Rashmi Mohan:
This is *ACM Bytecast,* a podcast series from the Association for Computing Machinery, the world's largest educational and scientific computing society. We talk to researchers, practitioners, and innovators who are at the intersection of computing research and practice. They share their experiences, the lessons they've learned, and their own visions for the future of computing. I am your host, Rashmi Mohan.

Rashmi Mohan:
Each of us dreams of working on a meaningful project that makes a deep impact to the lives of people. Our guest today lives that dream in the most tangible manner. Her pioneering work at the intersection of ML and healthcare improves outcomes for patients across multiple clinical areas. Suchi Saria is the John C. Malone Associate Professor of Computer Science at Johns Hopkins University and has been working in the field of machine learning and healthcare for many years. She leads large, ground-breaking projects with top government organizations like NSF, NIH, DARPA, and the FDA.

Rashmi Mohan:
She's been named in the World Economic Forums Young Global Leader list and in MIT Tech Review's 35 Innovators Under 35 amongst many other accolades, and is also the founder of Bayesian Health. Suchi, welcome to *ACM Bytecast*.

Suchi Saria:
Thank you for having me, Rashmi.

Rashmi Mohan:
It's entirely our pleasure, and I'd love to understand a common question that I ask all my guests because I get such fascinating answers is if you could please introduce yourself beyond what I have already said and talk about what you currently do, as well as give us some maybe insight into what drew you unit the field of computing.

Suchi Saria:
Sure. Funny you ask that. Takes me back to my super early days. Actually, I grew up in a little town in India. You're from India. You probably will find some of this familiar, where it's not really traditional where I grew up to ... Little girls aren't motivated or inspired to get into computing. It's something that that's not sort of the typical path. And in my scenario, what happened is I just had older cousins who were really into computing.

Suchi Saria:

And I was reading, and I grew up. I was always a tinkerer, always messing around with things, building things, unbuilding things, rebuilding things. I was reading a computer science book that talked about the next generation of AI, and the next generation of computing will be AI and these intelligent machines, and that was just fascinating. What was that going to be, and what would it take to build these smart machines? And that question fascinated me.

Suchi Saria:
So, I think that's really what motivated me into doing computer science. So, most of the early part of my career was mostly being fascinated by AI as a field, the research itself, the technology itself, and my first experience was in robotics, trying to build ... I don't know if you know Lego Mindstorm kits, but basically using Lego Mindstorm kits and then just my own programming to be able to build aspects of what would make a robot smart.

Suchi Saria:
One thing led to another, got into research very early. Happened to just be around really incredible, inspiring, early superstars in the field who took me in under their fold. I started doing research with them very early, got familiar with what state of the art was, starting pushing it. And then machine learning as a field was just starting to gain traction because historical work in AI was very much around expert-driven, more logic-based systems. And machine learning as a way of building smart AI was relatively new at the time, and it was really fun to sort of understand the techniques that existed.

Suchi Saria:
I love stats. I love CS, loved engineering as a whole, physics. So, it was just fun to put those ideas together to start just making progress through projects. So, that was really sort of my early upbringing in the field. One thing that many people don't know about me, which I've actually only recently discovered people find strange, and maybe young girls find inspiring, was that growing up, I actually went to art school for 10 years on the side. A good chunk of my life was painting and creating in charcoal and oil and spending a lot of energy perfecting art and my fascination with art and design.

Suchi Saria:
And in India, it was much more traditional and expected that because I was good at it, that's what I would do. And so, when I was in 12th grade ... You know how in India we have to take exams? So, we took exams for design and engineering. And I happened to clear both, so then I ended up choosing to go into engineering. But my other hobby and career path was to be a designer, which I wanted to design across the board, like create new fashions, create new beautiful places. So, anyway, maybe I'll still get to that career at some point, but yeah, that's how I got into it.

