Health Connective Show #14 – Adityo Prakash

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Michael: Welcome to the Health Connective Show. I'm your host, Michael Roberts. Today we're talking to Adityo Prakash. He's the founder and CEO of Verseon, where he leads the development of proprietary AI technology in physics modeling methods that enable the development of new medicines. Adityo, welcome to the show today. Thank you so much for joining us.

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Adityo: Thank you Michael, thanks for having me.

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Michael: So we're going to be discussing how AI and molecular science are playing a role in proactive health care. Really in health care in general really what's coming in health care. So really looking forward to your insight on this topic. We were talking just a bit before the show started recording, and I confess that I am no AI scientist. I'm not a doctor, so I'm coming at this from somebody who's definitely keeping a pulse on how AI is impacting business, how AI is going to be impacting our lives in a lot of different ways.

My last sort of deep dive into the space of healthcare and medicine is reading the book Deep Medicine from Eric Topol, just getting kind of an overview and I was listening to it actually a few years after it was published. So this is ChatGPT, you know, launches its on the scene. Everybody's talking about AI. And I go, oh shoot, I need to know something about this. I go get the audio book. I listen to it while I'm driving around, and so I get some sort of idea on how I can have positive impact in healthcare.

So we'll talk sort of like bigger picture holistic how these two fields are kind of overlapping. But for some background, for our listeners, first of all, can you just explain a bit about what vision does and how AI is playing a role?

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Adityo: We're seeing as a deep technology driven pharmaceutical company? We design completely new drugs using proprietary AI technology. Combined with our breakthroughs in quantum physics modeling of how drug molecules bind to proteins in our bodies, the drugs we design and develop can't be found by any other current method. They have such unique therapeutic profiles that every single one of them are poised to change the standard of care for major human diseases, from heart attacks, strokes, to diabetes and cancer. That's in a nutshell version that's pretty, pretty amazing.

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Michael: One of the things that I found pretty interesting. So I was doing some quick searching and reviewing and taking a deep look, checking out your LinkedIn. I'm a LinkedIn stalker for sure. One of the things that I found on there that was really interesting is you're talking about how there's a much more limited amount of data within healthcare specifically, I'm sure, like specifically within the field of drug development and trying to find these new, these new sorts of treatments. How is version approaching that? How are you handling those kinds of challenges when you can't just crawl the internet and get everything you need to know about how to make the next innovation? How is working on tackling that kind of problem when it.

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Adityo: Comes to availability of data in the broader context of healthcare? We have a ton of data and it can make a dramatic impact on healthcare in general. But when you narrow the focus down to actually finding new drugs, the, you know, main reason for the existence of the pharmaceutical industry there, we have a problem with relevant, actionable data on novel kinds of drug molecules, how they will react in our bodies, what they will do. We don't have sufficient data.

Okay, we're stuck with trial and error experiments that have been run on the last 100 plus years, and whatever data we have generated from that process, and we're feeding that to current AI. And that's not going to produce fundamentally new types of drugs that we have never seen before. This is where breakthroughs in other fields come in to aid in the process. To help AI with this data problem, fundamental breakthroughs in molecular physics can now help you design new kinds of drug molecules that nobody has ever made before.

So there is no experimental data to train AI, uh, figure out without having to do the experiment how the thing will bind to some protein in your body to change its function.

Once you do that and you see that, oh, this I try billions of new possibilities. And these guys are really good. These, you know, small subset of these guys are really good. Then you can go make them in the lab, feed that data to your own AI tools and help further tweak and optimize those groups. Your AI now is working on data that is not broadly available. No one else has it.

So it's the combination of breakthroughs in these other fields are working hand in hand with the right AI tools that can handle these kinds of new data, that will change how we come up with completely new medicines. And we're seeing the results of that with the kinds of drugs that we're developing, drugs that can prevent heart attacks and strokes from forming without increasing bleeding risk. No such drug exists today. But our drugs, you know, that are currently in human trials show exactly those kinds of results. Drugs that will that prevent diabetics from losing their eyesight, losing their end organs. Okay.

Something that can be taken today as a very safe oral pill. Contrast that with today's technology. What are the treatments that are available? Diabetes. If somebody has diabetes long enough, they're going to lose their eyesight over time. And today we don't have any treatment options for early stage disease. We wait till they're almost blind. Then we go in and say, now I can justify injecting you in the eye on a monthly basis with a repurposed cancer drug, and imagine getting jabbed in the eye on a monthly basis. So the kind of barbaric treatment we have, 50% of patients that get them see no improvement.

