Speaker 1: This episode is part of a special collaboration between ACM ByteCast and AMIA For Your Informatics podcast, a joint podcast series for the Association of Computing Machinery, the world's largest educational and scientific computing society, and the American Medical Informatics Association, the world's largest medical informatics community.

Dr. Sabrina Hsu...: In this new series, we talk to woman leaders, researchers, practitioners, and innovators who are at the intersection of computing research and practice to apply AI to healthcare and life science. They share their experiences in their interdisciplinary career path, the lessons learned for health equity and their own visions for the future of computing.

Okay. Hello, and welcome to the ACM-AMIA joined podcast series, this joint podcast series aim to explore the interdisciplinary field of medical informatics where both the practitioners of AI ML solution builders and the stakeholders in the healthcare ecosystem taken interest. I'm Dr. Sabrina Hsueh with the Association of Computing Machinery ByteCast series. My co-host today is Dr. Adela Grando from the For Your Informatics podcast with American Medical Informatics Association. In addition, we have the pleasure of speaking with our new series guest, Dr. Regina Barzilay.

Dr. Adela Grand...: Well, thank you so much for joining this podcast. And today, we have a very special guest. We have Dr. Regina Barzilay, and she has a very impressive CV. She's a school of engineering distinguished professor for AI and health in the MIT Department of Electrical Engineering and Computer Science. She's also a member of the MIT Computer Science and AI Laboratory. And in addition, she's an AI faculty lead for Jameel Clinic, which is an MIT Center for Machine Learning in Health. And her research interests are in the application of deep learning to chemistry and oncology. And she has received many, many awards including NSF, MIT, Microsoft, and UNESCO recognitions. So, Dr. Barzilay, thank you so much for joining us today.

Dr. Regina Barz...: Thank you very much for having me. Really excited to be here. Hi.

Dr. Sabrina Hsu...: Yeah. So, Dr. Barzilay, you're one of the nation's top AI leaders in computational linguistics, chemistry, and health AI. First, you bring some pressure for breast cancer now for colon cancer, you seem to have a magic finger to make things happen in those interdisciplinary fields. So our audience here are from both AMIA and ACM. As you know, they are scientists, clinicians, health IT practitioners, and students wondering if you can let our audience here know what contributed to your magic here to make your successful interdisciplinary contributor you are today. Are there any inflection points in your journey that leads you here you feel that's worthwhile sharing with our audience?

Dr. Regina Barz...: So first of all, thank you very much for kind words and I wanted to say that I did my PhD and I worked for maybe 15 or 16 years out of my PhD when I was a faculty at MIT only on natural language processing. In fact, I really stick to the subject and didn't even publish in any other application areas of language processing. And in 2014, I was diagnosed with breast cancer and for real, the first time in my life, I really encountered healthcare system because I gave birth obviously in the hospital, but it's not like really you understand in detail how the system works. And here when you are treated for a disease, you actually have a long-term encounter with the system starting with the diagnostics and going through the different options for care and post-care surveillance. At that point, even though 2014 was kind of before everybody on the street knew what is AI, I mean, it was beginning, it was really troublesome to see how very little of AI is in the healthcare system.

In fact, there was none. And I was treated in one of the most prominent centers in the country, which is Massachusetts General Hospital. And they did a good job in clinical profession, but it was really disheartening to see that despite the fact that a lot of questions that both physicians have, and the patients have, which are in nature prediction problems, there was no technology to solve them. And going through it, I felt that there is a unique mission of me when I already recovered is that I really need to try to go and to change something at least for one area, which I understood reasonably well after going through my own treatment. And at that point, I start slowly transitioning into this area. And also, what's interesting that I look at medical informatics maybe 20 years ago and a lot of medical informatics, I didn't find it's particularly interesting.