Rashmi Mohan:
That's wonderful. I mean, it's two parts, right? One is, I think, finding that inspiration. Like you were saying, you had cousins who maybe exposed you to the field. The ability to actually tinker with Lego Mindstorm early on, I'm sure that played a large part in just piquing your interest in the field in itself. And yeah, I'm sure that the design bits also influenced some of your decisions or the way you think about problems. I feel like every part of our education, intentional or otherwise, contributes towards where we are.

Rashmi Mohan:
But what the other thing that you brought up was ML was sort of really on the upswing when you started out your career. But computational biology as well was really sort of gaining momentum in the 90s. Were you at that inception of that curve, and how did you get about applying ML into healthcare?

Suchi Saria:
I have to say, I've been incredibly lucky in my career with sort of being early in a place so it's possible to really shape where things go. So, for instance, I'd say, in the 90s, there was this revolution of starting to measure more information in genomics. A lot of my field focuses more on the enormous amount of data we are collecting every day as a byproduct of daily care. So, when you go to a doctor's office, how you generate so much data. You generate data in the form of they measure your vitals, they measure your labs, they measure how you're feeling, what you're taking, how was your response, how are you doing on a daily basis.

Suchi Saria:
Now, people wear watches, so there's all this information being collected there, how much you're sleeping, what's your daily activity. And then there's all this information that comes when for any person who has any health-related challenges, they're under heightened observation, where they're getting labs and vitals and other forms of data about them a lot more often. And, to me, what was shocking was the use of that data in driving care delivery decisions.

Suchi Saria:
So, I'm not even talking about spending thousands of dollars collecting new data. I think that's going to just continually be the case in healthcare. We're just finding better and better ways to measure our health. But what we've lacked and still lack today, which is what's shocking to me, is our ability to leverage all this data we do collect to drive decisions. We spend more money optimizing what color of shoe to show you on your Google Ads page than whether you will

benefit from this particular medication or not, or should you choose a surgical option, or should you choose to do nothing and go do physical activity.

Suchi Saria:
So, there are hundreds of decisions that you make daily and your doctor makes daily around your health. And the use of data today in making those decisions is very, very limited.

Rashmi Mohan:
That's super interesting to me because I feel like there's two parts to this. And I think shoe reference particularly sort of hit home because that's kind of what we do use on a daily basis. That recommendation that comes to me on a retail site is something that hits me immediately. But having said that, if I were to think about it from a patient point of view, how are we able to convey the importance of this to a patient?

Rashmi Mohan:
I know that they record all of this information about me. How do I know that this is actually helping either improve my overall health or, in some ways, get me benefit in terms of maybe my spending, like how much I'm spending at a doctor's office, especially with a lot of the time since my insurance is covering it, that, in fact, may not even be directly sort of hitting me, right? So, how do you convey the importance of that to a patient or even to the caregiver?

Suchi Saria:
Absolutely. Let's think about something as simple as diagnosis. Diagnostic errors is the third leading cause of death. Delayed diagnosis leads to so much worse patient experiences, all the way from anxiety to not getting the right treatment and your disease progressing where it's much, much harder to treat than if you got, instead, early and timely diagnosis, and you could take the right actions in a timely way.

Suchi Saria:
Now, it's embarrassing to me that today, diagnostic errors is still the third leading cause of death. And from a patient point of view, it's so real. When you're struggling, you're trying to figure if you could use your data to start understanding more clearly what is the problem you're having, why is it you're having. Today, you go to a single doctor, and they say something. It's only a small number of occasions people have the luxury of even getting a second opinion to then figure out if that's correct.

Suchi Saria:

In that scenario, sometimes it's like mad obvious. Other times, it's not mad obvious. An example of this is my nephew. He was in the hospital. He was hospitalized for something totally different. In the process of his hospitalization, he ended up getting sepsis. It didn't get detected in a timely way, and it progressed to septic shock, and we, unfortunately, lost him. Of course, this is my nephew, so it means very personal things to me, but the reality is, this is not unique.

Suchi Saria:
The number of preventable deaths today that we could have avoided if we only had the ability to detect patients at risk and treat them in a timely way is just mind blowing to me. The use of data, the use of smart technology, to be able to identify patients in need and at risk in order to give them all proactive care is absolutely where we should be, and we're not. We've become so good at using these cycles for every other thing. Wouldn't it be great if we could use these cycles to actually improve patient outcomes?

