Artificial Intelligence in Health Care Delivery
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MICHAEL MCGINNIS
Good afternoon, everyone. I'm Michael McGinnis, executive officer of the National Academy of Medicine, and it's my great pleasure to join with my colleague, Dr. Karen Howard from the US Government Accountability Office to welcome you all to today's webinar on the issue of artificial intelligence in health care.

We are very pleased to be able to join with our colleagues at Government Accountability Office in this respect, it's very much in the spirit of what we heard yesterday in the virtual inauguration. That was highly effective in using our digital technology and linking people around the country, and indeed around the world in an important experience for our nation. The theme that the President emphasized was unity.

In the spirit of synergy and unity the National Academy of Medicine and the Government Accountability Office have joined to bring you this webinar, which will be divided into two parts. The first part will focus on GAOs activities in technology assessment and specifically on artificial intelligence and healthcare benefits and challenges of technology to augment patient care. And the second part will be conducted by the National Academy of Medicine artificial intelligence and health settings outside the hospital and clinic.

I'll just take a couple of minutes to tell you a little bit about the National Academy of Medicine and then turn it over to Dr. Howard for to lead us into the conversation that will be first focusing on the GAO.

The National Academy of Medicine is one of the three national academies that work together under the charter of the National Academy of Sciences, a Charter, which was signed by President Lincoln in order to bring together the best scientific advice possible for a series of difficult challenges that were confronting the nation at that time.

The Academy expanded its focus of activity, not only in terms of the content involved in the frequency and with which studies were requested by the various administrations. So following President Lincoln's charge, in 1916 we formed the National Research Council in order to keep a standing operating activity in place and we all hope that you'll get a chance to when you visit Washington to visit our building, which was built at that time on the Mall near the Lincoln Memorial.

In 1964 we added the National Academy of Engineering and in 1970 we added the Institute of Medicine, which is now the National Academy of Medicine. Our job in the National Academy of Medicine is fairly straightforward and that is to provide the facts and the evidence and the science related to medicine healthcare in biomedical health, public health and biomedical science and to work to help the administration and the nation identify and enhance productivity at the frontiers of health healthcare and biomedical science, the component of the National Academy of Medicine, which has been most involved in the work that is cooperative between GAO, and I am today is the work of the National Academy Medicines Leadership Consortium for a value in science driven health system which operates with four pillars of focus.

One is science and evidence. The second is the digital infrastructure. A third is payment and value and a fourth is culture and equity, all of which are obviously interacted and all of which we've seen are fundamentally important for progress over the past year, which we’ve been consumed by the COVID-19 pandemic.

So the issue that we're discussing today. The focus on the role in the future of artificial intelligence and health and healthcare is of central importance to us at the National Academy of Medicine, as it is to the nation and we're very pleased.

As I mentioned earlier, to be joined with the Government Accountability Office in the efforts to expand our nation's capacity in that respect, before I turn it over to Karen Howard. I want to give special thanks to Stanford University and the Stanford University School of Medicine and, in particular, Doctor Sonoo Thadaney Israni of the Stanford University School of Medicine, who have worked with us to ensure that CME credit is provided for participation in today's webinar.

So again, with the many thanks to all of you for joining with is obviously special thanks to our panelists and participants who you'll be hearing from and who've done the work that we're going to be describing today, I'll turn it over to Dr. Karen Howard, who's the director of Science, Technology analysis at the US Government Accountability Office, Karen.

KAREN HOWARD
Thank you, Dr McGinnis. As Michael mentioned, I am Karen Howard. I'm a director at the US Government Accountability Office or GAO.

For those who might not be familiar with GAO, we are a legislative branch agency that is whose mission is to support Congress and fulfilling its responsibilities. We are as an agency celebrating our 100th anniversary this year when we started back in 1921 we were the General Accounting Office and the purpose of the agency was to basically audit the books and expenditures of the federal government that was the mission of GAO for the first 50 or so years. But beginning in the 70s, the purview of GAO expanded to performance audits, where we conducted oversight of all of the activities of the federal government in in all possible realms that you can imagine, and more recently, providing more foresight work and insight for the Congress to assist and understanding the rapid change that's going on in our society today.

As Michael mentioned we have been partnering with the National Academy of Medicine on a three part series on AI and healthcare. The first of these reports was issued in December 2019 and it focused on AI and drug development. The second one is the one we're here to talk about today and it focuses on AI technologies to augment patient care. And the third one is just getting underway, it will be hopefully issued by the end of calendar year 2021 and it is focused on AI and medical diagnostics.

I'd like to thank the National Academy of Medicine for this very fruitful partnership we have enjoyed it very much. It has enriched and enhanced our work in countless ways.

Also, I'd like to thank the group of experts that came together with us to help us do this work and to ensure the accuracy and the relevance of this work to the medical and the technology communities. A few of these experts are joining us today as panelists. So you'll have the opportunity to hear from them firsthand and with that will turn to part one of the webinar.

So as you can see, just as an overview. I'm going to give a very brief introduction to the report that GAO put together and in coordination with the National Academy of Medicine on AI and healthcare benefits and challenges of technologies to augment patient care.

I'll obviously not be able to cover everything that's in the report, but hopefully hit some key highlights and whet your appetite to turn to the report itself which is fully available in the public sphere and then I'll be handing the presentation over to Jon Menaster who will introduce our panelists and moderate the panel discussion and the Q&A.

As I mentioned earlier, the Government Accountability Office does support Congress and its role. We are organized as an agency into mission teams each is focused on a particular area of the federal enterprise things such as defense healthcare International Affairs and Trade and so on.

My team is The Science Technology Assessment and analytics team or STAA as we call it. And as you might imagine. With a name like that we focus on science and technology and provide insight and foresight for the Congress, so that it can better understand the many technological changes that are going on in our world today. We provide this insight in several ways. Next slide please.

One of these is our group of science and tech spotlights and these are two page explainers on a given topic that aim to provide an understandable quick introduction to the topic, something that anybody with no science background could read and gain a better understanding of the topic and as you see a couple of them are pictured there one on coronaviruses that we issued in March.

One on contact tracing apps that we issued over the summer and several others listed down the right hand side that are related to the health and medical fields and we have a number of these and non-medical fields as well.

Another way that we assist Congress with understanding science and technology issues is through reports that we call technology assessments. These reports are a deep dive into a technology or a set of technologies where we're trying to explain what the technologies are and how they work, what the potential benefits are that those technologies may bring as they're developed and implemented and what challenges might be encountered in implementing those technologies and then options that policymakers could consider to help enhance the benefits and mitigate the challenges.

This slide shows a few of our recent health and medical related technology assessments, the one on the left is the artificial intelligence in drug development report that we issued in November of 2019 the first in the series with the National Academy of Medicine.

The second is on multiplex point of care essays for infectious diseases. The third one is one that we issued this past summer on COVID-19 data quality and modeling. And the fourth one is the one that we're here to talk about today. Artificial intelligence in healthcare to augment patient care. And you can see the report number up there, GAO 21-7, you can use that to search online and find the report. Next slide please.

So in this report, we took a look at a suite of technologies that can assist clinicians in a variety of ways to augment patient care. And you can see here we divided those applications, those tools, all of which are based on machine learning into two main categories in the orange categories at the top. We look at clinical applications where you'll find tools that can support population health management, for example, looking for trends across the population, monitoring individual patients guiding surgical care predicting health trajectories and recommending treatments and then we also looked at a category of technologies in the blue section of this graphic that can help automate laborious tasks record digital clinical notes and optimize operational processes and in each case in the report again I'm just giving you the highlights.

But there are detailed examples of these technologies, how they work. What some of their benefits are and so on. We do always in these technology assessments, look at the potential benefits that society and industry could reap from these technologies. In this report these fell into three main categories. The first is improving treatment of course for patients, which is a primary goal. The second is increasing, resource efficiency, including the use of staff time. And the third is reducing provider burden.

Again, the report itself contains many examples of how these technologies are able to read these benefits or have the potential to reach these benefits for those that are still in development. We also looked at the challenges to using AI tools to automate patient care and we found that there were in our assessment six primary buckets of challenges. Many of these will be familiar to those of you who have worked in the sphere of artificial intelligence before one of them. The first one is difficulties with accessing high quality data, of course, AI only works if you have massive amounts of data to train the algorithms. So there are often difficulties and accessing enough data to do high quality training processes with the algorithms.

Second is potential bias and data in this case in this field of healthcare. The data are of course biased toward those who are most commonly accessing the healthcare system or have the greatest access, particularly in the private sector. So that puts an inherent bias in the data that the bias toward those who have access to, to health care, particularly in the private sector.

Third is difficulties in scaling AI tools that are developed in one location, for instance, and within one medical system might work perfectly well in that system. But when you move them to a different system, perhaps from an urban setting to a rural setting or from a smaller health system to a larger one. They might not scale well to a different setting and sometimes even tools that were developed in a city medical system can’t transition well to another city medical system because the culture in the new city is different and the healthcare system is set up and works differently. So that creates challenges as well.
Three additional challenges. The fourth one is limited transparency of AI tools. And again, if you're familiar with the AI space, you know that one of the common concerns is whether the tools can be interpreted and explained appropriately that's very difficult to do when you have a tool that's finding its own patterns in the data. And then using those patterns and applying them to do data to new patients, for example, and their condition. It's very difficult to understand how the tool is doing that or to explain it.