So why do you need to do something for medical informatics if you can just do an LP tool and apply it to medical informatics, you can just apply it. And there were a lot of issues with the tools. So I didn't feel that we can actually deliver something that's going to, at the time, dramatically change care. But what was really clear to me in 2015 that AI has a lot of things to propose to medical informatics. So the field of AI matured enough that it can really make a big difference in patient care on one hand. And on the other hand, I understood the field better and I understood that there are unique needs that the general tool that you develop for other things cannot be straightforwardly apply because it interfaces a patient in the end. And that motivated a lot of my research to this day.

And also, it was really funny when I started working on chemistry, I actually didn't see, again after my own treatment, I was kind of in exploring state and somebody asked me to join the grant on utilizing machine learning. It was not even for chemist, it was extracting from chemical literature. I said, "Okay, fine. Maybe." I didn't even see the connection to health. So at the time, what happened was I was starting doing this grant, I didn't see much connection to drug discovery, but MIT is surrounded by the pharmaceutical company. In fact, right now, I see from my window, Moderna and I see Amgen. And at the time, I started talking to the people around and I realized, "Wow, this technique can really change drug discovery." And then slowly, I started doing more and more work on molecular modeling and drug discovery. So in some ways, you can say that this path was deliberate because I deliberately decided to switch from an

LP to clinical AI and the drug discovery. But there was some randomness in the process.

Dr. Sabrina Hsu...: Yeah. This process sometimes take a long time to fulfill. You started with that breast cancer journey a long time ago in 2014, but just lately we have seen more approval of AI-based digital pathology diagnosis test for breast cancer. Now, as I think about that's already 8 years now until it come to a fruitful realization of the dream you had before. I was wondering how did you feel about that process and in that process, what keeps you working and what's your fundamental goal, you think?

Dr. Regina Barz...: So in some ways, I'm very excited about the progress that we made. But on the other hand, I feel a lot of frustration. So the whole process of getting into clinical AI is very challenging for an outsider, it challenges in every single step. I developed tools with my student, Daniela, who is now professor at Berkeley UCSF and other students in my group. We developed tools that can take an image of breast, a mammogram and can predict the outcomes for the patients for the next five years. And the reason you can do it today is that we are relying with diagnostic example, is that the tumor should be large enough that the eye can actually see it. But as we all know from biology, cancer, it's not a disease that just happens from one day to the next day. So there is a long process in the tissue that needs to happen before the tumor becomes cancerous.

And what machine can do that when you train it in a large number of images where you know the outcome of this patient for five years can actually look at the image that today the doctor will say, "This patient is fine." We say, "No, this patient is likely to develop the disease within very short time." And it's important because the treatment of the disease is very different whether you discovered it when it's already progressed, or you do it in the earlier stages. So this way, we can actually change the medicine of treating when the symptoms are apparent to much, much earlier stages which much easier and more likely to succeed treatment. However, again, if you look at this whole process, how did we get in? It took me two years to get mammograms. To this day, in this country there is not one publicly available data set of mammograms.

They identify mammograms that if you are computer science researcher who want to contribute, that you can actually go and try it. It just doesn't exist. And if you are thinking about the amount of money that is in NCI and in age, it's mind-boggling. How could that be? And through the two years of this very, very challenging process, we finally got the data. Then the next things that you need to do is in academic, you need to go and have funding to support your students to do this work. And again, at the very beginning of this process, I applied to NCI, and DOD has a special program for breast cancer, and we didn't get any funding. And when you read the reviews that we got at the time, people were asking, "Why do you use neural models and deep planning instead of using SVM?"

So it really shows to you that the reviewers were completely unaware of what is the state of the art. And that point I was so mad that I decided I'm not even going to submit them, there is no way they don't even understand what the field is. You cannot add a tutorial together with your grant. So I was very lucky because multiple foundations supported this work and we were actually able to complete it. But it shouldn't be the way that a computer scientist who's interested to contribute either as a full-time, as part of their time cannot bring their talents and their energy to this field because the barriers are so extremely, extremely high. And then we passed those barriers, we build the models, we managed to publish it in top clinical venues. And then you are looking at the process of implementation. Again, it's very, very challenging.