And all we are trying to do is treat the symptoms. Obviously, we need to do far better than this. We're seeing with our cancer drugs, for instance, drugs that don't fall prey to tumor mutations even when the tumors mutate. Our novel chemo agents continue to work, and on and on for every program. We're seeing this fundamentally new kinds of properties. And to do that, you need the combination of these kinds of breakthroughs in quantum physics, modeling of how drug molecules behave inside our bodies, collect the data from there, feed it to AI to further tweak and optimize these drug molecules, and you get a whole new stream of medicines. Does that answer your question?

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Michael: It's fascinating stuff. Yeah, definitely. Definitely. It's fascinating because when I think of sort of like the general population and I'm including me in the general population, just in terms of understanding, like what can I do? Well, I can make me some cool new pictures when I put in a prompt, or I can write my homework for me instead of me having to do all the research. It may or may not be correct, but you know, it may help us, help us get there. And so I don't think generally people are kind of like tackling this sort of like data analysis like concept enough to go like, oh, this.

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Adityo: That's a very important point, Michael. AI needs a ton of data for training, and when you ask it for something similar, it knows what to predict, right? So when you look at that setup in many high tech applications, like the example, you are just giving, whether it's generating pictures to, you know, face recognition to self-driving cars or any kind of large language models, there is virtually no shortage of digital data, right? To train on billions of web pages and images and whatever else that are labeled. You can you can train AI on all of that stuff.

But by contrast, drug discovery only has experimental data on fewer than 10 million distinct types of chemicals that humanity has managed to make in the last 100 plus years. But the total number of drug like compounds, on the other hand, is over a billion, trillion, trillion. Think about that, okay? For most of us, we have no data. Yet the great medicines of the future lie in that unexplored ocean of possibilities. That's why you need the breakthroughs in these other fields to help you with that problem. Okay, this is interesting stuff.

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Michael: So you're suggesting that looking into other fields, grabbing what we can from these, these other areas, other.

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Adityo: Fields allow you to now get around the problems that AI has with training data in the in the field of drug discovery. Okay. Some people think generative AI is the holy grail to get around this problem, but by their very nature, generative AI predicts things that are strongly similar to the data on which they were trained. Okay. What we have seen through our work at vision is that we can get around this AI data bottleneck by first computationally designing these completely new molecules, using breakthroughs in molecular physics, and then making and testing the most promising ones in the lab, and finally feeding all of that new data to AI.

So we can ask the AI to help tweak these molecules further. So this is how I will be able to work hand in hand with these other breakthroughs in physics and biology to be able to change medicine. But going back to tons of available digital data, there are many other areas of healthcare where that is not a problem. You do not have a data bottleneck. Okay? AI is set up to have a massive impact on the broader healthcare context, right? Diagnosis and triage on one side and treatment recommendations and follow up care on the other side. If you want to talk about that, happy to discuss how we see all of those things fundamentally changing based on AI.

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Michael: Yeah. So going back to my very few sources that I can pull from as I'm talking through talking about this, but, you know, Doctor Topol talked about just how much radiology, you know, all the different kinds of scans are benefiting because there is such a larger data set that they can pull from, and they can start identifying things earlier and just sort of that process of people getting used to that kind of data.

Physicians still making the final calls, all of that kind of stuff. And then on the other side of the two topics that you brought up there, we had a guest on recently that was talking about just medication adherence and being able to help identify the people that are sort of falling behind, making sure that they're keeping up. But yeah. Interested to hear what your thoughts are around both sides of that when it.

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Adityo: Comes to diagnosis. You're indeed correct. I will be able to do a dramatically improved job of analyzing radiology images, cancer biopsies, other things like those we've all heard about those, the examples that you just gave. But I think I will go much further with its ability to diagnose things. Diagnosis needs to be looked at in a much broader context. You're not just going to look at some radiology images. You'll be able to look at all kinds of data, imaging data to blood test data, etc. and realize problems happening far, far earlier than you know we can today. All right.

So let's use an analogy we've all heard of, you know, let's say an asteroid coming towards the Earth. The earlier you can catch it with the smallest of intervention, you can veered off course. So it never hits right. But if you catch it too late, then you have to throw everything you have at it, and you still don't know if you can avert complete disaster, right? Modern medicine, the way it's structured today, we catch things too late and we throw everything we can at it. And often we do not have a disaster, right?