Fifth, there are difficulties with protecting patient privacy, of course, in in AI for healthcare the data that you're drawing from our healthcare data claims data and medical records and so on. And it's very important to protect patient privacy, but that can hamper the development of AI tools. And last, there is uncertainty about liability for add tools. This is just a relatively new field that hasn't had a lot of court activity yet. So, there haven't been a lot of decisions handed down if an AI tool makes a mistake, who's liable for that. Is it the technology developer. Is it the software program or is it the clinician who uses the tool.

These are questions that haven't yet been answered yet because there haven't been sufficient cases to test this, and much detail. And with those challenges and benefits we always present policy options and in order to understand this. I first want to explain how GAO or defines policymakers and, of course, since we're a legislative branch federal agency that works for Congress. That's where the mind immediately goes that these are suggestions for Congress. And that's true. But we view policymakers, more broadly, we include federal and state governments, federal executive branch agencies academic and research institutions and industry, which, of course, in this case is the medical system and clinicians within that system so policymakers for us is very broad.

When we present policy options we view these as a menu of options not exhaustive, but some ideas that could help that that wide ranging group of policymakers enhance the benefits of the technologies. And mitigate the challenges that the technologies might pose. So as you look at these kind of things along those lines. And we grouped our policy options for this particular report into six buckets.

The first is collaboration, there was a great deal of evidence indicating that interdisciplinary collaboration between technology developers and healthcare providers was not as strong as it could be, which made the tools, perhaps less useful than they might otherwise be.

Second category is data access variety of suggestions that we made and elaborated on in the report for how to develop or expand high quality data access mechanisms.

Third is best practices, it would be very helpful to establish best practices across the stakeholder community for the development, implementation and use of AI in the healthcare field.

Forth as interdisciplinary education, healthcare workers might have concerns about can I trust this AI tool or how do I properly use it because they're not in most cases technology developers, they may not understand the AI platform. They may not understand the software that's written underneath it and the decisions that it's producing. So an interdisciplinary education to allow them to better interpret and understand the ad tools would be helpful.

If this oversight clarity again to address this question about how are these tools being regulated, how might they be regulated in the future and where my legal liability fall into the picture. And last we always take a look at the status quo, because that's always an option is just to let the current system proceed as it has been and try to enhance the benefits and mitigate the challenges on its own. So again, just just an overview. There's a more detailed analysis and there were four, but these are the kinds of policy options we presented for consideration.

And with that, I would like to turn it over to Jon Menaster, who is a Senior Analyst at GAO and was the project leader on this study, he'll be introducing our panelists and moderating the discussion john

JON MENASTER
Thanks so much, Karen.

So again, I'm a senior analyst at the Government Accountability Office and I led this report, along with many great colleagues. Today I'm really honored to have three of our healthcare experts we consulted with while working on the report here to speak with us about the state of AI and healthcare.

So to get us going. I'm going to introduce each of our participants will have them all turn their cameras on and the four of us will have a great conversation. So first I'd like to introduce Dr Maurice Sendak, the population health and data science lead at the Duke Institute for Health Innovation where he helps lead interdisciplinary teams to build technologies that solve real clinical problems.

Next we have Merzyeh Ghassemi, an assistant professor at the University of Toronto in computer science and medicine. Merzyeh has a well established academic track record and personal research contributions across computer science and clinical venues.

Last but certainly not least, we have Ozanan Merieles, a practicing surgeon at the Massachusetts General Hospital and assistant professor of surgery at Harvard Medical School and a co founding director of the surgical artificial intelligence innovation laboratory.

So yeah, we're really excited to talk with the three of you, you were really helpful in making the report happen, we really appreciate that.

So I'm just going to kind of kick the discussion off while we're talking anyone watching the webinar feel free to use the Zoom Q&A button and ask questions, but we'll also have some initial questions and discussion time and then at the end, we'll move into a more formal question answer period.

So, Oz, as you were introduced last I'll check in with you first here. So you're the co founder and director of the surgical artificial intelligence innovation laboratory so maybe just tell us a little bit about what you do there and why you felt it was so important to create the organization.

OZANAN MEIRELES
Definitely, thanks for the question. So I'm the director of the laboratory and I have a bunch of PhDs, you know, under my direction there, and my guidance mentorship as well. They are both surgical residents in the middle of their residency training and also PhDs from, you know, from the main computer science folks. That's at the core appointment at MIT and Mass General and they are also under the guidance of Daniela Rus from CCL MIT.

Besides that, we also have different branches within SAIIL. We have our Associate Director for research and our associated director of engineering who also spend some time at the Research Institute of autonomous vehicles.

SAIIL was created, we felt it was necessary to create something like this because bed at six years ago when we started just working across the river with MIT about trying to investigate how can we make surgery better and especially using one thing that we have that quite permanent in surgery which the vision. When we do minimally invasive surgery laparoscopy and robotic surgery and endoscopy. We have a stable view of images that's being shared across all the other screens that gave us a huge opportunity to leverage computer vision to try to understand not just a single image, but that image over time. So then, having the temporal component and the spatial component we decided to research how computer vision and machine learning could influence on that.

Because there was the need to have a home for those likeminded people both surgeons and engineers to exist, and there was not such a thing like in the United States, at the moment, we decided to create a Mass General going back to the whole history of innovation that are a hospital has many of our surgeons are also engineers. And since then, we've been able to not just foster collaboration within Mass General but with Mass General MIT and other institutions in the United States, Canada, in Europe in Japan as well.

So the idea is that one is education is the first component. So we want to train those engineers insert and surgical back to the market and in take this mission forward. The second one is research. Right. We have a few grants, both for peer review grants and to research agreements from engineer to develop products to be meaningful. And finally, also engage with society, such a American college and others to help bring this idea in create policies and regulations on how to thoughtfully implement all those developments. So it's kind of broad, but that's pretty much what is what we do at say what is SAIIL.

It's been like half of my time doing surgeries and the other half of the time, you know, running this this enterprise.

JON MENASTER
Yeah, you're a busy guy. You're kind of plugged in all over the place here with a lot of different aspects of AI, especially as it you know connects with your work so maybe a good follow up there is you know kind of where have you seen AI provide the most value right now. What are you most excited about.

OZANAN MEIRELES
Yeah, so I see at the moment right now for surgery. I think that the best valid AI provide the same value that provides for the parts and healthcare which pretty much like leveraging natural language processing and, you know, machine learning to try to really dig in big data.

But what I what I see, that's going to be unique for surgery is the fact that soon you're going to be able to start having some interferences. They're going to provide us with like a real time, you know, argumentation or a cognitive capabilities, pretty much like help us how to do surgery better or either to make a procedure better and also just to make a procedure safer. Is that almost having like a second pair of eyes with us in the operating room. Once we get to that level. We can only imagine where we could potentially go and especially if you can actually leverage you know the beauty of machine learning and artificial intelligence is that we all can learn at the same time, if I'm doing one surgery. I learned or once and they have to, you know, sleep and rest and learning next day again.

But imagine if all the surgeons in the world would be able to share their knowledge and create this common conscious that we call the collective social consciousness where we're going to be able to tap in our there. You know triumph in our day or mistakes and just make the field better you know exponentially every day for all of us using a system such as this.

Jon Menaster
That sounds great. I like that idea of a collective consciousness of all the different surgeons coming together.

Just quickly to kick things off maybe talk a little bit about your work with, some of the nice work you've done creating that particular tool.

MARZYEH GHASSEMI
For I think for me as a computer scientist to start collaborating closely with ICU doctors and intend to this during my PhD. Really what I learned is that the ICU is a very data heavy environment, which is good for deep learning algorithms, right, because you have, you know, many inputs. You could look at and many potential outputs that you could predict like to somebody in a ventilator does somebody need to have. So for us, or what's kind of a suppressor.

But it's also a very biased environment, meaning we really we send you to the ICU when you're very sick. And we have the most data on you in the ICU. When you are the very sickest. And so I think some of what I have learned when working with the hospital data is you have to control very heavily for the confounded nature of health, right, because you don't have a lot of healthy examples and often you're good at predicting the sickest of the sick because that's where you have the most data on

I think focusing on ICU is where a lot of people, machine learning have started because that's where a lot of the resources are but I've seen an expansion out to other hospital environments where now we're looking at General internal medicine, we're looking at surgical site right now. I think that that kind of gradual expansion to whole hospital understanding of healthcare as a process is very important for machine learning.

JON MENASTER
Yeah, that makes a lot of sense. So for you, you know, you worked on the ICU intervene project, what are you working on right now maybe share a little bit about some of the stuff that you've worked on lately and what's exciting or new?

