Dr. Aaron Carroll:

Welcome back to the Healthcare Triage Podcast. Our guest today is Nitesh Chawla, who is the Frank M. Freimann Professor of Computer Science and Engineering at the University of Notre Dame, and the Founding Director of the Lucy Family Institute for Data and Society. Dr. Chawla, welcome.

Dr. Nitesh Chawla:

Thank you, Aaron. Pleasure to be here.

Dr. Aaron Carroll:

This Healthcare Triage podcast is co-sponsored by Indiana University School of Medicine, whose mission is to advance health in the State of Indiana and beyond by promoting innovation and excellence in education, research and patient care, and the Indiana Clinical and Translational Sciences Institute. A three-way partnership among Indiana University, Purdue University, and the University of Notre Dame, striving to make Indiana a healthier state by empowering research through pilot funding, research education, and training. More information on the Indiana CTSI can be found by visiting indianactsi.org. We'd like to share what we normally do by asking people to talk about how did you get to this position? I mean, how would you get interested in big data and what did your life and career look like getting from where you started to where you are now?

Dr. Nitesh Chawla:

Hey, I have one word answer, serendipity, but let me elaborate a bit on why it's serendipity. So I finished my undergraduate in Computer Science and Engineering in India in 1997, and I came to the U.S. I wanted to study at that time Fuzzy Logic. Why? Because it just sounded cool to say as an undergrad, Hey, what do you want to go to grad studies for? And you say, Fuzzy Logic. People go, wow, that sounds awesome. It's Fuzzy Logic. So I came to the U.S. and wanted to work with Lawry Hall and his team scholar in Fuzzy Logic at the University of South Florida. And as time progressed, I realized it's not quite for me. As cool it may sound, it's not quite for me. So then I switched to... There was a project in machine learning, this is 98, 99, in collaboration with some colleagues from Sandia National Labs and said, I'd be interested in this. Can I jump on board?

And then one thing led to another, and that's why I said it was serendipity, having a wonderful collaborator mentor from Sandia Labs and my advisor to allow me the flexibility to pursue a topic. And I started working on machine learning and finished my PhD in 2002. My PhD was titled Learning from Extreme Size and Imbalance of Data. Now, if I was a really good machine learning researcher, I would've called my PhD Learning from Big Data. Back in 2002, it would've been the most downloaded dissertation. But I chose to go with size and imbalance to indicate the size as in the bigger or the massiveness of it. Surprisingly, then I went into Banking for a couple of years. I didn't straight go into academia, I went into Banking for a couple of years and then I realized that I was missing the romance of academia. I was missing the idea of having the freedom of pursuit, having the freedom to be creative and pursue things that you are deeply passionate about. And so then I came to Notre Dame, I started my Tenure Track position in 2007.

Dr. Aaron Carroll:

So many questions. Let's start with what is Fuzzy Logic?

Dr. Nitesh Chawla:

Hey, if I could have answered it, I would've done my PhD in Fuzzy Logic at that time. I realize I wasn't there. But the idea of it back in the day was that if you think about things are not deterministic, it's nothing as zero or a one. The things are living in a gray area. If you think about in the nineties there were these age of washing machines coming out with Fuzzy Logic and sensors that will have some intelligence and be able to have a probabilistic or uncertainty based classification to things, where it is not exactly this, but it may be close to this. It is not exactly that, it would may be close to that. That's what is fuzzy logic is trying to get to.

Dr. Aaron Carroll:

What is machine learning? So clearly that's different.

Dr. Nitesh Chawla:

Yeah, so machine learning essentially is... Simplistic way of thinking about it is you write a computer program and then you give the computer program a set of data and then the computer program says, all right, thank you. That's my training experience. And then you also specify, this is the task that we are trying to solve and computer program, this is how I would measure how well you have done. So then that computer program in many ways is your machine learning algorithm. It takes the data that you're giving as the training input to do certain task and knows how well it did or didn't do on that task.

And it's no different than we may learn. Imagine me if I'm a student in the classroom, my instructor tells me, this is the material you need to learn and I will measure how well you have learned if you do well in the quiz and what grade you get. So it's a similar context where we are giving material information, data to a computer program to learn to infer patterns and then use it for a task, whether it's for a description or whether it is for a prediction. And then we take it from there.

Dr. Aaron Carroll:

Is that the same thing as Artificial Intelligence or is it different, and how?