Rashmi Mohan:
Absolutely. I think what you're saying makes immense sense. Looking at your journey as well, you started out with predicting outcomes for premature babies. Now, you're looking at chronic illnesses and how to manage them. A lot of your work is around improving these health outcomes. What would you say are the key problems that you see today that you really are burning to address?

Suchi Saria:
Yeah, so I'll answer that in two ways. So, the first is from the healthcare standpoint, and then from the technology standpoint. So, let's start from the healthcare standpoint because that's sort of where the main benefit is. At the end of the day, we need practical applications where our healthcare leaders or providers start to see, and patients start to see tangible examples of benefit.

Suchi Saria:
So, I think today, at the highest level, healthcare today is very reactive. When you have the ability to have foresight, when you have the ability to use your data to predict what's going to happen, where things are trended, you can then put your resources together to give what the patient needs in a timely way and get them to feel better quicker, so this notion of reactive. And why is it reactive today? The reason it's reactive today is because the whole healthcare system is built around one, patient comes to you when they have a problem. You look at the patient when they have a problem. You have literally 20 minutes to make a call in the best case.

Suchi Saria:

If you're in a hospital, you're even busier than that because you're trying to do 20 things at the same time. You have so many patients to look after. There's constantly urgent things that are happening that are drawing on your attention that are causing you to context switch. There's interrupts. There's constant escalations that need your attention. So, the point is, you have very limited time. It's reactive because you have limited time, patients coming to you when they have a problem, and then your job is in that very limited time to quickly make a decision about what to do next.

Suchi Saria:
And then the patient goes away. And then that's that. And you're busy, and you've moved on to the next thing. So, that paradigm is just not suited to being able to catch hard problems early enough. But, if we could flip it with data, with the right user machine learning, you could flip it. You could have the ability to continuously record data, which is actually happening today.

Suchi Saria:
So, one thing that would be helpful for the listeners to hear is in 2009, there was the High Tech Act. In 2010, the Affordable Care Act. Those legislations were incredibly powerful in accelerating the adoption of electronic medical records in the U.S, for example, which means we suddenly went from having home-grown electronic systems where we are partially recording data and disparate systems, across each health system users, its own disparate system, and many, many providers just used paper. You come in, and they're taking notes in their notepad in doctor's handwriting.

Suchi Saria:
So, the challenge was that infrastructure didn't allow for us to have the ability to really take advantage of that data because it was not in a place where we could liquidate it. But today, because of the legislation in 2009, 2010, we went through a five to six-year journey where, across the board, health systems went for implementing electronic infrastructure that allows them to record all these interactions with patients, record data like all of the information that's collected around. Clinical information, social information, historical information can now all be in a digital electronic form that can be leveraged.

Suchi Saria:
So, now, imagine putting all that data together with a service that's just basically continuously watching, pulling the data, integrating it, stitching it together across your past, and then putting it all together to identify what are the things you're at risk for, and then surfacing it to the right people, which are your providers, or you as a patient or the family, and making it very easy to act. I mean, why aren't we doing that?

Suchi Saria:
Because if we can do that, you could identify so many diseases. The breadcrumbs for those diseases are in the data way, way earlier than our current system. In our current system, we recognize, or we get to it. And part of it is because patients come to doctors when they're already aching and hurting, and things are already way down the pike. And wouldn't it be great if we could have detected some of these much earlier? And if so, we could prevent it or treat it.

Rashmi Mohan:
For sure. And I think the point that you bring up about predicting, and this seems to be such a classic marriage between the use of machine learning in this specific domain, because of the value you can get from predicting some of these issues ahead of time, can literally change a person's life. So, I completely resonate with what you're saying.

Rashmi Mohan:
You also mention technology challenges. What kind of technology challenges are you running into?