This is where we see AI with this more and more sophisticated diagnosing capabilities, be able to understand somebody moving towards a certain disease state far earlier than we can today. Okay, very early indications of something moving in the wrong direction for heart disease or cancer or something else. Right. And with the right and much more benign intervention, we can veer off course, head off the disease. We see those things fundamentally changing how we think about disease diagnosis, you know, and triage of patients who's a higher priority case versus lower priority or whatever else, or lower risk rather, etc. everybody is high priority.

But so that's one side of the equation. The other is actual treatment recommendations, the actual treatments people will get AI with all of the available data that keeps coming back to us, we'll be able to make better and better treatment recommendations. The right combination of therapies, not just one drug, you know, a silver bullet that you throw at somebody that doesn't often work right. The right combinations and the right dosages to, you know, have the effect right here. Of course, what we started talking about earlier makes a huge difference.

Clinicians need more options, better drugs with lower side effects. Many, many more of those, you know, to treat many more diseases than we can today. That's where the pharmaceutical breakthroughs that we were talking about, where AI, combined with all these other types of breakthroughs in other fields, can help give you more options. But what I need is to be able to do then, is look at the actual results in the field and be able to say, okay, I recommend this combination of therapies. Okay. Of course, the physician will have to look at it, you know, and say, is this working or not? Helping train the eye only further and further.

Remember, the beauty of AI is that it can benefit from millions of physicians, you know, providing their input and as opposed to a single physician with his or her limited scope with their own patients. Right. And that data across the whole globe can be now available to every physician. The benefit of all of that experience. Right. So that's the treatment recommendations. And then finally treatment needs to be not just take these drugs but also a follow up feedback loop. What we see today with modern medicine, the way it's structured in our country and many other parts of the world, it woefully lacks this feedback loop.

When I go to my doctor, unless I have some massive nasty cancer and I'm continually being followed up right, I get some prescription written, but my doctor doesn't even know if I took it. If it worked, you know there is no feedback and that's actually bad. That's part of the data that we need to even train AI better. So we need combinations of better mobile health apps, better medical devices that measure various things continuously. Okay. Combined with the

AI driven analysis to figure out whether that care is actually working, that follow up in the market. When you combine all of that, the early diagnosis, like we were talking about, or with the right combination of treatment recommendations and follow up care, health care changes completely right, we will be able to deliver better care quicker with fewer errors, all while reducing the workload of healthcare providers.

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Michael: So there's so many things that you're listing off here that I'm like, yes, I want to see it happen. I'm ready for it. But what about and so here's some of the what abouts that I've got in my head. So first of all, I guess I'll say like this really is the concept of moving from sick care to health care. Yes, this is what we hope for. Instead of it becoming a trainwreck with the right amount of data, with the right kind of AI trained on it. We absolutely should be able to move there, which is awesome. We were talking some about family members that I have that are, you know, that we're dealing with a health care journey ongoing, and the better that we can get at treating each of those, I'm thrilled to see.

So I you know, one of the things you talk about sort of that diagnostic side of this and I think that this is something that's come up in the press, I think from time to time, those very early interventions, there's a lot of worry, a lot of concern. Are we taking too drastic an action when we don't know what will finally happen with this patient? Are we over medicating? I think that that's a concern that people are going to have, like, yes, I want this. I'm hoping that this is going to be the way. But how do I, I guess like sort of find that trust. Where do I as a patient.

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Adityo: One is do you need explainable AI better understanding of what is AI prioritizing? What are the parameters that it considers more important than others? Right. We actually showed that our proprietary technology allows real time explainability. But even if you use other kinds of AI, we need more and more emphasis on explainability of AI. Okay, there's a lot of talk within the AI community about this, but only certain types of AI technology like ours.

We've shown that it can be effectively used in a sort of practical way, but that is important for doctors to be able to understand why it's making the decisions that it's making. You know, that same thing that that people worry about when you apply AI to, you know, triage, let's say people in the criminal justice system, whether it has tremendous bias for race or, you know, religion or something else, right? Medical care is no different. You know, you don't know whether it's biasing something, some specific health condition that shouldn't be biased so hard or if it is, it needs to be validated by humans, you know, with further follow up experiments. Right.