Dr. Nitesh Chawla:

So I would consider machine learning as an important subset of AI. AI also has things as search, as planning, agents. So there are different elements that may be part of AI as a discipline. machine learning essentially says that I'm going to develop an algorithm or a program that can learn or in full patterns from the data it's given. Now most of the AI that we are accustomed to, whether it's recently in the news, ChatGPT or other things, they are using machine learning. They're using machine learning methodologies to learn from the prior data to make a prediction or put together us sentences for your consumption.

Dr. Aaron Carroll:

And finally, just on the factual questions, so what do you mean when you say big data?

Dr. Nitesh Chawla:

Big data was a term that's about, I would say 10 years ago or so, started to come to mainstream because what people realized is, there is much larger volume of data that's been created. That was one. And then there is a variety of data. Right now we are dealing with data which is text data, images data, numbers. So you can think about different varieties of data that's coming to play. And then as we are capturing this data, whether it's from social media data or any scientific experiment data, et cetera, especially let's think about the social media data for a second. The other question that comes about is the veracity of the data. Is the data trusted? Is the data accurate?

Because now we are collecting data from a variety of sources and we don't know what may have governed the collection of data at those sources, but the data is coming to us at a much faster pace. And the fourth aspect of big data that came to fore is the velocity of data, that the data is now streaming in, it's changing rapidly, it's coming in database, and how do we now create systems and algorithms to handle such variety, volume, veracity, or velocity of data coming in at you and developing these algorithms, methods, technology to deal with it.

Dr. Aaron Carroll:

Can I get you to walk me through how you've used machine learning or big data in some of your work?

Dr. Nitesh Chawla:

A lot of my research, so there's two aspects to my research. One is we do quite a bit of work on fundamental advances in machine learning, data science, data mining algorithms, which we see, okay, this is a methodological advance and then those advances are used in fields to further build up research in machine learning, data science or other fields as they may find relevance. And then the other aspect of my research, which I'm very excited about as well, is the interdisciplinarity of machine learning data science. And from the interdisciplinarity, what I mean is if you think about AI, big data, machine learning, whatever term you may give it, right? We have gone through this journey of terms where whatever sticks in the market, the community embraces it. It was big data. Then data science became the sexiest profession because an article in Harvard Business Review said so, and now we are saying everything is AI, everything is theirs. Who knows what terms we stick to, but let's assume they all are akin to each other from that perspective.

Let me first start off backtrack a bit and rephrase the first part of the answer. So when I talked about we make fundamental advances in machine learning data science. So to your question about how we have used machine learning data science in my research, there's two aspects that we do in my research on machine learning data science. One is, it's fundamental advances. We pick on some compelling problems that may be inspired by the real world, that may be inspired by our own experiences, that may be inspired by some other research or contemporary research that's happening. And two aspects are learning from imbalanced data, and the learning from imbalanced data happens is, think about any real world setting. When we are trying to say predict, say whether disease prediction or we are trying to predict fraud or we are trying to recommend books or movies or we are trying to recommend what pages must come on the Google's very first page of the billions of documents out there, billions of webpages out there. Think about computer intrusion or spam.

Any of the real world challenges we may think about, the things that we are interested in. We are interested in predicting, say a disease. We are interested in predicting an adverse drug effect. We are interested in predicting or identifying what is fraud of millions of credit card transactions. We are interested in recommending out of hundreds of thousands or millions of books or movies out there, what would be of most interest in Nitesh. Now that is an imbalanced data problem because of all the possible things out there, what we are interested in getting to Nitesh, to personalize to him is what he would be interested in. Now if you say Nitesh is interested in everything and you missed the 1% I would be interested in, you would still be 99% accurate. That's a pretty damn thing. You can say, I'm 99% accurate. I missed the 1% of things he may be interested in, but I'm 99% accurate. What's the point?

So how do we develop learning algorithms to tackle this small class, to tackle this relatively rare class, to tackle what we call in machine learning literature is majority class, and minority class, we interested in tackling the minority class such that the algorithm can learn to focus on that small class, that minority class, or the rare class. So that was a set of algorithms we developed. That was my road to fame in machine learning, was in the imbalanced data. And then in the last decade or so, as data deluge started to come in, we also started to think about complex systems, transportation systems, airline networks, social networks, information networks that flow through. These are graphs, these are networks, things are connected to each other. We live in a connected world now.