Suchi Saria:
Absolutely. So, I think this makes sense now, right? So, the infrastructure of collecting data now exists. The data now exists. We're getting ever-increasing amounts of data. So, the question is, what are the bottlenecks? Why aren't we seeing this today? And we obviously know there are efforts that have wanted to do things like this but have underestimated what are all the bottlenecks we need to solve for?

Suchi Saria:
So, in my view, I mean at the highest level, I have to say there are a couple of big challenges that are really, really important. So, first is in healthcare, unlike some of the other fields like advertising or, say, genomics or, say, image recognition, you're not just collecting one type of data from one sensor. You're really collecting data from hundreds of sensors. Think of heart rate as sensor, blood pressure as a sensor, social needs as a sensor. Some of this is human-recorded data.

Suchi Saria:
When you're interacting with a nurse, and they're doing a full head-to-toe evaluation, they generate data around what they saw, and how did you feel, and your pain levels. And some of this data is very qualitative in nature. And so, a big part of this is the ability to integrate very diverse type of data that come in, and integrating that well really requires deep understanding of

the data itself, the way the data are measured, in technical speak, what the measurement error models are underlying this data, whether it's missing at random, missing non at random, missing completely at random, for example, and building technology that embraces the fact that you're doing heterogeneous, multi-modal data integration in order to actually draw high-quality outputs.

Suchi Saria:
So, that's one core part of the challenge. You have to figure out a way to integrate this data well, and that partly where you have data with very different amounts of noise and messiness. And so you've got to embrace that challenge.

Suchi Saria:
The second is safety. In many fields of ML now, when you're using it in problems like education, healthcare, it's extremely important to understand that somebody's going to use the output to make very important decisions. Therefore, you have to understand safety, risk, bias. And there are various ways in which you can do this not very well and generate outputs, which maybe look like from an accuracy perspective the way we are used to naively measuring accuracy in other fields, that the accuracies very, very, high. But, in reality. Those metrics give you a very limited part of the picture.

Suchi Saria:
In order to make these outputs actionable, they need to be actionable, interpretable, safe, bias-free, or bias-mitigated to the degree possible, and that's crucial. So, how do you do that, and what techniques promote that? And we spend a lot of time doing research in these first and second challenges I spoke about. And then third, over the last couple of years that I've sort of become intimately familiar with through my experiences at Bayesian is the notion of, what I call, human-machine teaming, which is how do you go from ... And I'm sort of leading a big grant in this space with the National Science Foundation as part of the frontier of work. They have a big Frontier of Work program. What does the frontier of human expertise looks like as new technologies come to bear to augment humans?

Suchi Saria:
And so, here, what we're trying to understand is basically, in a field like medicine and healthcare, you have experts at every level. So, you have care coordinators. You have case managers. You have nurses. You have physicians. And even physicians, you have specialists at every level. And how do you build systems or AI where it's possible to partner, to team, to collaborate? And the reason those ideas are fundamental is because, in one sense, if all you're really doing is automating a rule the provider already knows, like, "Hey, when the temperature rises above this, I want an alert," you could do that. That's what, historically, people have done in healthcare.

Suchi Saria:
You get extremely limited value out of it. It just gets to a lot of false alerting. People don't really trust it. They don't get a huge amount of value out of it. They can see a lot of value in what I described earlier as true AI, where basically you're able to integrate data, continuously watching the background, identifying these early signs and symptoms reliably, and then surfacing it because now, you're making their life better. They don't have the time to be watching all their patients, but if you can surface early, you can identify the ones where things are going downhill and reliably bring it up. Now, you're partnering with them, and partnering with them in a way where you're making their job easier, and you're making it very easy for them to take the right action, make the right decisions, where otherwise, they might have missed it.

Suchi Saria:
But to do that partnering and teaming well, there's a role for how the technology has to be built to enable teaming. And I think that's also sort of an important core challenge that we need to continually solve for. We can't just assume that the way we traditionally built AI to drive advertising is the same AI that is going to be the right partner for human experts like physicians and providers.