And it's not only true for breast cancer because if you think about the last time that you went to the doctor, did you see any AI there? And the answer will be none. Maybe there is some AI that helps them to schedule you or do this kind of thing. Of course, it is important not to underestimate it, but this is not something that will directly be changing patient outcomes. So the clinical system today for very realist reason, do not find a good way to really take this innovation and this novelty and bring it to improve patient care. And on one hand, again, as I said, I'm very excited because we developed this technology because there are already institutions that are using it. But on the other hand, the slow speed of adoption, the amount of non-research energy you have to put it to see it through is still very disappointing to me.

Dr. Adela Grand...: Well, thank you so much for sharing your personal story. We could feel your passion but also your frustration in your comments already in the first questions. And we want to continue talking about your journey. So we wonder, were you confronted with interdisciplinary changes? You mentioned some of them already, what did you do to overcome them?

Dr. Regina Barz...: So the big interdisciplinary challenge is it's really a cultural challenge. And whenever you are... I'm looking about myself and my colleague at MIT, that's how your scientific career works. You are working in a field X, you are taught how to write papers in Field X, how to obtain funding in that field. You know about the standards and whenever you're starting to branch out to this new field, this field didn't even exist, we were among the first one that started working on deep planning for chemistry. This field was pretty much built in the last seven, eight years. Then a lot of questions arise and as I already mentioned, funding is one of them because the funding agencies, places like NAH, they specialize in review more traditional statistics rather than deep learning algorithm because this, at the time at least, was not the reviewers training. This is problem number one.

Problem number two, when you start publishing the papers in the journals. I remember the first time when we start writing the paper, they are even structured differently than computer science papers. So after 16 years being a professor, I was relearning how do you write this paper so that they are acceptable to the audience. Very different style. And finally, after you've done all of that, you need to push it through the reviewing process because unless you publish it, it's not available to scientific community. Again, there is a lot of challenge for the reviewers in these clinical journals. How do they read and how do they separate among the papers which really talk about the contribution from the papers which are not. And this is a challenging growth process for the whole community.

So I think that my advice to somebody who is considering doing it is really being patient and be aware that there will be a lot of failures and it's not going to be your standard submission to ICML that you know how to make it. And there was a good likelihood if the paper is reasonably good, it would be accepted in the first or second try. You just need really to explore and be patient. And then there is, of course, another thing, how do you communicate with medical professionals that need to adapt it? So these people who are very busy, they have a lot of responsibilities to make sure that whatever they bring to the hospital is very safe and compliant with their regulators. It's not like you're just going to give somebody, and say, "Oh, try it."

And I remember at the beginning I was extremely naive. It was like, "Oh, I have this great thing, why wouldn't you take it? It's like nobody wants to take it." So you really need to learn and to understand how do you talk to these people and find the right people that can actually help you to do the transition. And I'm still learning. I cannot say that I have a magic power to do it, but let's put it this way. Now, I am better than even a year ago. So it's a ongoing growth process.

Dr. Sabrina Hsu...: Patience and communication are definitely important. And also communicating the values of impact with clinicians to see how we can have a common future together. Not to say that we cannot leave the room today without talking about ChatGPT and Midjourney AI, as that certainly has been claimed as an I feel moments. Did you feel that that has bringing more opportunities for communication and ease that burden of communication there with all this generality AI high that's coming up that to say that there is a chance to improve efficiency and situation awareness here?

Dr. Regina Barz...: Yeah, I think it is extremely exciting that we have now these tools that are broadly used and it's truly amazing. And it continues to amaze me because I remember when I just started doing my master's in natural language processing and I took my first class, there was not even one example. It was in '95 or '96, there was not even one example of program doing anything. Nothing. It was kind of theoretical class where you learn the grammar and stuff. So seeing that and then when I started at MIT roughly during the time Google put their first machine transition system and it was kind of funny because people will try different things and see how it works to create it as really a new technology. This was really amazing to see it and it's amazing to see that people use it the same way as they use electrical devices. We don't doubt.