MARZYEH GHASSEMI
I think what's exciting is I during my PhD. I really wanted to establish whether we could predict important clinical events like the need for an intervention with high fidelity. And I feel like we've established that you can actually. And now, now we're looking at in my lab, all of those questions that Karen actually highlighted right? You can predict it in one setting. Can you predict it in another setting. Are there ways to on the model side, try to make your model more robust when it hasn't seen data from another site.

Are there ways to make it more fair when it's been trained in an environment like Boston, where we have really small minority populations and then try to extend it to other places that are more diverse? Can we make it, you know, more private without losing a lot of the accuracy in small minority settings. So those are the kinds of things we're trying to think about not just can you train a really accurate high fidelity model, but can you make it robust private and fair.

JON MENASTER
Sure. Those are all the all the important things all the all the tricky parts that are trying to trying to come together here.

So Mark for you. I know you're also again involved in a lot. That's why you three are really great people to speak with about this so many irons in the fire. One of the things that I know you worked on was that was sepsis and you know census is of course a huge problem across the country. So maybe tell us a little bit about sepsis watch and how that got developed and kind of rolled out

MARK SENDAK
Yeah, I'd be happy to. One thing too. I, I look back now and I almost a view it like having kids where you have like the pre kid life and then the post kid life.

So my work on sepsis was part of my pre COVID life. So on my team, the Duke Institute for Health Innovation. We are situated under the CEO of the health system. But many of us also have appointments in the School of Medicine, but our positioning helps us stay very operationally focused. So the way that we identify the problems that we tackle is we work with our senior leadership to identify strategic priorities typically four or five priorities every year.

They can be broad statements like provider well being hospital safety hospital acquired infections. So the, the year that we started working on sepsis was 2016. There was a call for proposals related to in patient safety. One of our hospitalists QA leaders for inpatient care submitted the concept of using big data. Machine learning to improve the way that we were detecting sepsis historically we had implemented our electronic health record epic back in 2013. We had implemented, what was called a best practice advisory, this is a type of pop up that's rules based in our emergency departments to flag patients who had become septic and this type of configuration really drove people crazy it was the classic alarm fatigue story.

We published a paper. I think in 2018 86% of the alerts were cancelled for certain patients. It was firing up to 100 times a day because every time you logged on to a different computer, it would re fire. I see Mauricio his face, and yes, that was the face of every provider. So That since then there's been a decree in all of it work of like we have a really high bar to do pop ups in the EHR. That was while we were still learning about the reality of alarm fatigue, so ironically it took a really long time to turn that off. One thing you will see in healthcare is we are very bad at the innovating.

So there's a lot of inertia. Once you put something into practice to actually take it out of practice. So we already knew it wasn't working in 2016. So our frontline staff proposed to build better technology to identify folks and a huge part of the workflow was also we needed to route alerts to a team that was not at the front lines. Our frontline providers are very overwhelmed under a lot of stress at our flagship hospital. We have about 200 ED visits a day typically Long wait times in the waiting room so there's already a lot of things coming at folks. So we set up this team now. It's called a patient response team. But originally, it was the first proactive use of the rapid response team. So our team has emerged in the early 2000s, in response to patient safety complaints and really the Institute's for health improvement. Did a big push around 100,000 lives saved. So the idea was that anybody in a hospital should be able to kind of Pull a string or push a button and stop a process and call a team to come kind of evaluate the setting.

This was inspired by Toyota and factory manufacturing. So you need to have procedures in place where anybody can be empowered to kind of call a team remotely to come respond to an emergency. So that was part of standard of care at Duke. For several years, this rapid response team, but it was a very reactive role. Where they waited essentially until something bad was happening. And then they would get activated and then run into that room.

So sepsis watch was the first time we were trying to reconfigure this role to be more proactive. So we spent several years curating high quality data sets. Doing retrospective prospective evaluations, I can point folks to the papers. It was part of a close collaborators PhD developing the model and then many years of work to get it fully into practice in 2018. Now it's scaled to our three hospitals, we're scaling it to units outside of the emergency department. I will say in terms of Generalize ability. It's not just across institutions, taking something from Duke to UNC eight miles down the road. It can even be taking something from one end within the same health system to another, Ed.

Or going from the emergency department to inpatient wards. And so, yeah, it's a lot of time spent At the front lines collaborating directly with frontline providers understanding their workflows designing the workflows.

We typically do model design and development in in parallel with workflow design and development. The technology has to be informed by the frontline staff and the problems that they're facing. So It's lots of stakeholder engagement change management, I joke that the hardest parts of the work have nothing to do with technology, getting anybody to do anything differently is hard and in health care. We can be particularly stubborn about the workflows that we're used to.

JON MENASTER
Yeah, definitely something we heard a lot about in the report, and you mentioned that you kind of have your pre and post COVID life. So, you know, maybe if you if you want to just quickly highlight a project or two that you're working on in the post-COVID world. We'd be happy to hear about that.

MARK SENDAK
Yeah, so our first machine learning projects were around population health management. So over the last decade, we've seen a lot of changes in health care that have changed the way health systems, try to manage their populations. So in 2014 we were one of the early participants in a Medicare Shared Savings Program. So this was Duke now getting paid to effectively manage chronic disease and a population of 50,000 60,000 individuals. So that was an outpatient centered project trying to identify progressing

chronic kidney disease and intervene refer folks for specialty care so very much trying to look into the future and intervene on that set of patients.

And we've continued to do work in that outpatient population, particularly Medicare beneficiaries over the age of 65 and folks who are local and plugged into care. And then we had kind of a whole portfolio of projects focused on the inpatient setting sepsis being one of them. We have also since done adult ICU transfers people the attic ICU transfers. And cardiac deterioration. And once again, once we started to design these workflows and reconfigure the roles. It was easier to conceptualize. Okay. Now, if we do this.

What about modules to do this other set of items because each of these has its own set of interventions attached to it. Okay. And then so coven comes and we were pulled in, in early March, it was the head of critical care at do COO sent my team director an email. This was before any tests were even positive on the east coast. And we kind of huddled in and we said, okay, whatever you going to do to start preparing for this thing. So we started standing up.

It's called I ally influence a like illness. So this is a broad term to look at anything. This is what we were looking for. Before we were looking for comfort, because no one even knew how to test for code. So we just started monitoring influencer like illness and then we started building remote monitoring systems so that a patient could register into a system and then they would get two texts a day at 8pm submit their symptoms and then if there was anything concerning we could route it to a nurse to call folks. I will say to everything post-COVID has not been machine learning. This has been very basic technology, but the biggest learning for me, this whole last year was how systematically excluded populations have been from healthcare. So we stood up a system, the first week of April. That was twice daily symptom monitoring. Available in English and Spanish with nurses making phone calls to anybody with severe symptoms with volunteers making phone calls to anyone who lapsed on their surveys

Fast forward to now 12,000 people have used the system over 90% of them are white. There was a period over the summer Durham is in the south, North Carolina 13% of our local population is Latinx 87% of new infections were in the Latinx population. Our health record our hospital website. Our patient portal, nothing is available in Spanish. This is changing, but I mean, I think it was just such a reality check of The populations that are being hit hardest by these disease by this disease, literally, we were caught flat footed So what we ended up doing, we got out talking with a community meeting with community organizers faith based communities community based organizations quickly realized like, people don't want to give you their data.

There's a lot of fear. there's concern of use for research historical bias against participating and research. For good reason. So we actually ended up licensing all of the technology and covert policies outside of Duke implementing this outside of Duke, with support from our city, county

You don't have to use your real name to participate in the system. You don't have to give your birthday. Minimal information you can delete your record at any time, it's the type of very basic permission and governance controls. That we never have had to really deal with working with an EHR. I typically like I just go grab data that's there because it's there and There's no permissions to build a machine learning model. There's no, like, people can't delete their record. I mean, it can be a pain to even get your record.

So these very basic things that you realize, oh, wow. The system was not built To engage folks who don't trust the system. But then when they're getting pummeled you have to completely reimagine how you build the system. So, to me, a big learning was being fortunate to be in a position to be flexible and be able to build new types of IT tools in different settings public private partnerships.

But the reality was none of the community health workers that are state funded were hired within Duke. So, even from a personnel standpoint. They were hired within the faith based organizations community based organizations and then the technology systems that ended up reaching these communities were not Duke systems because we historically that that is not how the systems were designed or configured to put the needs of these individuals first. So to me, I look at data sets. Now in the EHR with a very, very different perspective than ever before.

JON MENASTER
Yeah, thanks. Always a good thing to keep in mind.

So what I want to do here before we turn it over to some great Q &A questions that are always coming in. And do a little lightning round here with a couple other questions. So, can I ask a question to each of you just give me whatever comes to mind first.

We've talked to Karen talked about a lot of different challenges and we can each of you brought up a lot of different issues that are kind of standing in the way of moving this forward and really making this work for the most people. So I'm just going to kind of ask each of you, if someone came up to you and maybe a PhD student new staff member and said, You know, I want to work on something and I want to, I want to work on. One thing I want to solve, you know, The biggest challenge or I want to really try and help you know. So what would you say is like the biggest challenge right now if someone was offering to tackle something for you. So, Marzyeh maybe I'll start with you.