Rashmi Mohan:
Yeah, that's an excellent point. There's multiple points that you brought up in that last section, which I want to dig deeper into. One part is just the huge responsibility associated with this kind of an application in comparison to many others, just the impact of this. When you talk about data [inaudible 00:23:34] and biases, et cetera, one of the things that in many other applications, you have a continual stream of data for a certain user. For example, if I'm browsing a retail site, you know on a daily basis what kind of products I'm clicking on, how long I'm spending reading a piece of content.

Rashmi Mohan:
In your case, when a patient comes into a healthcare clinic, it's not continuous. You can't really follow that one patient and their particular pattern. Is that a challenge at all where you have to sort of generalize over the larger sort of population and still get accurate results?

Suchi Saria:
Oh, yeah. Absolutely. So, I think there are a couple of things you noted there. So, the first thing is, the data is more complicated. The reason it's more complicated is because it's not your classic, every second, something is measured continuously. It's that things are measured very frequently.

Let's say you have a device on. You're going to measure it frequently. Now, you're done with the device. It's off.

Suchi Saria:
Let's say you have a heart rate monitor. You just had a big surgery. You're being monitored. People are worried about your recovery, so you might imagine putting a heart rate monitor for a 20-day period after the surgery itself, and you're going home. Over that period of 20 days, we're getting very good, high-quality measurements. And now, let's say you take it off. You're not using it anymore. A month later, you're going in for a checkup. You go in. You do a full set of labs. You do a full set of vitals, so you're getting a collection of deep data.

Suchi Saria:
Instead of getting a lot of heart rate data, you're getting 20 different kinds of data, but a snapshot in time for these 20 pieces. And you go on, go forth. You might have another checkup. In some cases, maybe it turns out the patient, actually, recovery didn't go so smoothly. They needed to be admitted back for a follow-up procedure. So, you'll get a huge amount of information back in again when they get admitted.

Suchi Saria:
So, what this tells you is basically instead of the predictable cadence that you might see on a website when a user enters a website or is browsing on the internet, what you're going to see is more like irregular and diverse, deep and wide data. But that's okay because, at the end of the day, even if you measured my creatine every two hours, it's not going to matter because the reality is my kidneys don't evolve that fast. My creatine once a day is a huge amount of information, maybe twice a day at best.

Suchi Saria:
On the flip side, something like blood pressure. If I am experiencing shock, it's going to change over a course of a couple of hours. So, what is important here is we're getting these different forms of data at different cadences, but we know how to think about taking these. We just have to be mindful of embracing the fact that the data that are being measured is a bit more intentional here. It's not just happen to be. It's intentional in the sense that physicians are recording something when they are worried about you about in that manner. And so that intentionality itself is information. And how do you take intentionality and the information together to start making inferences that say something?

Rashmi Mohan:

Yep. All this talk of data, Suchi, of course, we're going to talk about privacy. Data privacy is critical in any field when you're using consumer data, user data. Is there anything special in the healthcare field, even more sensitive? Is there anything special that you have to do while you're using this data?

Suchi Saria:
Yeah, I think there's technology solutions, and then there is philosophy, and you need both. You need to understand sort of the culture in which we want to exist, and then there's the getting the technology right to make it happen. So, the technology piece is much easier to think about. Today, we have access to very secure cloud-based infrastructure, where you can do monitoring in the most granular way to understand and encrypt data and to understand and secure your data.

Suchi Saria:
Let's just say at a high level, to figure out both a way to secure the data but also make it so that the access of the data itself is controlled in a very granular way. So, you're not just sort of just giving carte blanche access of the data to anything. It's only being used in a way that, in our example, for instance ... I'll give you something concrete at Bayesian. Beyond sort of the very regressed security measures that people think about, also thinking about what is the data being used.

Suchi Saria:
And in our scenario, for example, we use all the data to drive and power all of the machine-learning applications that are being used by providers in order to improve patient outcomes. But like you might see on any other, like the Facebook scenario where ... Then people think about secondary uses of the data, and what are the secondary uses of the data, and what is the policy around secondary use of the data?