So that explainability helps okay. And it's coming. It needs to happen and it needs to be applied. That's one thing. But the other is remember going back to the asteroid analogy, the earlier you figure out there is a trend and you over time you will have the feedback data to know that this is true. You know, that early you know, indication is actually correct. You will be able to get away with overall lower amount of intervention. Right? You know, small little changes, low doses of a particular drug and some other therapy could be some other food or medical, you know, lifestyle intervention. And your you have completely averted the situation where it's now clearly upon you and you have to do something drastic.

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Michael: That’s great. The other thing that that you threw out there that I'm very optimistic about, but again, concerned about is that feedback loop. Right. Like and I'll especially talk about like, you know, our country's medical system or you know, where you're not in like a single payer system and all that kind of stuff. We're like, yeah, I would love that. I would love for all this, this information to be available so that we can get this sort of like real time sense of this is going in the right direction. This is not we do work.

We as a company at Health Connective, we end up working with different medical technology companies, and we see the struggles that companies are facing right now of yes, I know that when we did the clinical trials, we showed improvement. But what's the real world data on an ongoing basis for this hospital or for that hospital? So that feedback loop of getting that information back to somebody that can help interpret it and make sure that we're going in the right direction.

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Adityo: This is not actually as big of a technology challenge as people think. The challenge is to get people to play ball right. Everybody wants to hoard their own data for their own personal professional business benefits. Okay? And that is what gets in the way of everything I can't help you with sort of avert human sort of what should I call it, humans being obstinate humans. Being greedy humans being all kinds of things. You know, if we just cooperated a little better, we would have collectively far better outcomes. And the market will grow and everybody will actually make more money.

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Michael: Yeah. It's again, I'm very optimistic about.

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Adityo: Our health outcomes.

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Michael: Yeah. Absolutely. Absolutely. So we're looking at this from a very, very large picture. We talked some about like man, if we could just find ways for different areas of health care to be able to come together more often. Seems like we'd make some big some progress in some major ways. What about health care professionals running working at a hospital? They're working at their own practice. What can they do to either be a part of this? Start implementing this? How can they start thinking towards this? Is this something that they need to work with in terms of like different societies that they're a part of? Where can a doctor or a physician get started with this process today?

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Adityo: I think when it comes to actual healthcare delivery for doctors, you will see more and more sort of programs by professional societies, etc., bringing doctors up to speed their EMR, you know, changing where they can actually get more of this, you know, help integrated into the system and into the workflow. And doctors will have to adapt to use an analogy. Remember, in the old days, accountants used to use big paper sheets to keep track of, you know, ledgers, right?

Those accountants that were in practice at the time when the spreadsheets on computers came along, had to kind of train themselves to make that transition, right? Or they retired and went away. Same thing is going to happen with the medical profession, the new generation of doctors that are getting trained. They'll probably make the transition a little bit easier. But many of the older professionals will also have to make that transition, much like using spreadsheets on a computer instead of a piece of paper.

Much like using calculators, AI is just, you know, another great aid to their profession that'll just come there to help them. You know, with, as I said, better understanding of the patient's condition and the diagnosis that's at their fingertips now thanks to AI and the treatment recommendation. So they all they need to do now is say, okay, does this make sense?

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Michael: Yeah, absolutely. Do you have, I guess, sources that you look to? I think that it may be like useful references for other physicians, useful references for other people that are kind of looking into this field because so much is happening in this whole space. Right. Just AI is developing so fast. Do you have sort of go to resources that you look for, for news that you look to, for, for these kinds of developments? I'd have to.

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Adityo: Think about it. Remember, we kind of live in the middle of it. So, you know, our perspective may be a little skewed, but I also completely understand and empathize with the fact that with all of the changes that are going on at the speed they're happening, combined with the fact that there is so much hype that gets way ahead of reality quite often, that is very hard for somebody from the outside, including physicians, to be able to sort out what's hype and what's real and what's going to really work for them and what's not. You know, this is always a problem, you know, when there is a big technological change happening, right? You always have that. And that does take some time to settle. Sure.

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Michael: It's funny because there's so many things that are talking about, again, like in the marketing world, how fast everybody's LinkedIn profile changes from blockchain expert to AI expert to, you know, from whatever the big thing was ten minutes ago to to now being this. But yeah, there definitely is a different sense of I think everybody kind of feeling like, okay, this is something that's actually going to continue to be useful beyond just ten minutes.