MARZYEH GHASSEMI
The biggest technical challenge is finding spaces where patients with similar health problems look similar. It's almost impossible. It gets an unsolved problem and it's very, very hard.

You know we know how to work well with images because we use calm delusional neural networks where things that are close and pixel space are also close in models face. We don't have to work well with text data because we use recurrent neural networks where you conditionally generate words based on prior words that were stated, because that's how the data actually exists right

We can build models that have efficient computation infrastructure to mimic how the data was created so that when they learn a representation. Things that are similar are in a similar latent or hidden space. And we can't do that with health data because we haven't found good representations yet. And so I think finding representations were similar clinical presentation bubbles up to the similar laden space location would be amazing.

JON MENASTER
Oz. How about you.

OZANAN MEIRELES
Yeah, based on what Karen presented, I would say two things. One is the access to high quality data. We're not just like the large amount of data but diverse data becomes a huge problem. When we get sometimes you have what's happening in the industry. When I say industry both academia and corporations is the creation of silence, and then you build your own data set and then you don't even want to disclose all you have is a data set. So how can we actually validate those. So for us, researchers should be able to create something that's going to be able to extrapolate to different hospitals to different settings rural and urban to different countries is access to high quality diverse data sets that can actually validate how good they are, where they come from.

The second thing is the liability. I think that's going to be hugely important, especially in health care because when you say even the AI system made a recommendation for a surgeon or a clinician to do something and something goes wrong. Who is to blame right who develop the system was the clinician who accepted that information, you know, or what do we need to do. And that's going to be such a, like a huge field of discussions.

Marzyeh, do you want to comment on that.

MARZYEH GHASSEMI

I just want to say, the model will be wrong sometimes. There's no way to have a perfect model. And so, addressing the liability question but also asking the question before that, which is how do we build models so that when they are wrong. You're not so over reliant on them. You think if I must be wrong. The model does he write something I've been worried about

OZANAN MEIRELES
Youre absolutely right. And we discuss this internally all the time with the projects were making. For example, one of the projects to the detection of the critical view of safety which the a step of the operational laparoscopically suspect to me when if you do, you're wrong. The complication extremely high.

But let's save the machine makes a suggestion that I, as a surgeon disagree. And even though there is a complication. After that, you know, what was always the patient's factors. I mean, could I be blamed. Because I didn't listen to the model we should build like some systems that if there is a discrepancy between the AI in the condition. Maybe somebody just going to sell them entry is a tiebreaker or something. But it should build those because people need to be comfortable about using those systems, not to be like, like, like a watchdog of those of the clinicians

MARK SENDAK
I think we're a great group because our answers are totally different. I will say last mile implementation and I've seen this throughout my work in Health Innovation. There's a lot of great research coming up with new concepts. Developing new concepts but huge translational gap in terms of actually getting these things into practice, working with frontline staff to develop, implement workflows.

So that's true in my pre COVID work. So in patient workflows, how to develop the notification systems. How to iterate on them. Implementing the same system in multiple hospitals. We actually had different workflows and the different hospitals and post coven

I would say it was last mile implementation magnified immensely. So I'll tell you a story that to me has a lot of parallels with our work in machine learning because it's around how do you build confidence with uncertainty. So folks may be familiar with the concept of rapid antigen tests and cheap tests that are becoming more commonplace. So our federal government HHS purchased 150 million rapid antigen tests. Those are now given two states and states are distributing those. So we're helping implement rapid antigen testing and a few local public schools and so these are tests that are imperfect and to Marzyeh’s point no model is perfect, but some are useful no test is perfect. Some are useful.

So now there's a 20 page PDF, there's a two minute training video from the the biotech company and you have school principals being told. Now you need to use this test. So, I mean, we worked with our clinical lab director to develop protocols. We actually took some tests we couldn't even get our hands on these tests because they're not commercially available. They're purely in government contracts.

So we're developing the training material developing competency based assessments to make sure that lay people with a high school diploma know how to use these tests have quality control develop the follow up procedures. Do we need to get PCR testing afterwards if there's a risk of because the specifications are different and symptomatic versus asymptomatic and certain subgroups.

Do you want to increase the frequency because you can make an imperfect test more useful if you do it more frequently. So these basic concepts about it is probability it is uncertainty, but having to build those capabilities in that last mile whether the end. Honestly, whether the end user is a physician or a high school teacher like we should not be making assumptions about the statistical sophistication of our end user for using these tools.

So to me, I think that's really a big part of the future, because what's going to happen with coven and I think this is going to be a long term thing is that more and more types of non healthcare providers will become healthcare consumers for innovations that they have to put into practice and from what I'm seeing the small businesses and every school we talked to. There is a huge need for better ways to disseminate that expertise.

JON MENASTER
So first I'm going to take a question from Ryan who asks, in general, in terms of market acceptance. Would you say the general receptiveness by clinical professionals and adopting AI assistance is more of an ego side or is it more on the skeptical side? With all of the various health care providers feeling about AI tools.

OZANAN MEIRELES
Yeah, I can comment on that because having been doing some internal like research your Mass General to find out how, what's the acceptance of surgeons to have a second pair of eyes, helping them to guide to surgery.

In the answer. It depends. It depends which generation coming from because the very young residency training, the ones who are very involved, the simulation. They're very eager and they're welcome to have something like that, you know, with them.

The, the more established surgeons be practice for like 20, 30 years plus in general, they do not like to have anyone commenting on what they are doing the procedures because that's the nature of their culture in something in between, which are like, I would say evolving more closer to the younger surgeons a comparison I can make is, like, I mean three decades ago driving cars with no GPS, right, you got to know the city, how we drive then. Now you add GPS and the younger generation who is whatever you know 21 years old driving right now that person cannot drive without a GPS, a ways to get you there. So it's kind of like it is evolving.

MARK SENDAK
I was gonna say, I can point people to we published an analysis, led by an amazing undergrad, where he interviewed nurses and physicians, so both it varies by type of professional and it varies over time.

So the idea that you need support with your clinical decisions is not something that people like eagerly sign up for, I think, something that we have observed is the value of personal feedback. So one of the things, this was like a utility. We built out after we launched sepsis watch. But it's a feedback system where people get reports themselves for patients date cared for. Whether the sepsis bundle was a failure. The items weren't delivered in time, whether it was a success and whether the model accurately or inaccurately predicted for that patient so every model is going to be wrong sometimes, but it's important for physicians to see when the model is right and when the model is wrong. And I think that you can drive more buy in by.

We've written a lot about what transparency means and how effective transparency is for building trust. There's lots of different types of transparency. Transparency doesn't just mean explain ability or interpret ability. Any type of feedback loop or insight you can give people into how something is working in practice when they use it. I think can be really helpful for people. So we've observed a lot more enthusiasm. Once we create more ways to share feedback and insights back with the folks on the ground.

JON MENASTER
Thanks. And so I'm going to ask another one from these. Who is asking what happens after the use of an AI tool. So an AI tool does something and by doing something, it will probably generate some data. What happened to that data afterwards. How is that data, potentially used again, is it fed back into the system. In most cases, and how is the privacy of the patient protected with that new data.

MARZYEH GHASSEMI

I can take this one for many applications that kind of data that we store about you would be maintained. In a new deployment. So let's say we have something that's alerting for ventilation, you need to be ventilated right? We're still going to record in the EHR decisions that were made, even if there's a new alert system. Right. I think the issue is if we now feed that data back into the machine learning algorithm and then learn again from it. We could potentially be propagating errors that we're not aware of.

I think that we need a pretty hefty audit system for decisions that are made pre and post deployments. I don't think that it's a it's a bad thing. I think it's like the lovely GPS analogy. Right. I don't know many people now who can just navigate around their city. We've become reliant on this tool that tool means that we're lost a lot less and we can go a lot further

But it also means we've sort of lost this fold capacity for exploring our city with some rough understanding of objects and landmarks. But, as in terms of patient privacy. I'd like to say I think patient privacy is often invoked by corporations, rightly so because they might be tying that identity to other information they have about the patient.

I know you just got laparoscopic surgery. Maybe I should also sell you a diet plan right in the context of learning optimal treatments and trying to improve treatment availability. I don't think privacy carries the same maybe wait or burden because we're not tying it to other extra information about individuals purchasing habits or their lifestyle.

OZANAN MEIRELES
I want to add to Marzyeh’s great comments. So we're going to say these also brings another problem. That's what's the data ownership right does become a very like, you know, like hot topic in sometimes it's almost like a scene as a hype.