Suchi Saria:
And I think that's where this philosophy matters and the culture matters. At Bayesian, we take sort of a very particular point of view, which is we want to use the data to improve patient outcomes, and that drives our ethos of access. But more broadly, in healthcare, I think a lot of concerns arise from not having very clear philosophy and understanding of use. When the data's getting collected, who's using it? What are they using it for? Who else has access to it?

Suchi Saria:
And I think people are becoming more aware. People are cleaning this up. And I think there's a lot of fear that sometimes the data is just being used in order to treat it like an asset for generating extra cash or revenue without very clear dotted line to how is it impacting outcomes.

Rashmi Mohan:
Yeah, I think the point to bring up are the ethical considerations of how you use this. If that responsibility lies with the creators of this technology, is there a need for regulation there?

Suchi Saria:
Yeah, I think this is such a hard and interesting question. How we are doing it today, I think really, today, it's a bit chaotic, I have to say. I think it's so new, and it's all happened so fast. People are trying to sort out what's the right approach. Is it through regulation? Is it through responsible partnerships? So you've seen the AI partnership group, where they've brought in industry leaders from across the board to come together to think together about what are responsible AI practices. We did the same thing in healthcare, where we got a collection of the top leaders, researchers in the field to come together and think about what are the responsible machine learning and health AI and health practices.

Suchi Saria:
And certainly, I mean, regulation, if done right, can be very effective. Regulation, if done wrong, can be very, very wasteful. So, the question is, I think the jury's out. I think we're figuring it out, figuring out what is going to work at scale. But along the way, one thing that's very important is we need more leaders who think hard about it, who take a responsible stance, use that to lead by example. We need that because that's the basis for forming anything that scales, and we need more research leaders. We need more practitioners who are leaders clearly stating policy, clearly, transparently discussing policy.

Suchi Saria:
I think transparency's also crucial. I think today, there isn't a whole lot of transparency, and so just sort of bringing transparency itself so that we can actually have a discussion out in the open. Is it okay for large health systems to be making money from the data they're collecting, where the only purpose of the company is to be able to monetize data, to get another stream of revenue? Maybe it's okay because you know that the revenue they get is actually then put back into improving patient care. So, maybe it's okay.

Suchi Saria:
Maybe it's not okay because they're using it to monetize, and they're seeing this as a revenue stream, and it's not really. And that's preventing them from liquidating the data for other use cases to other companies because they're worried by sharing, that's reducing the value of the data they're able to monetize. I don't know. But I think these examples of types of discussions we're

having, we ought to be having more of. And we need more responsible leaders voicing their opinion transparently.

Rashmi Mohan:
No, absolutely. I think having that dialogue and transparency, as you call out, is supercritical. And I think also, like you said, having those examples of people who are taking a stand and understanding what their journey is like, just having that access to that information will help drive a lot of these choices as well.

Rashmi Mohan:
One of the things I want to go back to in the few problems that you had called out earlier was really about partnership. Suchi, what was really interesting to me about your journey is how you've made this transition from research to practice so seamlessly. That's the theme of this podcast as well, but you seem to make that transition back and forth easily. You make it look easy, but I can't imagine that it is. I'd love to hear your thoughts around that. Was it hard? Is it continuously hard?

Suchi Saria:
Yeah, it's actually both hard and easy at the same time. So I can tell you what about it and what about it is not hard for me. I'd say the part that was actually not as hard for me was making time. It's been absolutely phenomenal to be able to bring ... We work so hard in research. My Ph.D. students, my post-docs, my scientists, they stay up till 3:00 AM sometimes working on these papers because they truly, deeply care. We care about impact and impact at scale.

Suchi Saria:
So, why are we working so hard? Because we truly, deeply care about impact. And the reality is that's what the life of most researchers are. They want to make an impact. But to make an impact, turns out sometimes, we can write all the papers we want. The papers alone don't get you to impact. The papers are an amazing starting point for what doing it well and doing it thoughtfully would look like. And to me, in healthcare, one of the big gaps I saw was, on the one hand, there was enormous need. But on the flip side, the challenges like how we were going about in industry addressing those challenges, coming at it from a research expertise point of view, didn't make sense to me.