So how do we look at this complex system, this notion of connected world and build machine learning algorithms to infer or develop from these graphs of complex. So these are the two aspects of what I see is, it's fundamental, yet inspired by real world challenges. The other important hat that we wear in the lab and the institute is we ask ourselves, we need to address some of the societal grand challenges, whether it's in health inequity disparities or invasive speeches management or climate change adaptation or thinking about opioid misuse, opioid use reduction or power to your P studies. These are complex wicked problems that require an interdisciplinary mindset, that require... Or chemical synthesis is another example. That require domain centered yet data-driven thinking and applications. So that's another facet of our work where we are taking an innovations in machine learning, data science, working with a team of interdisciplinary collaborators and trying to translate our innovations in service of society. Not just stopping at a research paper but taking the tough leap on saying, we are going to take these innovations and make them work in the real world.

Dr. Aaron Carroll:

Can you give me a concrete example of some of your work? What problem did you focus on and how did you use this to attack it?

Dr. Nitesh Chawla:

I'll give you an example, right? I'll give you a couple of examples. One example is we have this ongoing research interest in healthcare and we were really focused on patient-centered outcomes, personalizing healthcare journeys, et cetera. And we've developed a series of methods algorithms that essentially personalize my potential risk for diseases. Think about it this way, we go to netflix.com and Netflix says, "Hey, welcome Nitesh, these are the movies you would like." And Aaron, you may say, "Yes, thank you Netflix. I'm going to try those movies tonight and if I don't like it, I'll change the movie or the TV show." Now imagine a disease.com that says, "Hey, welcome, Nitesh. These are the diseases you would like. Take your pick." Of course, we are not recommending diseases, but that's the idea. Could we create just as we are creating this customer of one journey on all things web to today? Everyone is trying to get to that customer of one to personalize, is do you have a patient of one.

How do we get to that individual who may have different social circumstances, clinical circumstances, economic circumstances, and yet they may be very similar to each other, based on the lifestyle, environments, and structure and social environments that we live in. We have similarities. We are not that different from each other. So that was the idea of some of the works that we have done. And today what we are doing is we are working with a hospital in Mexico City where we are collaborating with the hospital and the Institute of Public Health, working with underserved populations who have healthcare access challenges, who have significant inequity challenges. As we are thinking about big data technology and everything else, a lot of these low medium income countries have not achieved digital age 1.0. While we may be talking about digital age 4.0 here. So as a result, there is access, not only from a health services, access to technologies that we all are benefiting from in many ways.

So how do we bring these things together? So we've taken our innovations, deployed them as an application, and we are doing a large long study, about 204 families are enrolled in this about addressing risk and what kinds of diagnosis interventions, and et cetera could be done for children with cancer and their family. So we are incorporating information. The algorithms do some triaging, but the patients don't quite see that result. The Physicians see it, the Physicians interpret the diagnosis, the risk triaging, which is inclusive of the social determinants of health and the clinical factors. And then the Physicians create a much better communications and an intervention portfolio with the families. It's been a hard journey to translate research from... It's like almost productizing your research. It's trying to find that product market fit, that startups do, and you're doing it while being in a research environment.

You're doing it while there is not a necessary funding mandate that says, "We are celebrating, you've done great publications, great research." But we're saying no, we want to go further, we want to actually deliver them so someone can benefit and use from it, and that requires some full hardiness here. But you're being committed to this idea of how do we address it. So that's an example in an LMIC. Then we are also working in our community on child lead health poisoning. We have this NSF funded initiative. What we have addressed is that our city South Bend, it's a fantastic city to live in. The most desirable city in Indiana, if I may say, or the Midwest. My friends in Indianapolis may not agree, but hey. But we have been featured in New York Times for reasons that we are too proud of. A child lead poisoning.

And then we started asking, what is going on? Where is the gap? Why are we not able to address it? So we are collaborating on this NSF funded initiative with city and county governments, with citizens, with organizations, community health workers to truly get to the bottom of how we can assist in faster diagnosis, assist in faster intervention, et cetera, because it is a problem that needs to be addressed. The families that face the challenge of child lead health poisoning are already battling a socioeconomic status challenge. And now we are saying, hey, the children may have developmental dealers because they've been exposed to led poisoning. So it's like a double whammy on these kids and families.