Who does the data below that the data belongs to the patient. This belongs to the clinician this belongs to the manufacturer of those belongs to the healthcare system. And I think the data wouldn't exist was a founding director of all of them together was for a surgeon operating in the patient with the device was created by a company in a health care system to create something

And the in science we have always like, you know, people have donated tissue and blood you know, like information to further the science, you know, like there was like the bio banks and we don't see much problems with the bio banks. But somehow with data that's being gathered through, you know, especially training AI is this becomes a huge you know like problem that people are trying to answer in one thing that I think the GAO national academies and you know our legislators could help us is actually to come up a very clear guidelines, you know that plays on the federal level, where should we stand, you know, and actually listen to all the stakeholders, including patients, you know, clinicians, you know, like companies to actually come up with the right guidelines, where we can start from and not be just being fearful about the unknown.

MARK SENDAK
Two quick things to this question. First off, when what happens after the data is generated by an AI system in most of our implementations. I actually don't think any yet has had any direct action take place, even if it’s operational. Having a human in the loop workflow where that then prompts review by a clinical expert who then determines what the best course of action is putting the output from the AI system into context with other information and then to the point about privacy. This is also like a post covert world learning for myself is distinguishing privacy from safety. So many of what we've been doing in Durham, the last six to nine months is creating space for in building new relationships with our Latin next community.

And I lived in LA for five years before moving to North Carolina North Carolina has a much higher proportion of new arrivals migrants, many of them undocumented, and there is just a lack of safety and so if someone does not feel safe, like people talk about private privacy preserving technologies. I think for us. There was just the a-ha moment of let’s assume that we don't need your identifiers anywhere they do not need to exist in any digital form whether their privacy preserved or not to be able to connect you to a service. And so just trying to acknowledge the lack of safety. Unfortunately, I know that yesterday. There's a big transition, but I don't think that safety issues going to go away.

And when I started digging into some of the questions I was getting I was even troubled I got the question over the summer of why is there ice enforcement at hospitals in a postcode world than there has been cases. These are real things, and there was the of course the controversy in the fall of CDC data then going to HHS in a new data system being used. So I think as a government, we have to really address safety before we can start to get people to trust even privacy.

MARZYEH GHASSEMI
I really want to echo what Mark just said. We have huge issues where we'll train a model and it just won't work on African Americans, which is horrifying. That's, that's not okay. But we need some data. Right. But in order to get African Americans to participate in systems and allow us to use their data. I really don't think this is about privacy, right, like we're public researcher saying we're going to sell you a Fitbit right they're worried about their safety. And yeah, like they're worried about physical safety. But also, am I going to be harassed. Am I going to be deported. Will I have to report to a government agency because of my behavior, they're worried about safety. And I think that's something very different from privacy and we should apply that.

OZANAN MEIRELES
That's why I think like when I agree with both of you guys just said is like if you go back all the policies that the GAO put in the report, you know, the best practices. I think that's probably one of the best we can do. You know, work all together, government, industry, academia, you know, because there is a lot of good work being done a lot of times, you just don't know. And if the Geo, for example, could facilitate something this there'll be fantastic collaboration best practices.

MARK SENDAK
I think a key here is that for certain technical problems there needs to be non technical solutions where the policies that we need to have in place. And I think we'd be happy to talk to her about those and what those would look like. But there. There's no algorithm that will fix these things. There's no algorithm that will obfuscate data to make someone feel safe if they don't feel safe to begin with.

JON MENASTER
I think those are all great points. And I think we're about at time. So I'm going to, I'm going to wrap things up. Just want to say thanks again to all of our panelists. If you were all here in person, this would be the part where there would be thunderous applause and everyone would be cheering. You guys were great. It was really informative.

I can just let everyone know that, again, just a quick reminder that this is eligible for CME, and we're going to also be sending everybody the slide deck, as well as the recording for the event. So that will have the information there. You don't need to try and you know scribble all this down right now. But if you're eligible, please go ahead and get your credits.

So I’m honored to be able to introduce a close colleague and friend of mine at the National Academy of Medicine, Mahnoor Ahmed, an Associate Program Officer at the NAM. Her portfolio consists of digital health and evidence generation.

NOOR AHMED
Thanks so much. Good afternoon, everyone. I'm so fortunate to have been part of an 11 person author team some of whom you will hear from later during the session that developed our review of the possibilities AI holds for augmenting care outside of the hospital and clinic setting or HSOCH for short. This report is a companion to the GAO report that was just presented and during the next 10 minutes I'll present the highlights of our paper which are timely, given the current circumstances.

So first define what we mean by HSOCH. So looking at the left, two thirds of this diagram shows settings outside of the four walls of the hospital or medical office to areas where people live, work, go to school.

This also refers to new modes of care delivery, such as retail clinics and community centers that offer health and supportive services. The aim is to extend care from hospitals and clinics that are traditionally considered the locus of care to where people spend most of their time and understand the context in which they live for richer, more nuanced care delivery.

So what's driving this change are a number of factors. So on the left side, or six, though we all know too well the rising cost of care in the United States, compared to our peers, yet the United States lags behind and its outcomes with highest rates of suicide disease burden. And even with the $3.8 trillion that we spent in 2019 31% of its spend on hospital care. The US ranks high among his peers and hospitalization for preventable diseases, and that's what you're seeing on the left side.

But what's interesting, or the optimistic trends that we see on the right. So if there's an increased focus on social determinants of health to take into consideration of persons environments and socio economic factors.

One study showed that investment in social determinants of health five pairs reduces costs by 11%. There's also this acknowledgement of the expansive growth of mobile health devices wearable devices. As you can see on the graph to the right shows this upward growth. And with that comes the opportunity to broaden access to care to promote it under resourced areas to address shortcomings and to equitably and ethically distribute the benefits.

So although digital divide issues exist me help you know one of the cases that M health us among black and Hispanic adults is the same as white adults. And so we're seeing a great opportunity here because many of these racial minority communities are actually using cell phones for health information.

So what we really focused on is this cumulative growth of mobile health devices and consumer health products.

Along with AI that is open the door for shifting care to the HSOCH setting. So many examples we highlight in this report, focus on the coupling of AI with these other digital health tools. For receiving individual level care, we see that the most mature example on the left is AI used for supporting telehealth and during COVID 19 telehealth has proven to be a lifeblood for patients and clinicians to keep in touch and monitor progress.

I should just mentioned before moving on the type of AI that we use here is mainly computer vision and computer vision is a technique that allows computers to emulate human sensory capabilities such as vision and smell. Natural Language Processing is widely used. Also, and it's the ability for computers to parse and comprehend human speech and record and respond accordingly. So examples of this are chat bots and chat bots have been used by number of health systems for COVID triaging. It can also be employed as scribes to capture and to jot down human speech and help clinicians with keeping track of medical records and be exchanged between patients.

So the next bucket that we see on the right is the application of AI for enhancing clinical care and this is cured, that is either received in the office or is to supplement the office care or to even act as a substitute, so in an in person visit when you go see a clinician or physician, the clinician gets an isolated snapshot of a person's health as integrated with remote sensing tools. Those such as a Fitbit or an Apple Watch can provide it continuous read of a person's glucose status, for example.

It can also provide a read of the heart rate and can detect risks of certain conditions, as we've seen with the FDA is approval of the Apple Watch for possible atrial fibrillation event. So the technique of AI that is used mainly in this space, our machine learning techniques which is another subset of AI that uses high level computation to draw inferences between data.

The other thing is that we also see a growing example of blood pressure management tools. Remote blood pressure cuffs are being developed in conjunction with AI coaching tools to intervene when a blood pressure reducing strategy such as hypertension education or on nutrition coaching through voice or text and can also promote medication adherence and an area that is a growing interest and that's our third bucket is managing mental health and well being.

A number of studies are showing the devastating long lasting mental toll of the pandemic anxiety, depression, suicide or increasing due to month of I self isolation. So we're also seeing that the power of these remote sensing tools that can capture digital communications by voice calls and text messages Facebook posts Instagram posts social media activity, including physical activity and then gathered from your wearables and can be analyzed using machine learning techniques as we discussed before for risk identification and prediction related to mental health conditions with mobile devices, mostly powered on and often the hands of the owner of these sets of tools really position mental health field to provide a precision medicine and this has been a long standing goal for other clinical settings and for specialties but it is really important in this instance to deliver the right treatment at the right time to the right patient.

So achieving population health and a strong public health response to build is to build really on these individual level insights on a large scale using tools that we've just described for chronic diseases as opposed like a huge burden on society individuals and the health system. So these tools also combine social variables such as education, labor status ones occupation household income to really understand trends and a community.

Again, we're seeing a combination of NLP natural language processing machine learning computer vision being used to scan various sources of data and make analyses. So with regard to COVID 19 we saw one great example. The blue.ai program which utilize all these sources of data. In addition to flight travel patterns of social media data early on, to really provide an early warning sign to the disease in December 2019. There are other public health applications also, you know, for detecting toxicity and household chemicals, as well as to measure the air quality and environments that could be used for asthma management.

So in understanding the value AI holds for care delivery and age stock. We have come to realize the many challenges and some of these have been already covered and they are very generalizable to all types of AI. But there's some unique considerations when we're thinking about the H sock environment and who the users are and what sort of data is being used. So you'll notice the first three being data. Data is very prominent because, of course, it's no surprise that data is the foundation of AI. So with regard to AI tools especially coupled with consumer technologies. The lack of data standards to meaningfully integrate the data with clinical data and make it actionable, but not to overwhelm the clinician and consumer poses a big challenge.

