AI Ignition

Ignite your AI curiosity with Daphne Koller

How do we take responsibility for the varied uses of AI?

Beena Ammanath: Hi everyone! My name is Beena Ammanath. I am the executive director of the Deloitte AI Institute. Today on AI ignition, we have Daphne Koller, founder and CEO of Insitro; cofounder of Coursera, and adjunct professor of Computer Science and Pathology at Stanford. She spends her time at the intersection of machine learning and biomedicine, working to heighten the impact of the former on the latter. We're so excited to have her with us.

Daphne, welcome to the show! I am so excited to speak with you today. You have a fascinating background, started in computer science and then you founded a couple of companies. How did you become interested in the intersection of machine learning and biology? Can you walk us through your journey?

Daphne Koller: Thank you, Beena, and it's really wonderful to be here. I'm so excited to chat with you. I got interested in machine learning actually as it was becoming a field in the early 90s. I was one of the newcomers, early joiners into the field, and joined Stanford University as their first machine learning faculty, hired in 1995. At the time, I didn't really know anything about biology, but the datasets that were available to machine learning researchers at the time that I started were not super inspirational, either technically or in terms of the purpose that they served. So, I became interested in biological and medical datasets around 1999, 2000, as the first higher throughput, they're considered tiny by today's standards, datasets for medicine and biology were starting to emerge. So some of the first clinical datasets, the first microarray datasets that measured human transcriptional profiles, or even at that point also model organisms, and then the first, the Human Genome project, the human RNA sequencing, and then over time as new datasets started to emerge, there was always sort of the technical challenge of what could one get from those datasets that was a level beyond the relatively simple statistical analyses that were applied to the first cut. So, initially that was more of a technical interest, but then as I found out more about the field, I became more interested in domain in its own right. And so around 2002, 2003, I really started to have a bifurcated lab as a Stanford professor, where half of my lab did core machine learning published in traditional computer science venues, like NeurIPS and ICML, and the other half did biology

and it was published in Nature, Science, and Cell. The funny part was that my computer science colleagues didn't even realize I did biology, and my biology colleagues didn't realize that I was still a computer scientist, and so it was weird to have this almost like two-part existence.

Beena Ammanath: You've spoken about the need for the two sciences to collaborate and work effectively together. I think you're doing it at your company, Insitro. Can you share a little bit of background on what prompted you to start the company?

Daphne Koller: So, what caused me to start the company was, in fact, very much what you said, Beena. And it happened after, there was a step in my journey that we skipped, of departing from Stanford to found Coursera, and we might come back to that or not, but I left Stanford in 2012 and then in 2016 Coursera was on a good trajectory and I looked around and, as a reminder, the machine learning revolution really started to take off around 2012. So, I've been almost on the sidelines of that and then in 2016, I looked around and I said, wow, machine learning is really transforming the world across multiple sectors where it's not having a lot of impact on the life sciences. And I felt like someone such as myself that had the experience of truly working in both disciplines might be able to bridge the gap and create that company that really drew on the best of both disciplines. So ultimately, after a stop at Calico, that led me to the formation of Insitro, where the vision of the company, and it's in the name, I mean, Insitro is a combination of in silico and in vitro. It's in our logo and it's in every aspect of our culture, really bringing those two communities together into a meaningful dialogue that begins not at the point where we have a dataset that you want your computational people to analyze, and not even at the earlier stage, where the experiment is being designed, but actually at the point of asking what are the problems that we need to work on, where the two fields can come together to combine value that is considerably larger than either could provide on its own. And we find that our best work comes when the problems that we're working on would never have been contemplated without that truly synergistic interaction between two communities.

Beena Ammanath: From a timing perspective, do you think now is the right time to apply machine learning methods to biopharma and biomedicine? What makes you think, because we've seen AI winters and when AI took off and then there was a lot of angst around it, then we had a winter, and now it's back in the realm. Is there a timing aspect to it?

Daphne Koller: Oh, absolutely. I don't think Insitro would have been effective if it had started three or four years ago because, truth to be told, three to four years ago, even the large datasets were rather small and the tools for generating data were not nearly as robust and mature. One of the things that we see in the last few years is that on the data creation side, there are two threads that are occurring in parallel, each of which is an incredibly powerful source of data. One is, there is an increasing number of large human cohorts, large bio banks, or collections of electronic health records, combined with genomic data, that provide us an unprecedented ability to interrogate human biology and actual human organisms as opposed to the tiny, tiny datasets that were available even five years ago. One of the largest of those is the UK Biobank with its 500,000 people, but now in the US, there is all of us that's aimed to be a million, there are various hospital systems that are starting to do really interesting research on various patient populations. And so I think that's a really exciting source of data that allows us to use humans as a model system for humans rather than mice, or even worms or flies. The other thread that is enabling this is the development in the last decade or so of a suite of tools that are sort of the in vitro side of this equation, where we can now create in the lab and intervene in the lab in model systems that are much more faithfully recapitulating human biology and doing so at an unprecedented fidelity in scale.
If you go back 20 years, people would spend their entire career interrogating individual genes and then microarrays and the human genome and so on came along and allowed us to do things at a somewhat

larger scale, but oftentimes, in systems that were not really well suited, like yeast or cancer cells, and oftentimes with tools that were very hard to use and clunky. I remember how long it took us when I was collaborating with some colleagues to even create a collection of single knockouts and double knockouts of genes in yeast.