So we have taken upon ourselves to go through this collaboration and again, to be successful, we acknowledge that we must listen to these community members. It's not just as an academic going, I have this thing in my lab, it's going to magically change the world and bring world peace. It starts with listening, collaborating. All of us are equally footed partners in this collaboration and taking it from there. A scientific example I would say is we have another large NSF under initiative on how to use machine learning AI to accelerate chemical synthesis, whether it's in molecule discovery or [inaudible 00:19:48] of molecules or improved output of molecules, et cetera. How machine learning AI is. Again, chemistry and machine learning, AI coming together to really revolutionize the field of chemical synthesis.

Dr. Aaron Carroll:

Can I get you to talk a bit though about how you use the machine learning to do that? I mean, I'm a pediatrician, I completely understand we screen kids for lead, if it's high, we try to fix their environment. But how are you bringing machine learning and big data to make a difference in ways that we otherwise couldn't. Let's start with lead?

Dr. Nitesh Chawla:

Let's start with lead. So I think if we sort of think about the process that happens. So we have a team at Notre Dame, has this lead assessment kit. The community health workers, et cetera, may take them to a family who may do an assessment and then they use the system to communicate the results of the assessment, et cetera. Now, not all of these families actually get tested at a pediatrician or it may be too late by the time they're tested at their pediatrician. So the idea is, can some of these families actually get this initial assessment kit? And if that's positive for presence of lead, can we now, based on their... Not just a positive on the presence of lead, so based on the other knowledge that we have, along with this assessment kit, there's a risk that needs to be not evaluated by a pediatrician, by a clinician.

The first challenge is not every family gets that assessment kit because we don't know what's state of the house. And then the second challenge is, once they get it, not everything may get communicated to be addressed by a clinician. So now let's say that a clinician does address it, that they first says, okay, this is lead, now some intervention needs to happen at the household, at the place to live in. Now if they're tenants or they're owners, that introduces yet another challenge. Now there are funds available from the government to actually address to mitigate the lead risk. Now that becomes yet another form of applying for that grant, applying for that fund. If it's a landlord, the landlord needs to do it. If it's a tenant, how do we handle that if you're not a homeowner and so on. So along this journey, as you can imagine, people get dropped. And it's not just a data ml, it's not really a big data problem, right?

It's essentially can we learn, can we personalize, can we reduce the barriers of individuals from truly achieving the objective of assessment if needed intervention? Some of the filling up of forms on the grant applications could be cumbersome. How do we help overcome that? Could we populate that information? So we are really looking at seeing where those gaps are and seeing what can be done. And ultimately it would be a policy interference that would be needed. But there are still things that we can do to get as many kids assessed for, diagnosed for, and given a pathway to intervention. And then bringing in, and engaging with, once we have all the data and the risk, depending on all the permissions and everything else, realize this for [inaudible 00:23:15], is there a possibility to now have the school as a partner with these children, knowing that this is a challenge, this could be a developmental delay possibility for this child, what can we do?

Dr. Aaron Carroll:

How does that work with what you're doing in Mexico? I mean again, specifically, how does the machine learning and big data make a difference in ways that we... Or do things that we otherwise couldn't do?

Dr. Nitesh Chawla:

No, absolutely. So I think the work in Mexico, I believe, is a really good example of machine learning, data science that we are doing. So just as a background, what we first started with them was a collaboration. We got connected and in the Latin American countries, there's a center-lier or Chilean index for cancer risk for children, and there's no such thing in Mexico. So we said, hey, if we were interested in collaborating with them and we started digging into that index and starting to see that what we can do within this, this is the hospital that we are working with, at Hospital Infantil, Mexico, the Federico Gomez. And first thing first was to do this study. There is no digital data. They couldn't write a query and said, give me all children with these things. It's like you go to the basement, children's life is in a set of stack of paper files and then you digitize.

You look for the things that we were looking for, neutropenic fever, what happens and the risks associated with it in these children with cancer. And we digitize that data, then somebody has to verify that digitization. And then if there's disagreements in the original digitization and the verification, the third party has to come in and resolve to see who was correct. There could be human error in typing when they disagree. So we went through that, we collected that, and then we published a paper recently together with them and where we talked about the clinical indicators, markers of neutropenic fever, et cetera, and Javi addressing it. And mind it, I have no medical background whatsoever. And that's what I love about these interdisciplinary projects is we all have to listen to each other. None of us can imagine to solve a problem which is so confounded with many things that it's not just a clinical medical problem, it's not just a social sciences problem, it's not just a technical problem.