It also poses undue burden on AI developers to clean and standardize that data, as we heard from in the previous panel. And that data is really important in terms of feeding it back into the algorithm and refining and making adjustments. So the paper talks about if you ongoing efforts such as fire resources Odyssey that are efforts that are trying to structure and wrangle healthcare data, but we're just not there yet.

The second bucket is of course privacy issues and it's been a long standing topic. It's complicated by the fact in this arena that the data is most of it is captured from mhealth apps and use on AI. So AI, which is used to help build upon health related data. And so most of this is not is either sourced by entities AI entities developers that are not HIPAA compliant wearable tech companies are also not HIPAA compliant, excuse me, not HIPAA covered. So these non HIPAA entity non covered HIPAA entities therefore don't need to obtain individual authorization.

So broader protections for data are needed knowledge in but the range of health data that exists and there needs to be unified protections, because some classes of data are governed by different sets of rules and many of these rules are fragmented between different sets of data.

The next bucket of course is bias and algorithmic and data bias and it is important to really have a representative database. So these tools can be more useful. For communities that need the most. And that is really what we're trying to establish and achieve with AI tools and each stock. So we'll be discussing in the next panel discussion some specific examples and the consequences of bias being introduced into a system.

Digital Health tools are also evolving and adoption among consumers is working. It is growing at a rapid pace so with clinical adoption still lagging for these tools offer care continuity and care access. The must be recognized and AI, including as the tools that they deliver value they can drive down costs and improve outcomes. And so they must be reimbursed and covered accordingly.

However, there are still some concerns regarding the accuracy of machine learning algorithms. And so, that does affect liability and coverage recognition. We talked about in the paper, the variability of results, specific to the apple and while way cardiac tools. And these questions about reliability have raised safety concerns and as I mentioned liability concerns that has come up quite a bit in our conversations. And so with both safety and rely and liability issues as it relates to transparency, they have to be balanced and abroad. Safety framework needs to be developed.

Developed to ensure patient trust and confidence in these tools and it goes beyond the jurisdiction of the FDA. So, for example, consumer grade wearables and at home monitoring devices. When they are marketed as general well wellness devices like outside of the FDA is jurisdiction and we'll be discussing that a little bit more in our panel discussion. And the liability landscape needs to be better understood to really understand the boundaries of where liability falls. Whether it is sometimes you know if there is an arm a consequence or an adverse reaction where it falls within the health system or the developer or the consumer itself. So next slide.

So I want to thank my fantastic collaborators here on this project and I want to turn it over to our panel discussion that's going to be led by one of them.

Sonoo Thadaney Israni is the executive director of the Stanford PRESCENCE center and will be leading a discussion with four other co authors. Thank you so much.

SONOO THADANEY- ISRANI
Thank you.

Good afternoon, everyone. It gives me great pleasure to first introduce the panelists are will be joining me on this panel. Starting with Dr. Michael Matheny, who’s a practicing general internist and a board certified and co- director of the Vanderbilt University center for improving the public's health informatics.

Second, we have John Curtin a Professor of Psychology at the University of Wisconsin in Madison, where he also serves as the Director of Clinical training and the director of addiction research. His program of research focuses on the use of personal sensing and machine learning techniques for psychiatric diagnosis and risk predictions precision medicine and just in time interventions for substance use and other psychiatric disorders.

Third, we have Dr. Sanjay Basu who's a practicing internal medicine physician and the director of research at the Center for primary care at Harvard Medical School and the vice president of research and population health at collective health. His work has focused on addressing social determinants of health, primary care workforce and financing and the development and validation of tools for improving population health.

Last but certainly not least is Dr. Barbara Evans was a professor of law and professor of engineering at the University of Florida. She has expertise in biotechnology law data privacy and access and regulation of artificial intelligence and machine learning medical software, among other topics.

Welcome, everyone. Thank you so much for joining us. And thank you so much for being part of the team that co authored the paper that Noor gave an excellent summary of. We don't have a ton of time. So the first thing I'm going to say to our audience is many of the questions that you're asking through the Q&A

are answered if you would read the papers authored by both the NAM group as well as the GMO team. So if we don't get to all your questions, please consider reading those.

I'd actually like to start with both Michael and Sanjay, if I may, and focus on the world of unintended consequences. Is there a particular story or instance that you can recount that illustrates how racial or socio economic bias and use of AI algorithms negatively impacted real life patient care outcomes. Do you think that these unique situations and health settings outside hospitals and clinics where AI could be more susceptible to those sort of biases compared to hospitals and clinics settings. Michael, let’s start with you.

MICHAEL MATHENY
Thank you. And I just want to thank the organizers of the webinar for the opportunity to come and speak. You know, I think the one I do a lot of work in public health and population health and the one that stands out to me and that was a real cautionary tale was the work that was published in 2019 in Science around an algorithm that was built by a large healthcare claims organization to help their network sort of assess people that were at high risk for complications and to try to basically identify them and a population health framework and help sort of invite them in for additional care additional clinic visits and other things. And what they what they found, which was a, you know, you know, predictable but completely unintentional on their part was they used an outcome of healthcare expenditures or health care costs as their as their target outcome as their training and what that what happened in that result is that, you know, because white patients were getting more health care unit cost utilization for a given level of clinical severity, then black and other minority patients and they found that, essentially, it was further increasing priority for the white patients and decreasing priority for the black patients and African Americans to get additional health care.

I love the story, not only because of the cautionary tale, but because of what happened. So they contacted the company was very open with them worked with them to evaluate different outcomes in different ways to redesign the data frames and the feature space and actually show that if you pivoted the outcome to you know, to the severity of chronic illness in the population, instead of health care costs expenditures, they're able to adjust out 80% of the systemic racial bias and the algorithm and show that they're able to actually that if they implemented the new algorithm, it would have drastically changed the proportion of African American patients that received additional care.

So, you know, I suppose a cautionary tale for us and I think a way that those of us in academia and industry and government can really work together proactively to help try to fix these algorithms intuitively over time.

SONOO THADANEY- ISRANI
Thanks Michael. You bring up a great point, which has been brought up in the last panel and in the papers as well is hindsight can be 20/20. But given this cautionary tale engage that diverse group of stakeholders to think through the algorithms that are built, both in terms of the framing, but also in terms of data and other things. Thanks, Michael. Sanjay, what would you add to that, anything?

SANJAY BASU
Thank you to you and the other organizers for having this webinar. I think the example I chose is complimentary to Michael's. It involves heart disease risk algorithm that physicians use in order to help determine whether to prescribe status to patients, and several years ago, the American College of Cardiology and American Heart Association produced an update with great intentions, they started to finally incorporate some cohorts of African American adults in addition to the classical similar primarily white adult populations.

Ironically, the effort resulted in a risk score that can give you bizarre results for African American adults because it was overfitting a small amount of data. And so in clinic we could see that patient who is somewhat obviously at high risk for myocardial infarction stroke with somebody with diabetes or smoking or other risk factors would often be given an artificially low score, simply because of that overfitting process.

A revised score in this case has been proposed, but hasn't been adopted widely sort of to Michael's point that there hasn't been a broad enough set of attention to this issue to get results and convergence on a revised scores. I think it remains a cautionary tale today.

SONOO THADANEY- ISRANI
Thanks, Sanjay and, you know, each time I ask a question I'll ask a couple of the panel. But I leave it open to others to jump in if you have other things to add so John and Barbara, anything to add to that or we can move on.

So moving from unintended consequences. I'd like to shift that is the questioning more two domains of healthcare that have benefited from the increased use of AI so john maybe we can start with you to ask your opinion either currently any missed opportunities or low hanging fruit for AI in what we're calling HSOCH, which has health settings outside the hospital or clinic that could be applied readily in be impactful certain aspects of the realities of COVID 19 right now or retail clinics or public health or mental health.

JOHN CURTIN
I mean, so I was the mental health care expert on the team. And so naturally, my mind immediately turns and there are certainly important opportunities for the development and refinement of AI powered apps to provide continuing our aftercare support for patients in recovery from substance use disorders. So, in the US, we do an okay job of assisting patients with substance use disorders to become initially abstinent, we have short term innovation programs intensive day treatment programs outpatient programs and they typically succeed in assisting patients to establish abstinence, but substance use disorder and chronic relapsing disorders and we do a horrible job of providing continuing care long term. And this really presents as a really serious and really costly public health concern.

And so there's great opportunity for AI powered and health apps that are accessible through smartphones to play an important role here. And as an example. Give an example here from the Center for Health enhancement system Studies at the University of Wisconsin. And so we've developed and evaluated such an app for continuing care support for substance use disorder may give you a sense of the richness that it can offer it has medication and appointment managers, it can help identify AA and NA groups where they are in my meeting.