Suchi Saria:
And on the flip side, I saw there was state-of-the-art research that could really, truly tackle some of these challenges, but they weren't really making it out because the current mechanism of publications alone doesn't get you there. And to do it well, you need to understand not just the

ML, the modeling, the algorithms. That's crucial, but there's also product, delivery, integration, experience, delight. All of that matters to get adoption. All of that matters to get to outcomes because obviously, if people won't use it, you're not going to get there. In order to use it, it's the end-to-end solution.

Suchi Saria:
And so, to me, the part that was easy is we're all motivated by impact. When you're motivated by impact, working backwards, it seemed easy to think about how the two worlds fit together, from bringing state-of-the-art research ... My first company experience was actually another company that was spun out of Stanford that was also in the data space called Aster. And it was just really fun to see when you take state-of-the-art research, you go use that to then build solutions that are tackling hard problems in the industry, what's possible if done right.

Suchi Saria:
So, here it was the same experience, bringing state-of-the-art research. And then, in healthcare, there's so many problems. We're not short of problems. Marrying the two and doing it well has just been really, really fun. And really, that part has not felt what's hard. What has felt hard is culture. What has felt hard is going against the grain because there's an expectation in academia that when you're an academic, the only part you should care ... There's traditional academia, and traditionally in academia, it's very easy to get suckered up into situations where people think that the only thing that matters is the papers you publish. And it's the bean-counting of papers you publish.

Suchi Saria:
Fortunately, I'm in an environment like Hopkins where my dean is just super ... He is just sort of a visionary leader, really truly cares about impact at scale, is very supportive of the way we're marrying industry and practice. But if you are in environments where your peers aren't that supportive, where they don't understand why you would care to do impact at scale, why sort of the typical currency of academia, typical academic research currency of just writing papers alone isn't adequate, I think that that's where it's hard. So, I think it's the culture bit that's what I find the hardest, and kind of helping people understand, like remember why we were here, to begin with. It was impact at scale.

Rashmi Mohan:
Yeah, I mean, I think that you hit the nail on the head. I think we all look to do that, whether we're in industry or academia. But what would be your advice to maybe researchers early in career or even students who are thinking about a career in contributing research? What should be

some of the considerations that they should think about as they're entering this phase of their life?

Suchi Saria:
Yeah, the things that I really benefited from is find mentors who energize you. Find people who inspire you. It was really helpful for me very early on to find people or readings. Reading, that inspired me. And because then you don't have to fit the mold. You don't have to be like everybody else around you. You can find the people who inspire you, and maybe if they're taking non-traditional paths, you can chalk your path. If somebody else can do it, you can do it. You don't have to be around.

Suchi Saria:
To me, a big part of it ... and maybe this is partly me coming from India, where there's a norm, and there's an expectation of a norm and fitting a norm, and to me, that was very burdensome. I was so excited that I had the freedom, was given the freedom. And I don't know exactly how, but was stubborn enough to break out of the mold and be able to be inspired by people who ... I used to read a lot of biographies and found people that inspired me, felt like if they could do it, I could do it. And it was just really fun to figure out, chart my own course, what needed to be done. And then find people who could make it happen.

Suchi Saria:
And then along the way, the most important thing, you need to have a lot of fun because what's the point of doing it all if you're not having fun. And when done right, I mean, work is fun for me. When I have my day off, I do exactly what I do on a workday.

Rashmi Mohan:
I was just going to ask you, what do you do outside of work?

Suchi Saria:
Yeah. My life is all very neatly stitched together into things where I love creating things. This is going to sound so cliché. It's like Silicon Valley, maybe what people might call B.S. But I just love the idea of using my engineering superpowers. Engineers are creators. Engineers are value creators. At the end of the day, what the field gives you is a lot of ability to make things that didn't exist before.

Suchi Saria:
And so, to me, I love the idea of using our superpowers to figure out what can we do to make the world a better place. When I have free time, I sit and think. And I love reading. I used to do a lot

of art. I don't get time to do it anymore, but I love reading. I love being able to think about where there are gaps and how can we then use our superpowers to close those gaps.