So then we did that. And then something else that continued to bother me was that as you go to this hospital, kudos to the teams that do all this great work. They have finite capacity, finite limited number of beds, but more mothers and children need that attention. They don't know who should go to a shelter nearby, who should be admitted as yet, or who could go back to the communities and they could coordinate with the healthcare partner there or coordinate with the families based on some information. A lot is not known about these families and the families also take a risk because it's unsafe sometimes to be traveling. So we then started to ask that, okay, can we begin to digitize some of these things so the information could be more readily available and shareable. Then we asked our... The hospital had this oncology forms, and ER forms, all our paper based, we digitized those. Step one.

Then we asked ourselves, okay, they are these social workers that enroll these families and these social workers are asking these interesting questions of these families because they're also interested in nutrition as you know, and as a pediatrician, that nutrition is an important treatment for any of these diagnosis and lack of a good nutrition can only increase the risk for fever and neutropenia and hence risk of morbidity severe, morbidity or mortality in many cases. And then we said, there are other things that we can know and learn about these communities. That's where social sciences comes in. So we approach the Institute of Public Health, which is a national institute in Mexico, and we said, can you help us build out a survey of things that we should be asking these families? Can you help us build out? And then they had their anthropologists and they said, we'll just observe families first.

A week they spent observing and they gave us survey questions and then we had some psychiatrists come up with what kind of mental health indicators they may be interested in. So then we built that social economic determinants form, social determinants form if you will, that captured these questions, albeit in the context of use, in the context of delivery. And then we basically put that all together as an application. And now what we are doing is we are collecting this data. The families are enrolled, the physicians and the social services work with the families over there, and we are building out a risk model and we know the outcomes of some of these children, whether they got an infection, they got bacterial [inaudible 00:28:21] or a septic or a neutropenia fever. So we know some of these outcomes and we are tracking those. And then we would be able to build a model that says collectively this is what a good risk triage model based on social and clinical determinants for this individual family is.

So right now we are in the mode of collection of data. We have a risk model based on clinical indicators that we published, but now we are trying to collect additional data to update that model and provide the hospital, not only a mechanism of risk triaging, but also a mechanism of communicating with families for the families to communicate back on conditions and things like that and get educational material from the hospital, social workers, we are helping them curate all this data. So these things didn't exist, so we had to stand up the technological infrastructure to do other things.

Dr. Aaron Carroll:

How are you using machine learning big data to improve chemical synthesis and in what areas?

Dr. Nitesh Chawla:

Just a couple of fundamental questions from a chemical synthesis perspective. One is if you imagine the life of a chemist where there are certain molecules that may go together under certain conditions of temperature, pressure, et cetera. And if it used by certain mixes, if you will, legions if you will, to create an output. Now it's one thing creating that output. The other is making sure you have enough yield, you have the right product, et cetera. Now when we look at that problem statement, that is an extensive wet lab experimentation. Could we, based on everything that we know in the literature about molecules and reactions and how they go together, be predictive about what kinds of conditions and et cetera could result in this kind of an improved yield. If we can do that, we can save a significant time on the bench. And why I believe machine learning is a good example for that is, imagine looking at a molecule in front of you right now, you have atoms connected and there are bonds and you have valence and all the other information.

But it also has an all battle information. It's a three-dimensional structure as well. But if we look at a molecule, it's a graph. Things are connected. As I said to you earlier, we look at the world in graphs. So if we take those graphs, everything that we know in the literature or otherwise or electronic lab notebooks, we learn from those understanding what kind of... This is the big data variety thing. So we not only have the molecular information, we also have temperature information or other things, information. And we also have the legion information and we have prior outcomes and [inaudible 00:31:14] that were generated by prior reactions, we know all that. And we know we are constrained by the domain of physical chemistry. So there are certain physical laws that are governing how things work together. So now the machine learning algorithm task here is, I have all this information, I have ways of representing that information in the form of a data, like a graph, that I can learn from.

Just going back to the definition of machine learning I was giving you earlier, now I'm going to make a prediction about if I put these two things together under these conditions, what's the best yield I can get? So we have done quite a bit of work on that. And now what we are trying to do is not only predict the yield, not only predict the output properties of putting two molecules together, but also trying to explain why this happens, why some of these synthesis pathways are chosen. And that's a more complex problem because that clearly requires the chemistry domain to be infused with the AI domain to be able to provide that interpretation. So we are super excited. I mean we just got a large NSF funded center led by Notre Dame, and we have collaborators from all over the country, from MIT to UC, Berkeley, to Caltech to Utah, CMU, UCLA, the University of Tennessee.