However, it's also interesting because it didn't come in the same way as electrical device as somebody made the analogy. So it works many times but sometimes it is like boom and something is totally wrong. So I think that really understanding how can it be utilized in healthcare, which is again extremely regulated in a way which is safe and secure and where we have control over the outcomes is really important. And I think right now, we have this wonderful, in some ways untamed beast that needs to go through some process of how we can in a proper way bring it into the healthcare. But I think a lot of tasks like for instance, writing notes, which every doctor detest, which takes so much time and which also not only... The problem is not only that it take so much time, the problem is that many times, and there are a lot of discussion, especially in the context of health equity. That the doctor summarizes whatever picks their mind may not necessarily summarize the whole story, bringing their personal bias like we all do in the summary of the encounter.

So bringing the technologies that can make it much more equal, of course, with the human input, I think it's going to really be an important way to improve the outcomes.

Dr. Sabrina Hsu...: Yeah, I think in the Stanford AI Index, they already find that the current model is 20% more toxic than the version we had just three years ago. Those days of R one so that's say a lot about bringing in bias. Are there other limitations you think people should be aware or just among all this pressing issue, which one did you feel that's the most needed to be addressed in-

Dr. Regina Barz...: You mean to be addressed? Can you be more specific? In which area I use it?

Dr. Sabrina Hsu...: For this new trend of coming up with using language models for generality AI?

Dr. Regina Barz...: So I think one of the central challenges is, again, to improve models, and we work on it at MIT. There are people who work, of course, in other universities is how do you really quantify the uncertainty? Because we always had this misconception and it relates to interpretable AI and others where we say, "Oh, human, if they see it, they can decide what is true or not true, what is right and not right." But the problem is that our capacity, our knowledge is limited. Our recognized patterns is limited. So it can fool you completely. And one of my students defended as a joke. He asked ChatGPT to put my publication list and ChatGPT put a list of publication and they look reasonable. Just none of them were mine and some of them related to them, it's like there was nothing to do it.

There was my name added. But you can see disability hallucinate is really amazing. So if it would not be me in the audience, there will be somebody else to say, "Yeah, it is feasible." And we need to have a machine learning tools that can actually control other machine learning tools. We need to have stronger uncertainty estimation tools that we can highlight to the human says, "Here, the uncertainty of the model is really high," rather than thinking, "Oh the human can check it out." Because at the end, if human needs to check out every single sentence, human as well can write it down.

So you really need to say this is a part where it's not clear or identify other tools for monitoring because it's, again, if you think about any other device that we bring to our home, the consumer devices, they all come with some safety device like buttons, whatever on your microwave or in anything, they will tell you something is off. So we need to create for these models a mechanism to tell us when they are unsure and make it part of this decision making when we stop relying so much on human mind because it is limited.

Dr. Sabrina Hsu...: How far along did you think we might see something that was real potential here?

Dr. Regina Barz...: I think that we are already seeing a lot and I think there are a lot of devices and applications that are already being placed in the healthcare system. People really exploring the question of how to utilize it for taking physician notes. I think it's extremely promising application. I think, for instance, even asking questions like patient who is prepared for procedures or who is questioned, even this type of information. So because the patients today are doing the searches of Google when they have questions 'cause they don't have access to the clinician 24/7. But having a machine help you can really be important for that.

Dr. Sabrina Hsu...: Yeah, and also humanity. You mentioned in your previous interview with Dr. Les Freeman that one of your favorite science fiction is Flowers for Algernon, where we see that the augmented intelligence didn't necessarily lead human to a happier life ever after. What did you see that we in the middle of computer science and medicine can have humility here?