Rashmi Mohan:
I love how you say ... Sorry, I didn't mean to [crosstalk 00:40:38].

Suchi Saria:
Yeah, go ahead.

Rashmi Mohan:
I was saying, I love how you call it a superpower. I feel so much more energized today because you're absolutely right. The ability to build and create is something unique that we have as engineers, and to use that in a meaningful way is very joyful.

Suchi Saria:
Absolutely. We all need our engineering capes. When I wake up in the morning, I'm so excited. I wear my little cape, and I'm like, "Today is going to be the best day."

Rashmi Mohan:
Fantastic. Suchi, I would love to understand when you have so many ideas, where do you find your inspiration? How do you determine what you're going to focus on next?

Suchi Saria:
I think for me, I feel like I've been on what feels now like a 10-year path to trying to think about how do we bring ... It is inevitable that I think five years from now, people will say it's crazy, maybe even three years from now, hopefully, two years from now. But five years from now, people will say it's crazy that we weren't using data to drive decisions every day in healthcare in a more proactive way. So, to me, how do we make that happen? And how do we make that happen faster has been my focus. That is what I think about. That is what captures my imagination all day long.

Suchi Saria:
When I read, I think about what are the barriers? Why isn't it happening? Is it financial? Is it administrative? Is it technology? Is it people? Is it the way we're talking about it? Is it not enough use cases? Is it not high enough important use cases? It's impact at scale. So, you have to really understand impact. One thing I did a lot as a kid was I used to love doing just hard things because I wanted to prove to everyone I was badass. And I apologize for using that word on your podcast, but that's true.

Suchi Saria:
When you're a kid in India, it's survival of the fittest, and it was all about solving the biggest, hardest thing around me. And, at some point in my life, I realized, "Oh, wait. That was really cool, but I need to move from solving biggest, hardest thing to ... " To really to make an impact, it needs to be not just hard, but important. And important means understanding the relationship of your creation with the world. If you create it, what will it do? What will it impact? How will it impact? How do you measure impact? How do you know you will succeed?

Suchi Saria:
So, I think I really use impact to drive my focus, not just sort of it will be fun to build, it's hard to build, but also, is it actually important? And then if it's important and hard and fun ... fun is just easy ... then that's sort of what's driven my focus. And for me, really last 10 years has just been all about the central question I raised. The data is there. The infrastructure is there. The technology is there now or is very close to getting there. In many, many use cases, it's already there. So, how could we mobilize this technology to move to a world where we're not operating the way we did 200 years ago? Our healthcare system today is just the way it was 200 years ago.

Suchi Saria:
You go in. You go into the doc. They listen to you. They record what you say, and then they give you what you need to do all within that moment. And that's what we did 200 years ago. That's what we do today. And that's kind of a little bit like earth-shattering embarrassing to me. I think we could be doing things differently, and we ought to be doing this faster and now.

Rashmi Mohan:
That is shocking to know that, and you're absolutely right, to not leverage all of this knowledge, technology, and resources that we have would be a shame if we weren't able to make that impact. For our final byte, Suchi, what would you say is something that you're most looking forward to in this field over the next five years?

Suchi Saria:
I would love in the next five years to be able to show that maybe we cut diagnostic errors by 50%. Wouldn't that be remarkable? I think if we move fast enough, I think that's possible.

Rashmi Mohan:
That would be incredible, yeah. Absolutely. And I think the point that you bring up about the fact that we haven't made a whole lot of progress in the last couple of centuries, and the time is now.

And really, I think, it would be a marvelous outcome for the world if what you said actually became true.

Suchi Saria:
Thank you so much, Rashmi, for your very thoughtful and insightful questions. I really enjoyed them.

Rashmi Mohan:
No, thank you, Suchi. I think it was an absolute pleasure to have you on *ACM Bytecast*, and good luck for the future. We're super excited to see all the magical things that you're going to do in the years to come.

Rashmi Mohan:
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