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Adityo: You're absolutely right, Michael. AI is something that's going to continue to be useful and change almost every aspect of our lives. But at the same time, as I said, sometimes the hype gets completely way ahead of reality. And while we can tell a friend that, oh, that's hype and that's real, and we can help them easily sort through that, but many people don't have a friend like that, right? And they're unfortunately left dazed and confused about what's real and what what's not. Sometimes people get overexcited about something that shouldn't be. On the other hand, there are real changes happening in the background they ought to be aware of, and there is nobody to help them with that. That is a problem that I don't think, you know, anybody has fully solved yet.

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Michael: One of the conversations I'm having with a lot of folks right now is that concept of trust and accountability. Just as organizations, as people, as as all of these different things. This is kind of the thing that's going to become like the number one measure of companies. And number one measure of, of people in general is how can I trust what you're saying to some degree? And so you're talking about accountable AI having some sort of explainable AI.

I mean, this is going to be kind of critical for each of us, right? Like this is why you can trust me. This is why, you know, and I can't tell you how many conversations. Around this around the topic of AI itself. And again, I'm no expert in AI or anything like that, but just the outlandish claims that I'm hearing from people that are just like, well, I heard this, you know, aliens are coming for us or like whatever. Like the crazy, you know, conspiracy theory is. But like, I think that there's definitely a lot of that kind of fear around this because it is such a big development. It is such a big shift in how things have been done.

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Adityo: You're absolutely correct. But for those of us who have a long enough perspective, this is like the new.com. I mean, the rise of the internet changed their lives completely, right? One cannot argue about that. But while the whole dotcom way was building, there was a lot of, you know, junk out there, too, that people got overexcited about. It's true. For any such change, it'll always happen.

And humans, I don't think, have figured out how to sort through that very efficiently. But eventually the dust does settle and you realize that your lives have changed, you know? And here are the tools that really work. And at some point, people stop making those outlandish, outlandish claims because you know, those nobody anymore believes them because the hype wave has passed, as.

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Michael: Has gone on a little bit. Let me throw a few more kinds of ideas that you so that we can get your perspective on this. Because again, so I'm coming at this from a very different background. When OpenAI publishes ChatGPT last year or year before, it's almost been a year and a half now since all that started rolling out. So this rolls out and you start asking it questions and ChatGPT starts making up answers, you know, citing sources that does not exist, you know, all of those kinds of things.

And so, for better or for worse, some of the early missteps of companies like those really shaped people's perceptions of how AI works just in general, whether ChatGPT knows the, you know, capital of Idaho or doesn't like, I'm not that concerned about it. But when you start thinking about, like, your healthcare data going into that thing, like how do companies address, like how do I systems in healthcare hallucinate or these are the kinds of problems that you have to be on the lookout for.

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Adityo: These are the problems why everything hasn't already changed, right? Some people predicted just a few years ago that there will be no radiologists. We shouldn't graduate a single new one of them. Okay, because I will do all of it, but seems like no radiologist has lost his or her job yet. There will be no need for this and that and whatever else you know. The list goes on, right? Why hasn't it happened? Because these corner cases and errors in those weird corner cases continue to happen in this AI paradigm, especially this deep learning paradigm. Okay.

And we haven't completely overcome that. While most of the time it's giving you great answers, it's making errors every so often. And in the context of healthcare, especially critical life-saving decisions, a type of healthcare you cannot afford to you know, have those kinds of errors. So you need a human overseer that, you know, makes sure that things don't go awry. Right. So we have continued to require that. And this will go on for a while.

But at the same time, AI technology will continue to improve. Okay. Where those kinds of corner cases become rarer and rarer and rarer. Remember one thing though even humans makers, the medical law is replete with stories of, you know, crazy human errors when those shouldn't have happened. Right? So at some point when you can get the AI to be, say, better than humans in terms of error rates, you're in good shape. But clearly, as you pointed out, we're not there yet.

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Michael: These are the kinds of AI, like I said, just kinds of fears that I hear in conversation regularly on these kinds of things.

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Adityo: But medical AI built in or built specifically for a certain purposes, we can already do better than the kinds of, you know, makeup instances that ChatGPT gives you. Okay. But still, all of these kinds of tools make corner case mistakes. Same reason we haven't solved, you know, despite the gazillion examples, uh, that they're trained on, uh, we still haven't, you know, sort of fully solved the problem of self-driving cars, right after hundreds of billions of dollars spent on this problem by many, many companies. We are continuing to make we continue to make progress, though. It's getting better and better. But do they still make weird corner case mistakes every so often? Yes they do.