Dr. Regina Barz...: I think it's a slightly different point. I think there are two different points. One is there are a lot of tasks we have today which are very mundane, which take a lot of effort and we are relying on humans. Human resources are limited. Even if you are in the best healthcare system, unless you have private physician to whom you can call 24/7, which 99.9% of us don't have, you really can benefit from getting information for not being the one. Everybody joke, Dr. Google and clinicians are very skeptical about it. But on the other hand, you are thinking about... Any patient, before you have a procedure, you want to get more information, you go to Google, what is the alternative? Of course, if there will be a doctor whom you can call all the time, you would use it, but we don't. So I think that providing better information services would really make a difference.

It made a difference how our shopping experience could improve with Amazon or how our booking reservation, even your cell phone which recognizes your face, you don't need to type the password. So there are millions of things that got significantly improved with this new technology. Now, going back to the question, what I meant when I said in Flowers for Algernon, there is always assumption that the smarter you are, the happier you are in life. And as a person, it's about the services that are provided to you that there's smarter. And I think the book made a very good point. There are many other aspects in humanities, not only your smartness that contribute to your overall happiness. I see it as a faculty at MIT. I see it as a person, but I think that the places where we are bringing this AI, especially in the areas like healthcare is really to help us to do better tasks that we are already doing or feeling that it will be great to have the automation there.

Dr. Sabrina Hsu...: Thank you for sharing.

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Dr. Adela Grand...: Well, let's continue talking a little more about combining AI and medicine. You touched a lot on that already, but I wonder what would you recommend female professionals especially who wants to start working in this interdisciplinary field? Were there any career moves that you did in the beginning that you found helpful, and you would like to share with female professionals?

Dr. Regina Barz...: So one thing that actually I think it's extremely important for female professionals, a lot of topics that I selected that I work on relate to female type of diseases. And I'm not saying that we shouldn't study diseases that affect the male population, but we know there are lots and lots of studies that show that due years of inequities, where the funding was available and who was running the studies. A lot of diseases that affect women actually not studied well at all, like my colleague and friend, Professor Linda Griffith from MIT, for instance, was affected all her life very severely with endometriosis and she started an open program on endometriosis despite the fact that it affects calculated 15% of women causing severe pain and affecting fertility.

This disease was not properly studied. The biology of it, and if you are trying to look at many areas of medicine, the answers are extremely unsatisfactory. So to me, a big driving factor of why I do something and what gives me power to go and listen to this rejection again and again because I really care about making change in certain area. And I think that this is really important because at the end, if you are not doing it, would you really assume that somebody else is going to do it? So I think that having something that motivates you and helps you to stay against the expected rejection, it's really important. And also what helped me, I think I firmly believe that there are lots of people in the world who want to help you and even though you may not know who they are, especially when you're looking into disability and you are looking, there is this whole mass of people at MGH or whatever, part of it is really going out there and talking to people and trying to find the ones where it will be productive collaboration and relation.

So it is kind of challenging balance. On one hand, you need to be very, very strict on your time because you go with the whole visiting and talking, and you need to find collaborative where it's really was to go but it was exploring. So a lot of research that I did really was just starting the conversation and learning and pursuing it further. I didn't have skill very well-developed when I was traditional NLP researcher because most of my research and communications were at MIT with my students and very close colleagues. But when we moved out of this realm, I think that really going out there, communicating, finding the right supporters really helped.

Dr. Sabrina Hsu...: Yeah. And many of our audience are in the same situation as you're switching from one field to another interdisciplinary field and try to pick up how to communicate in that field better. So in that process, did you find any useful resources you can recommend to those that entering this interdisciplinary career now, either clinician learning more about AI or AI scientists learning more about medicine? Are there any advice you have there?