And then we also building a data chemist network wherein what we are trying to say is that, instead of calling people Data Scientists, they will be much more specific kind of a Data Scientist, in my opinion, that'll be produced in the world today, where there'll be domain informed Data Scientists. So imagine these are Data Chemists who understand chemistry way are better than the computer scientists world, but now they're dangerously harmed with data science knowledge and skills. Now that domain infusion with that AI ML data science background is going to be a beautiful magical combination. So they are Data Chemist. Now imagine things like this happening in every domain. Imagine a Data Humanist or a Data Economist or data, things like that.

Dr. Aaron Carroll:

What are you most excited about in the near term?

Dr. Nitesh Chawla:

What I'm excited about in the near term is there is an embrace of data science machine learning AI, even now our syllabi for classes that have nothing to do with AI, whether in high school or middle school or in colleges or universities are talking about ChatGPT. It is an AI thing. How you may use or not use for your classes, things like that. But now it's an opportunity for us. I mean, yes, there are positives, negatives with that, wouldn't get into that, it is a moment in time or an opportunity for us to embrace this momentum. However, also a momentum opportunity for us to really think about the guardrails, the ethics of doing it right? We should not let the technology speed momentum go past beyond our more normative approach. And as a computer scientist, I'm dipping my head to my Philosophers and my Social Scientists and Humanists out there, that we have to take a normative approach here and ask what are possible things that we can think about misuses of this? How do we address those?

Dr. Aaron Carroll:

What are the major concerns of misuse that you're worried about right now?

Dr. Nitesh Chawla:

We've seen with any and all technology, right, Aaron, that back day social media, we didn't imagine misinformation, disinformation and what's happened, right? Deep learning happened. Deep fakes came to being. Now with ChatGPT, folks are worried about the advice of ChatGPT. It sounds so real that folks will use it, misuse it, et cetera, whether it's for the classroom purposes or things like that. And then there's other things that people are worried about. AI to be used in the field of healthcare will remove Radiologists or Physicians. Or in the manufacturing world, it would displace humans in the world of manufacturing. I don't believe AI is replacing, or at least in my generation or the generation next, but it's a human machine collaboration. It's us understanding about how AI advances or ML advances combined with a human could be further up in some of the tasks that we do, shows that we do, provide further efficiencies.

There could be domains of expertise that these things can be used, which may assist somebody better, human assistive technologies and as well as things are what we are talking about the work in Mexico, how we take these AI advances and pause, as I said earlier, not only to collectively think about what it means as we are advancing this. How do we evaluate, we don't know how to monitor some of these AI systems. We don't. We don't know how to truly evaluate some of these AI systems. It's not just accuracy and error or my position recall curve or my sensitivity specificity. That's great as a study, but not when it's deployed. Is it actually achieving what we said it would do? We have no idea today, right? Let's say there's an Academic who says, I'm going to truly focus on AI for society or data for society, build these products and take them out to the communities, come tenure and promotion time. How do we measure that person?

There's no h-index or Google Scholar for this, right? So we have to rethink many of these things that we do today. So this is where I feel I'm so excited about is these things are across campuses and sectors and not-for-profit or government sectors should require us to have this dialogue that says, all right, let this go. But let's think about it. Let's think about the future that we are creating and how do we truly democratize access on one side we have of lowly sourced populations all over the world. On the other side, we are worried about folks using ChatGPT in their classroom. Tale of two cities in many ways. So how do we overcome this? And that's what I'm excited about because it's time to have this dialogue, time to be inclusive on AI, time to be thinking through what future it could be, time to reflect on the lessons that we have learned and not let this be another AI venture. We have seen many of those.

Dr. Aaron Carroll:

Well, I hope you'll come back in the future again and we can explore some of those ideas further.

Dr. Nitesh Chawla:

I would love to, Aaron. Thank you

Dr. Aaron Carroll:

Once again. This Healthcare Triage Podcast is co-sponsored by Indiana University School of Medicine, whose mission is to advance health in the state of Indiana and beyond by promoting innovation and excellence in education, research and patient care, and the Indiana Clinical and Translational Sciences Institute. A three-way partnership among Indiana University, Purdue University, and the University of Notre Dame. Striving to make Indiana a healthier state by empowering research through pilot funding, research education, and training. More information on the Indiana CTSI can be found by visiting indianactsi.org.