healthcare), run by Stanford online; board member in Coalition for Health AI, unpaid; cofounder and stockholder in Prealize Health (a predictive analytics company) and Atropos Health (an on-demand evidence generation company); and advisor, option grantee in Curai Health, a tech enabled primary care company. Dr Lungren reports as an employee at Microsoft. Dr Larson reports as a shareholder at Bunker Hill Health. Dr Datta reports as staff at Stanford University School of Medicine. Dr O'Hara reports grants or contracts from the National Institutes of Health Stanford Center for Clinical & Translational Education and Research UL1TR003142, National Institutes of Health Microstructural changes in gray and white matter in aging and AD R01AG073362, National Institutes of Health Institutional Career Development Core KL2TR003143, National Institutes of Health Sleep in Autism Spectrum Disorder P50HD019861, National Institutes of Health Interactive Effects of Aging and Alzheimer Disease on Brain Networks R01AG072470, and National Institutes of Health Accelerating Cognition-guided signatures to enhance translation in Depression 1U01MH136062-01; and participation at the National Annual National Center for Advancing Translational Sciences Clinical and Translational Science Award meeting in Washington DC—support provided for this meeting by the National Institutes of Health Stanford Center for Clinical & Translational Education and Research UL1TR003142. Dr Harrington reports as support—randomized clinical trial leader—Jansen and CSL Behring; consulting fees from Atropos Health, Chiesi, Bitterroot Bio, Edwards Life Sciences, Bristol Meyers Squibb, Element Science, Bridge Bio, Foresight, Merck, and Medscape; payment or honoraria from CSL Behring and Medscape; participation on a data safety monitoring board—Baim Institute, Harvard, UColorado, and Merck; leadership or fiduciary role in American Heart Association and Cytokinetics; and stock or stock options in Atropos Health, Element Science, Bitterroot Bio, and Foresight.

Abbreviations and Acronyms:

AI	artificial intelligence
AIMI Center	Stanford Center for Artificial Intelligence in Medicine and Imaging
CT	computed tomography
EHR	electronic health record
FDA	Food and Drug Administration
HAI	Stanford Institute for Human Centered Artificial Intelligence
ML	machine learning

STARR	Stanford Research Repository

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