It provides social support the discussion groups with others struggling with SUDs. It has healthy or unhealthy events counters report patients committed to increasing positive or morning activities in their lives provides digital interventions such as guided mindfulness meditation guided relaxation for stress reduction and limited forms of cognitive behavioral therapy, they can provide in digitally.

Even as a clinician dashboard that can be activated, if there is clinical aftercare support in place to allow for bi directional communication and patient monitoring and so you know already on. It's a wonderful tool, but it's a tool that actually can. Well, let me say that mean it's a wonderful tool. And it's actually substantial evidence that it's actually quite effective. So, for example, there was a recent randomized control trial that demonstrated that the app cut heavy drinking days in half and increased point prevalence abstinence by about 15% over a year versus treatment as usual. And of course treatment as usual for continuing carries is relatively weak.

But critically these apps can still get smarter and at least these two ways by incorporating AI algorithms, combined with personal sensing and so if that term personal sensing isn't familiar with you. It's something that presents a lot of opportunity outside the healthcare setting. And so what it involves really is picking up or monitoring all the digital breadcrumbs that we drop throughout our lives, day to day smartphones can monitor our geo position through GPS services.

They have access to our Savior communications our voice and SMS logs. Our SMS content on you can push out brief questions to smartphones that patient is can answer periodically throughout the day and they can be connected to sleep sensors in the bed. And you can use all of these sorts of longitudinal person sense personal sensing signals to do one of the couple of different things that are really quite powerful one. You can do risk prediction. And so this is the work that my lab does with the signals. You know, we've been working on developing a model to predict future lapses back to alcohol use among patients who are in recovery from alcohol use disorders, and more recently patients with opioid use disorder as well. And we can already predict with 95% accuracy whether or not someone who's in recovery and who's abstinent from alcohol who drink on a subsequent day into the future. Using data from their past from this monitoring and so when you have a risk prediction signal like that you can feed that back to the patient to alert them to something that's challenging for them though what substance use disorders provide or requires constant lifelong monitoring and so with this monitoring system in place. Patients can be alerted to degradations in the integrity of their recovery.

And similarly clinicians if connected through the dashboard can use a signal like this to monitor, who among their large caseload might be most in need of further support. So you can have efficient resource allocation as well. These signals can also be used for treatment recommendations as well. And so, you know, the app itself is primarily designed to provide intervention support but there are lots and lots of tools and services, but by monitoring, which of these signals are contributing to increasing risk.

We can start to recommend back to the patient what they should be doing as well. And so if the risk is because there's changes in their social network. It appears from cell your communications from GPS signal that they're interacting more with a former drug or alcohol using peers, rather than their healthy network. They can be directed to reconnect to a true gauging more healthy activities with their supportive peer groups if their signals that indicate poor sleep or high stress. They can be directed towards the guided relaxation, or the mindfulness interventions and so you know by powering these apps with AI, we can start to both identify times of great need intervene just in time and also potentially intervene with the appropriate interventions at that time I should also end by noting that the potential impact of these mobile health apps is really increased for at least a few reasons.

First, they're really massively scalable and cost efficient way for the most part they're automated and so a patient can carry this around in their pocket without the need for additional conditions support in the moment. Meaning, they they're used best when they're connected with ongoing clinical care, but most of the support is available on your phone. And that means that it's available, regardless of where you are, so we can get penetration into rural settings where healthcare services often aren't available and you can get 24 seven access. One of the challenges in the mental health care spaces. Most of these interventions are done, you know, in a time limited fashion, you meet with your therapist once a week or once a month for your hour, and now we have access to these interventions 24/7.

And then finally, you know, to address the COVID-19 piece, I mean, I think we're all aware that that COVID has substantially increased the need for mental health services in our country right now. The stresses of really exacerbated existing and produce new mental health problems. And similarly, increased problems which with alcohol and substance use disorders as well. And at the same time, removed a lot of the traditional mental health care support that was provided in person. And so apps like these really present a great opportunity to address those sorts of news as well. So really excited about that domain these applications.

SONOO THADANEY- ISRANI
Thanks John. You point out how the COVID, within the cruelties it created constraints and those constraints then forced innovation. And a piece I will observe, as you heard me observed many times is the challenge of what you just pointed out, and laid out. Is it works very well for people who have the privilege of technology and the privilege of being on one side of the digital divide. I'm actually going to turn to Barbara before I turn to Sanjay and Michael for examples to have Barbara perhaps weigh in on some of the legal and ethical considerations of using data to reinforce behaviors and in whether it's mental health or anything else.

Barbara Evans
Thank you. The example that John gave shows the enormous power of this technology, but also validates the reason people have privacy concerns someone's tracking who I'm hanging around with and whether I'm with a good crowd or a bad crowd. Under of our major privacy regulations like HIPAA law enforcement

can get my data without my consent, if they follow certain procedures and so you understand the depth of privacy concerns people have about this and that is crucial because we're at a place now with this AI technology becoming part of our health ecosystem. And I don't just mean in the clinic, but public health population health research where we can make great strides. If we do this, but there will be a reluctance.

Unless we can provide a more credible privacy protection framework than we ever have before. And what makes it so critical, is this question of bias that these systems are leaving out people who do not have large access to health care and in some sense, that's not a bias is not a problem of AI. It's a problem of the surrounding healthcare system.

Ultimately to repair and make it unbiased, we have to make sure everybody has access, not only to health care, but to the first rate healthcare occurring and academic medical centers that have the resources to do AI research and not everybody has that and it seems unfair to blame that on AI. The problem is we need to get our healthcare access sorted out, in a way, we have not yet done but that may take a while. And also, I think we're just fighting saying we want these new systems coming on to be better than the healthcare system. They're coming into and we have to solve by us but that means solving privacy. Right now we have this very primitive privacy framework that relies on consent as it's only privacy protection, which doesn't really protect your data.

To protect privacy, you need things like privacy by design. You need restrictions on downstream uses of data and sharing. Things other than whether someone consented, and then to get around the consent we build AI systems that use de identified data. But when you strip the identifiers off, including zip codes you lose the ability to audit whether the system is representative of the entire population. So unless we can audit detect and call out the bias in the training data sets and the operational data sets, we're never going to fix that. And to do that, we need a different privacy framework that will let us retain identifiers, to the extent needed to detect bias the systems to a large degree, and this is my last point whether people are properly reflected in these AI tools, you know, whether their group of your whether women, whether it's a ratio group, whether we're adequately reflected is beyond our control. It depends on our healthcare access to a large degree, but it is somewhat in our control. And I think we need an education effort, people have, I think, just we're all concerned about privacy and we've become very reluctant to share our data and skeptical of it, but we need for people to understand that even if you feel traumatized by uses of your data, perhaps because of historical bias and research or historical injustices, even if you feel that way, you need to realize that unless you share your data, these important tools are not going to be helpful to you and to people like you. So we need to message to people that there is a cost to privacy, if it boils down to, refusing to let your data be used of because you need to be in there to be reflected and to get unbiased results. I'll pause there and invite others, but I think we need new laws. Basically, we're in a different era and the laws we did in the 1970s will hold us back.

SONOO THADANEY- ISRANI
Thank you, Barbara. I think you point out astutely that the challenges that we have a society that has its historical challenges around inequity and the lack of justice and it's about fixing that underlying situation and as many of you know the center that I run here at Stanford called PRESCENCE very much focuses on the humans in the system which connects to the last mile discussion that marks and I brought up in the last panel where we can't forget that healthcare in the end is being given to humans and the humans around them, which is the friends and family. There's been given by humans physicians clinicians are the support system, etc. and all of which lives within a society with its own lack of equity inclusion and justice.

I'm switching to Sanjay essentially examples of opportunities in the EHR world as it relates to say COVID management or something else, public health related.

SANJAY BASU
One of the points that I have been thinking about with regard to that question is how to properly account for payers in the space. So even though we’re talking about health care outside of clinic and hospital. Many of us have derived our foundations from clinic and hospital and are now reaching community. And in that sense, need to be aware of our own biases and interacting with people who have the opposite orientation, those who are starting from community and our interacting with healthcare.

So in that context, I feel like a lot of the challenges we see is who is going to pay for services in the home or in the community that are not naturally oriented towards our most predominantly fee for service healthcare system. It's really interesting to see how much more Medicare and CMS have been advancing along this route, rather than private payers, for example, Medicare. Now recently reimbursing hospital at home programs that provide monitoring for people in rural or other areas or during coven people who are in areas where the hospital is full but needs to be monitored for oxygenation and other vital signs and remotely.

Medicare will pay, but most commercial insurers have yet to pay, despite the randomized trials demonstrating both safety and actually surprising to me improvements and outcomes which in retrospect may not be that surprising given reduction and delirium and hospital acquired infections and so on. So I wonder how we can be cognizant of particularly engaging healthcare payers to pay outside of the healthcare space or someone else to fund the work because the implementation in practice by community based organizations requires funds, particularly when some of those who are trying and the public health space are very constrained. And the idea of applying AI to them. Seems like a luxury more fanciful future idea when our public health system is currently struggling with.