Dr. Regina Barz...: So I didn't really find any resources to read about. I think that since it's so interpersonal in terms of connecting to people, you really need to try and to find the group that will work for you and type of collaborators that work for you. As a computer scientist, we are in a lucky position. There are many more clinicians that there are computer scientists who are interested in this field. So we are in a huge imbalance here. So I think just trying to connect to your local hospital and identifying if they have researchers can be the first step. I never actually heard of anybody from MIT who said, "You know, I'm interested in the field X," and they couldn't find. It's typically happens in another direction. There are a lot of clinicians from various disciplines that want to collaborate with, I have limited bandwidth and unfortunately, to most of them, I say no unless I can find some colleagues.

So just my advice would be just go ahead and try and don't be afraid because you need to understand something about the disease indeed. But there are lots of obligations and all useful things you need to do without going and taking a course in physiology. So there are some cases where you need to understand more because the field is so open, you can find something that you are contributing and you're making a difference without becoming a specialist in some clinical area. But I have to tell you, and this may be my first time sharing it publicly, that there were some interactions were very, very surprising. And at the end, as I'm an MIT professor, as any faculty in any other institution, you can have freedom to interact with people that you have similar views, that are similar to you in many ways, so it's easy. Then I was reaching out.

In the beginning of my career, I had a variety of very colorful encounters and some of them still keep me in my mind. I just want to share one so that when one of the listeners encounters whatever difficulty they will encounter, which is normal part of the process, they would maybe listen to the story, and it will tell you that there are other crazy stories that happened. So I remember that at one point I went to a hospital to MGH and I was discussing with them where the servers with the data will be located and they decided they want to move it to some city nearby, which was fine. So I asked them, "What's the problem? It's fine with me?" And it was me, my female clinical collaborator, another four men who deal with these matters, the news that I'm professor of electrical engineering and computer science.

And what happened next was really interesting. So then the person told me, "Oh, the machines are going to be working slowly." I said, "Why?" They said, "Because now, electrons need to fly from that city from Needham to MGH. And I was a bit confused, I said, "What do you mean?" And then he draw me a picture of a bus. Imagine yourself in a bus. Draw me a picture in a bus and say, the reservoir of water can be located in Needham and then the water needs to come to your bus so it takes time. So I was in total shock.

It was so bizarre that I couldn't even comment, which saved my face because I didn't engage in a negative energy here, and I was surprised that they didn't say anything. But at the end, my thought is if I am going to upset this person, I'm not going to get the data and I'm not going to get the service. So it's better that I shut up and just keep the story in my head. I would never have such encounter at MIT. But it was a funny story and I think that whenever you are entering this interdisciplinary film, you will have your own set of stories and you need to have a good humor to laugh at them and keep our eyes on the goal, which is to ensure that we can get the data and resources we need because it requires, again, communicative and interacting with different types of people.

Dr. Adela Grand...: Well, you mentioned a little about health equity before. So I mean, this is a hot topic. There have been a lot of discussion about the potential of AI to both drive health equity but also to do harm. So lots of examples of bias and AI unfortunately. So we wanted to ask you, what is health equity to you and what do you think is the most pressing issue now?

Dr. Regina Barz...: I first want to say that the issue of equity was there for decades. And if you look even at very traditional statistical models that are currently used that are parts of the FDA approved protocols are biased. And there was a lot of documentation about it, let me give you example from breast cancer like Tyrer Cuzick, which predicts based on your family history and other things, predicts your risk of breast cancer. You can utilize a prediction of this model to recommend patients for MRI, to give them chemo preventative treatments and other things. This model, according to the authors, was trained decades ago on white women in London. It's used across the whole United States. It is known that it doesn't work well on variety of population. It's close to random on Asian population, doesn't work very well on African American population. So these things were there and we now have a chance to revisit it and be very open about it.