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Michael: Let me shift gears a little bit here as well. So at the top of the show, you were talking some about developing entirely new types of medicine using these kinds of AI tools. I think I probably know the answer to this, but I'd be interested to hear it's so it goes to a completely different type of development, but it still has to go through human trials. It still has to go through the full approval process. Is anything different about that process? Like once the the idea is formed and it gets to testing and it gets to review and approval like. Is anything shift in that part of the process?

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Adityo: Two things. The good thing about drug discovery is that you still have to vet it in vitro and test tubes than in animals than in humans. Okay, so just the fact that I might have made a 400 case error somewhere else doesn't matter, because you know, you'll throw that out right when you take it further downstream as you do the testing. Uh, something interesting happens. Remember, the right way to design it, like we are saying, is not just use AI on existing data.

You're designing completely new drugs, atom by atom on the computer using these breakthroughs in molecular physics, what we call deep quantum modeling. Right. But once it finds something new that AI has never seen, you can convert that into actual lab data, right? You have made the drug a molecule. You have tested it in the in the lab. You've figured out all its other properties in the body. You can feed it to AI, you can make other variants around this and feed all of that data to AI.

Now, I can help you say, oh, you're still having some issue with, you know, say liver talks or something else. Okay. Let me tell you. Perhaps you can make this change based on the examples you just train me on. Okay. This is a new stuff, right? If why don't you make this one change and maybe it'll work. Remember, even if it makes a mistake, fine. But, you know, it's actually making the work of the humans much, much quicker and more efficient, right? It recommends 2 or 3 different options, maybe ten different options. You go make them figure out that, you know, six of them are working great.

Any of those than humans pick the best you know to take them to clinical trials or best treat right. You can do that. Now, I can also help you. It's a completely different type of application of AI. Now in this drug optimization space we were just discussing. But yet another application of AI now is in clinical trials. You have the drug in clinical trials. Maybe you don't have just one drug. You have 2 or 3 like we always do adverse one for the same disease. Okay.

And we can now take all of the patient data, the clinical trial data, and try to do AI driven analysis to figure out, okay, drug A is working better for this population versus drug B versus drug C based on their genetic signatures and other things like those health histories, epigenetic signatures, whole proteome analysis okay. And we say, oh, this is how we need to, you know, personalized drugs so that we can have many more options and give you just the right drug that that will be best for your specific, you know, makeup. We have all heard about the term personalized medicine, right.

What does it really mean? Today? Let's say you and I both get diagnosed with quote unquote, the same disease, some big, you know, catch all phrase. You go to your doctor, they do the test and they say you are in luck. You know, this drug will work for you. I go to my doctor and they say, oh no, I'm out of luck. The drug won't work. That's called personalized medicine. That's called precision medicine. I say that's crap. Okay. What needs to happen is that your doctor needs to say drug. I'll work better.

Good for you. My doctor should say drug B or C or D will work good for me. We don't have those kinds of choices today. We need those choices. Okay. So more of those choices that we can develop with the kinds of platform that we have built adversely on, etc., the better off society will be, you know, in terms of how well and how efficiently we treat disease, we shouldn't have to use the exact same thing to treat everybody that generally comes under the same broad umbrella of a specific disease.

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Michael: Is this where pharma as a whole is going? Is, or smaller groups moving more nimbly to this type of development? How is this playing out?

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Adityo: This is where the industry over time needs to go. And in many cases, big Pharma is coming in. When they're finding new things developed at a smaller company, they're trying to license it, they're trying to buy the company, whereas things like those. But over time, this is while where this is, this needs to go. We are not yet there. We need the kinds of molecular physics breakthroughs we were just talking about, combined with AI to get us there. And it's only beginning to happen, and we are seeing the fruits of that, you know, work.

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Michael: I'm very excited about this vision of the future. What's more is that I'm excited that we're actively working to get there. It's not just a wouldn't it be nice if all these things could actually come to come to happen? So, Aditya, thank you so much. This is a truly fascinating conversation. I feel like I could just keep plugging more questions at you with, uh, throwing more things that you would. Just different ideas. And somebody said this one time, what do you think about this? So, um, thank you so much to you. And thank you for our listeners for, for tuning in. For more on the Health Connective show, please visit HC show for previous episodes and Health Connective as a company. Thanks so much.

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Adityo: Thank you Michael.