Frankly, what others are doing much better as we see right now with vaccination and contact racing and so on. So I would suggest we pay them for their attention to how we might incorporate payers and how we might incorporate funders into this in order to support the community based initiatives to improve health outside of the hospital, clinic environment.

SONOO THADANEY- ISRANI
Thanks. Michael, what would you add?

MICHAEL MATHENY
Yes. Okay, I'll keep it brief. But I, you know, I'd really like to highlight the, the, the opportunity space of self management and self diagnosis along the lines of what john mentioned in mental health, but I think, you know, it applies to many domains, you know, you've got the self continuous glucose monitors hooked to insulin pumps for diabetic, you've got skin lesion detection from somebody that you know is using an app at home to sort of see like, what's that weird thing on their on their hand and you know you have applications from like the one lead Apple Watch. In fact, one of our co authors on the chapter is doing research about the impact of all of these tools in the community and as they generate medically relevant diagnostic information, you know, how do you interface that back into healthcare proper.

How do you improve. Everyone's health care was still sort of managing the workflows, both in and outside of the healthcare and so I think it's a tremendous opportunity. I think COVID is an interesting story that covert sort of highlighted, I think public education that needs to happen. The Apple one lead EKG watch also has a function on it for pulse oximetry, which became, you know, suddenly in the public discussion space, you know, given that COVID has a syndrome where you are hypoxic and you don't really feel hypoxic and so a lot of people started using that. Well, the apple. The one lead EKG function is FDA approved the pulse ox is classed as entertainment. And so a lot of consumers didn't understand the difference didn't see the, the, so I think there's education issues, there's, there's a tremendous opportunity for basically deploying healthcare diagnostics and maintenance and self management out in the community with these AI tools.

SONOO THADANEY- ISRANI
Thanks Michael. And as you well know, even the regular pulse oximeter his ability to give accurate readings for people are darker skin is worse back to disparities and lack of equity.

So a common refrain that we've heard from our last panel the papers that we all co- authored has to do with garbage in, garbage out. So only as good as the data. So what considerations, do you think should be given around data collection, especially when it relates to vulnerable populations, children, minorities.

JOHN CURTIN
Let's try to connect a few different themes that are coming through here. I mean, first this issue of privacy and trust is has come up and I want to offer one observation there first, before I dig into. How do we get data to resolve some of these issues. You know, we've been struck that at least in when we work with on selected samples of patients with alcohol use disorders. Patients with substance use disorders. And then individuals in the youth community to do either like risk prediction for relapse risk or we've done some work using, for example, Facebook to do diagnostic screening for alcohol use disorders and substance use disorders. We've been struck by how willing. People are to share their data. And it's been we collect probably the most sensitive data.

There are, as I said, we monitor geolocation people give us their full access to their cellular and SMS logs and their SMS content in the study where we're doing diagnostic work. People give us full access to their public and private facing Facebook information all their direct messaging and yknow, it's been surprising there to us initially because I mean part of this initial work was, would this be possible, would people trust us. And we've been surprised that they have and that is not in any way to take away from I completely agree. Barbara that you know people trust us. I don't know that they should, because I don't know that the protections in place. I mean, I mean, we, as researchers have protections in place Certificate of confidentiality to, you know, to these protect against or diminish the likelihood of data, getting subpoenaed.

But you know where these when these apps are released into the real world. I think privacy and protection concerns are paramount. I said, I started that would saying I'm unselective samples because our work now is pushing into try to tune these apps to work with communities of color and also as Barbara said we need data from participants patients of color. If these apps in these algorithms are going to work with those communities and I think it’s critical that we attend to at least three separate issues there. We will a we need data from those communities. And we've already heard examples here. And I think we're all aware of other examples where algorithms don't work.

If you don't have diverse samples that for which they're trained on but in order to get individuals from communities of color to participate. You have to be actively thinking about it and working on him. So in the work that we're doing right now, for example, we've partnered with black pastors and black organizations and he happens to be to live in Madison, and so we're working with his community center in a variety of ways. We went to him and humbly asked first and foremost what does, what does your community need. We don't even know what they need to start and for us to impose our perspective and what they need would be, you know, short sighted. And so we started partnering them just getting a sense of what the community needs. How could these apps address concerns in the community. And then we've partnered with them. Hiring their staff to do participant recruiting for us to do onboarding for us and that that's there to build trust in the community.

And so I think you need partners in the community. If you're going to build that trust. And then the teams that are doing the work have to include scientists and modelers of color on the development teams. I mean, again, if, if it was me, just a light scientist doing this I have major blind spots that won't allow me to even know what I don't know. And so we have to work hard to have diverse development teams as well as connections into these communities of color. If we're going to be able to collect these data to build algorithms that actually conserve these communities of color. And so, I mean that's something that we're thinking about really carefully these days.

SONOO THADANEY- ISRANI
Great points John on the idea of humility about engaging people who have different experiences and lenses to bring to the discussion. And then this idea of partnership versus I’m here to get A, B, and C from you so I can use it for x, y, and z.

BARBARA EVANS
This you know data collected and research settings are obviously very important. But ultimately, we need to be capturing data in regular routine healthcare settings to and what I think sometimes isn't understood that much more is involved in that than just grabbing the data. It takes an enormous amount of personnel

effort to put the data in a consistent format common data model help when the it's not clear what does it really say. And it's really a big ask to have community health care centers that are already burned heavily and trying to provide care to people who are not receiving enough care to say, now we want you to do all of this data curating and ultimately

This is an infrastructure problem. We don't think of it that way but up previously in our nation's history at various points we decided we need railroads. We need power grids we and we built infrastructure. We did it with private capital but regulated it to create incentives up the discussion of regulation that's happening around AI is consumer safety regulation, sort of, should you do this or that.

We need to be having a conversation about infrastructure regulation of we can use private capital and private companies to build data comments and to make these investments in curating data and make it inclusive. But there needs to be an economic framework that says if you build the data comments. It better not be discriminatory everybody better be in it, just the way the phone company can't say we're not going to give you phone service because of your color.

We need infrastructure regulation and we're not going to get this done unless we think much more broadly about the regulatory scheme that's needed to encompass not just FDA role, but many, many other state and federal entities and private bodies that need to be thinking big about this.

SONOO THADANEY- ISRANI

Thank you, Barbara. I'm afraid we've run out of time, so I will end with a summary, which I think is my one of my favorite quotes where he says humans are always far greater at building technology versus using it wisely. And I hope that the work of the team here as well as the geo team has given our audience and stakeholders, an opportunity to reflect on what it means to build in use this technology wisely.

Thank you all very much. I'm going to turn it over, back to Karen and Michael to wrap up for the afternoon.

Thank you.

Karen Howard
Sure, I, I'm very grateful for this discussion. It's been very interesting and informative. I truly appreciate the wide variety of perspectives. Our panelists brought to the discussion and I'm thankful as well for the many participants across the country who were listening and joining with us in this discussion. Thank you for all the great questions in the Q&A box. A lot of good food for thought there, Michael.

Michael McGinnis
Yes. Thank you, Karen. I'd like to underscore the your observations. I'll make three brief comments.

First, it's very clear that the progress. At hand is impressive is substantial and is inspiring, whether we're talking about the potential for the application of AI machine learning to activities within the clinic or outside the clinic, we had some very enlightening and insightful reflections from this terrific panel.

Secondly, or related to that though we had some important observations about the challenges that we face the challenges related to the socialization, the challenges related to the social circumstances, the challenges related to the real world, the challenges related to the last mile to pick up on marks term so that brings me to the second point and that is that it seems that while we're enthusiastic inspired and encouraged by their technical prospects, it really is all about people and whether we're working to build the capacity of AI interfaces with services in a fashion that will help those services sing on behalf of better health and healthcare.

We need to ensure that people are very much involved in the development process and they're the they're the starting points for the building process. And when it comes to applying these technologies and working for to play to people's comfort zones.

Again progress the rate limiting factor is going to be the extent of which we have failed in our engaging people that at every step of the way so that when we do have a population for which using these technologies is a personal use that they are in charge of and not just one that is imposed on them, whether in fact, or an impression that we're going to be challenged with the progress achieving the progress as possible. So in a very efficient manner, all of you, as leaders in the field have underscored some of the key opportunities and challenges that we can take action on which is the third point I wanted to make. And that is where this is the starting point for us.

It's a snapshot in time of where we are both as a society, and with respect to the NAM and the GAO's engagement and leadership, the questions that you have asked as participants have been spectacular. And we're going to do what we can to ensure that we use those questions to build upon the agenda and in that same vein, we would love to have your ongoing suggestions about how we can improve the prospects. What is it that we can do that will help increase the comfort level within among individuals that amongst society for the progress that we have at hand. And so please do be in touch at any time with us. I think that the contact points are illustrated in the slide and we look forward very much to the follow up. So again, thank you to Karen and colleagues. Thank you to the panelists and thank you to the audience for not only for being with us here, but for continuing with us on the journey. Enjoy.