Now, what is needed? So we know, of course, that the bias doesn't come from the model per se. It's how did you train the model? And the key aspect is to ensure that when we are training and testing these models, they are tried and tested on the sample that is the representative of the population. Or if you're deploying the model now and you're applying it to somebody who you've never seen for whatever reason, the model is to say, "I don't know. Do whatever you'll do without me." And we're not quite there yet, both from the technical perspective and from the data perspective. If you look at the dataset that we use to develop our newer model called Sybil, which predicts lung cancer resource very well, that model was trained on the dataset called NLSD, which comes from national low-dose CT trial was funded by NCI. That dataset, which is an amazing dataset, really great resource, likely shared with the public, doesn't almost have any African American population. If I'm not mistaken, less than 5%.

So whatever model you're going to develop is not guaranteed to work well on the population that is not represented. We actually went out and we are now tested it. For instance, on the Asian population in Taiwan, it worked quite well, but there is an element of surprise, you really need to validate and test. But you can say that whenever these type of resources are released by federal bodies, we need to ensure that they are really representative of all of us and not just a subset of a population. This is point number one. The point number two relates to FDA regulations and to deployment. And I know that AMIA is very much involved in the process. But there is a big question, when the tool is already in production, how we can ensure that it doesn't do mistakes and it runs on a person who is different?

And now the implicit assumption of the regulation is that if I publicize about this tool where they were tried and when they were tested, the doctor can make this decision. But how the doctor can make the decision? Computer scientists, who develop the model cannot do this decision. We cannot just look at the statistic and say, "Yeah, this patient is different." Because in addition to known things like gender, age, race, there are many other things how one can be different. And we really need anti-regulation. Again, remove the human intuition as a main way to decide whether it is good or bad. But to have these very strong statistical models, again say, "No, you cannot be using it on this patient." To summarize, I think there is more technologies that needs to be developed to make it safe, but also it is a lot of place on collecting the data, which is representative of all of us.

Dr. Sabrina Hsu...: So did you feel there is anything that people like us in the middle of medicine and computer science can help in this area to make this feel move forward?

Dr. Regina Barz...: I think that there are several things that we as a computer scientist or people who work on medical informatics can do. The first one, as I said, there is a lot of technologies that is currently lacking, like uncertainty estimation for very long time in planning is more after. So rather than the primary area because whenever you are, I don't know, try to recognize your face on iPhone, do many other things. Even if you translated something incorrectly, it's not a big deal. Well, here we are talking about high stake applications where certainty is really important.

So clearly, producing more tools in this area, it would be I think influential for the field that is separate kind of unique needs for medical applications that I think are still meant with the technical community. But I also think we as a professional, who understand technology and are interested to apply it to this important area, need to be very active in regulatory process because we are trying to regulate technologies. It develops really fast. For instance, FDA regulations that came out, they're antiquated at the time that the technology is published. So there is a huge lag. So being really not trying to regulate now something that is going to change in half a year and as you know regulatory process is very slow. How do we think about it? And I think we as professionals really need to be part of that conversations from the very beginning.

Dr. Sabrina Hsu...: Yeah, I know FDA is taking a very community-based approach now on this to cohort comments on their discussion papers on AI.

Dr. Regina Barz...: Absolutely, absolutely. And actually, I'm writing one right now, but I think that it's really important for our community. It's not a natural thing for us to do, but I think it's really important for our community because none of us have a full picture. As technology people, the technology in here, but we don't really understand maybe the regulatory landscape very well or the clinical landscape. On the other hand, people who are strong in those may not understand what technology can and cannot do. So I think that really bringing the communities together is really important.

Dr. Sabrina Hsu...: Yeah. What I noticed also in these two years, the attitude of technology changes a lot from now wanting regulation to hoping to have regulation in place. So a lot more movement will certainly be seen in this area.