Today, with tools like CRISPR, which allows genome-wide intervention at screening of the effects of genes and cellular systems, the ability to create cellular systems that are derived from natural human biology. These things called induced-pluripotent stem cells that allow us to collect cells from you or from me and generate neurons with our respective genetics in them and our respective propensity to different diseases and really create a system in which we can study the effect of those at the cellular level. The ability to measure cells using microscopy, using transcriptomics, using a whole slew of modalities. All of these enable us to interrogate the biology of disease and explore different therapeutic interventions, in ways that are entirely unprecedented before. So, that actually puts us in a position where we have the opportunity already available to us, very large datasets that contain incredible value and what's missing is the tools to interrogate those datasets and extract value from them, and that's where machine learning, I think, is a wonderful complementary technology and it's a synthesis of those two disciplines that I think is where a new field will form, a field that I'm calling digital biology and I think it is a really incredible opportunity for people who are new to science to go into a brand new field with a lot of potential.

Beena Ammanath: I love the term digital biology and so double clicking a little bit on the drug development process, what parts of that process are really amenable for machine learning to make an impact, and are there parts of the process that AI or machine learning really can't help much with?

Daphne Koller: That's a great question. I think one of the things that we experienced in the early days of Insitro was that we would go talk to a pharma company and either they would treat this with a certain quizzical disbelief, or maybe say, yeah, it's going to be kind of like a computer-aided drug design. It might help accelerate a little piece of the process by a little bit of time, but it's not going to really change. It's not really going to move the needle across the spectrum. I think we have moved away from that and there's now a growing recognition that machine learning will be transformative across multiple steps in the process. So, we are already starting to see its effects in interrogating disease biology, which is the area that we started out in at Insitro. We're already seeing quite a number of companies that are showing quite surprising acceleration of the target to drug design aspect, which is very challenging using traditional tools and often takes three to five years and a lot of money and a lot of chemist hours. I think we're seeing machine learning accelerating math piece and we see actually a lot of work on the clinical trial side of the world, where we're starting to measure people using wearable devices, having data collection that is ongoing. I think that's again, all of these are kind of at an early stage, but you can see the trajectory really emerging.

Where I think machine learning is not going to help as much as—fundamentally certain things take as long as they take, because human biology proceeds at a certain rate, and there's only so much you can do. We certainly see that even on the lab side, where growing a particular type of cell might take 30 days, and it takes that cell 30 days to get to where you need it to go, and you can throw all the machine learning in the world at it, it's still going to take 30 days before it's showing the right biology, so you can interrogate the processes that you're looking to interrogate. We certainly see the same on the clinical trial side, where if it takes a disease a certain amount of time to progress and you want to show that you've changed that trajectory then there's only so much you can do. I will say, though, that even there on the clinical trial side, there are opportunities to sort of shorten in some way. So, for example, if you're able to detect earlier that patients are responding by having finer resolution instrumentation of a patient's state, that can certainly shorten clinical trials, subject of course to regulatory approval. And you can also potentially shorten clinical

trials by better selection of the patient population, since recruitment is actually one of the slowest phases of the clinical trial. So, all that is great, but you're still, fundamentally, human biology proceeds at the pace that it proceeds.

Beena Ammanath: That's the truth there. You talked about the processes. What's your take from a disease lens? Like you're building a platform that combines human genetics, stem cells, functional genomics, and machine learning. Are some diseases more amenable to this approach, and which ones are not as appropriate from a disease perspective?

Daphne Koller: No, absolutely. The diseases that you would expect to be able to interrogate using in vitro assays are ones that where a large part of the disease process is encapsulated within one or a small number of cell types, because we can't model entire organismal systemic disease, where there is a relatively strong genetic basis, because we don't always know and it may not even be possible to really create the right kind of environmental effects in a lab dish as you have for a person, the kind of environmental insults that are disease causing. So you need to assume that the genetics has a sufficiently large effect that you will be able to see that in the right cellular system. And then, of course, the cell systems that you're building need to be ones that are relatively robust and can be constructed effectively, and our ability to what's called differentiate stem cells into different lineages is really great for some lineages, where there is some cell types you can get 95% differentiation in 12 days and there's others where you basically pray for 60 days and eventually you get 5 or 10% of the cells to convert. So, you need to pick your diseases with all of those criteria in mind.