Dr. Regina Barz...: Absolutely, and the problem is that we see very little. Again, as I said, AI in healthcare. And the problem is that today for the individual doctor, a lot is in stake to bring it in. Technologies that didn't study in medical school, they may not understand what is it. So the role of regulation even further increases here because remember, when the doctor gives appeal to the patient, they know that it was FDA jobs to make sure that it's safe and secure and they feel more comfortable moving to a new treatment. If you're not really sure what it will do, our natural reaction when you're responsible for patient safety is to say, "Thank you very much. Let me use something else." So I think that, in my understanding, regulatory science would really increase insignificance and also will be essential to the translation.

Dr. Adela Grand...: Well, and you touched a little about health equity and I know you have done a lot of work on that, so we want to give you the opportunity to talk about it. What you have done to facilitate health equity in your work.

Dr. Regina Barz...: Even at our beginning, when we started working on breast cancer, at the time the health equity in AI was not such a big topic, but when we started doing what we're doing to computer science just running baseline. I couldn't believe that when you run these models it's therapeutic and other traditional models they use today on some population, they're close to random and those are models that are used in clinical care. It became to us very clear that we absolutely have to... When any tools that we develop besides training and testing on the same population, this is your first step, is really to do broad testing in other populations. So for instance, in Journal of Clinical Oncology, when we published results of our risk assessment model for breast, we tested the model in seven different hospitals. Some of them were in hospitals which are primarily treating African American population like Emory in Atlanta, in places like Taiwan, which clearly focuses on Asian population, in Israel, in others.

And really, really felt that before we put the model, we need to ensure that it works across all these different types of people. And in this case, we demonstrated it. Similarly, when we published Sybil, it was tried and tested on the data from the trial, but then we tested it in Taiwan, and we tested it and held out MGH population. We are now focusing even to further expand the reach of the testing. But in parallel, we started working on these tools that really tell you whether the model is calibrated on a population. Can you trust uncertainty that the model gives you and how do you teach the model to abstain? And also, even all the sort of ad hoc decisions that we are making. If I give you now the model and you're in hospital X, how many samples do you need to collect to ensure with certain probability that the model is calibrated well?

And when we started this, let's just do 10,000 and in many hospitals 10,000, it's a lot. But maybe in some hospital you need 20,000, who knows? Because it really depends how different is this population. So creating an appropriate machine learning tools that can really, instead of just doing a decision from my hand, the clearly proper mathematical mechanism is really important and we are working on developing these types of tools.

Dr. Sabrina Hsu...: Yes, we need to wrap on now, but before we break, we want to mention that in AMIA we have started hosting a series of events for AI innovation showcase to bring out more health AI practitioner to discuss how to evaluate health AI and ACM, KDD, for example. We are also hosting a series of events to hopefully bring those two groups together to discuss more so as to encourage the self-regulation industrial standards will emerge. We're hoping to see more participation from your group as well. Great. And in the meantime, did you have any parting words for us here before we break?

Dr. Regina Barz...: Thank you very much for having me. And I think that for many of us, the healthcare is something very personal because there is no person who never went to the hospital and who never was in the situation when they wish they would have extra information or extra predictive tools. And I think it's a great area, even though it has a lot of, as we discussed, challenges, it's very rewarding to see how the change happens. And I'm hoping that there will be some listeners who are considering to expand their interest in this field that it would encourage them to explore this opportunity.

Dr. Sabrina Hsu...: Thank you. And, Adela, did you have any last questions in there?

Dr. Adela Grand...: No, no more questions. That was awesome. I really enjoy your talk. You brought so many hot topics. I mean, you just brought all together all these really hot topics that everyone is talking about from the technical but also clinical perspective was excellent. Thank you so much.

Dr. Regina Barz...: Thank you. Thank you very much. Really enjoyed it. Thank you.

Dr. Sabrina Hsu...: Thank you for listening to today's episode. ACM ByteCast is a production of the Association for Computing Machinery Practitioner Board. And AMIA's For Your Informatics is a production of Women In AMIA. To learn more about ACM, visit acm.org. And to learn more about AMIA, visit amia.org.

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