Beena Ammanath: The other big factor is you're working a lot with human data. Even somebody who has not studied biology beyond high school, I know that clinical trial populations and some of the other available data are really not representative of the general population, whether from a race or gender or ethnicity perspective. How do you think about avoiding bias as you're building a platform, so that as you are helping the drug development process, it works for the general population and not just certain subsets of it? How do you address that?

Daphne Koller: I think that's a great question, and it has multiple parts to the answer. At first cut, I would say that while people have different genetic backgrounds and therefore the prevalence of different genetic variations that are disease causing can be greater in some ethnic groups and lower in others. For example, sickle cell disease in African Americans is a very clear example of that. The biology of those diseases is not that different across different populations, and so if you are able to detect that a particular gene, or more broadly a pathway, is implicated in disease, chances are that it will be implicated across different ethnic backgrounds and so if you find a drug that targets that pathway, it might be more helpful in some populations and maybe less helpful to a smaller group in another, but it's not like you're just treating one population.

That's one part of the response. The other part, I think, is that fortunately, this issue that you've just flagged is not something that has been lost in the community at large and while a lot of the earlier datasets were very much biased toward mostly European populations, certainly the biobanks, but also clinical trial populations. I think the recent public dialogue regarding diversity and inclusion has highlighted the importance of having more diverse populations in clinical trials and in biobanks, and as a consequence, there is a greater effort to collect data from more diverse populations. So, whereas the UK Biobank is primarily Eurocentric, they are now planning to have an expansion that would include a lot of other ethnic backgrounds, and in the United States the "all of us "project really made it a priority from the very beginning to try and recruit diverse participants into the cohort, and so I'm hopeful that as those efforts mature, there will be a greater availability of data that would open up the opportunity to interrogate

disease biology across these different ethnicities, compare and contrast, and really find treatments that are useful for different populations.

Beena Ammanath: OK, I'm going to change gears a little bit and I would love to hear about Coursera. So we had Andrew Ng as a guest on this podcast earlier and you were the cofounder. What prompted you to start Coursera?

Daphne Koller: So, there are two parts to the answer. One is what prompted me to get interested in education to begin with and then the second is what prompted me to start Coursera. So, what prompted me to get interested in education, it's been something that I worked on at Stanford for many years, even before Coursera, and a lot of the ideas that ultimately went into Coursera emerged from work that I and colleagues had led at Stanford on things like, how do you improve the quality of education even for on campus Stanford students using flipped classrooms and active learning and all sorts of things that we know are best pedagogical practices. So, we kind of built an internal platform at Stanford to support those efforts as part of a longstanding interest that I had in education in general, and then that culminated in the launch of those Stanford books that really had all these 100,000 people or so in each one of them. Then of course the question was great, so we did that and why did I leave Stanford to pursue that, and I think it's because I had this incredible sense that this could be transformative to the world, and while I certainly enjoyed my work at Stanford and I thought it was important, the opportunity to have such an immediate impact on so many people and not just the number, but also the fact that these were people from all countries, all age groups, and all walks of life, that all of a sudden had access to this incredible opportunity to learn something and transform their lives, that I felt like I couldn't just say, "Oh that was fun. I'm glad we did that," and then just go back to Stanford and write more papers. I really felt like if there was an opportunity to change the world, it was imperative for me to take that, and so I put my research on hold, kind of shut down my lab, and went on what was supposed to be a two-year leave of absence, except that I never returned because what I was doing I felt was so important and so exciting that I really wanted to see it through.

Beena Ammanath: And you started another education startup—cofounded a startup last year, during the pandemic. Tell us more about that.

Daphne Koller: So that company is called Engageli and it emerged directly from observing my two teenage daughters as their school transitioned from in-person to online, and they're both strong students, academic high performers and such. Then, once we walked by their home offices as they were supposedly doing online school, we found that they had each turned off their camera and their microphone five minutes into the class and one of them was perfecting her Sims game and the other was working her way through the Netflix catalog, and if that's what my high-performing kids with a great school with low student-teacher ratio, what does that mean for other kids who are trying to learn online?
So, the platform that we founded in Engageli is really something that's focused on almost the other side of the coin to what Coursera did. Coursera really focused on creating a lot of content that provided an enormous catalog of knowledge to people, but there wasn't really a teaching element to it, at least not after the beginning, the content is there, people consume it, there's like automated exercises and things like that, there's no teacher. This is the opposite. This is really all about teaching and creating a platform that is built from the ground up for having an instructor engaged with students, having students engaged with other students and really create that community, that interaction, that active learning, interactive and active learning experience that is so fundamental to understanding, and obviously content is a big part of that and content can be taught by the instructor in real time, or it can be something that is taken from a platform like Coursera, but really the platform is about that interaction between human beings. If you look at all of the research on what makes for effective learning, it's really all about that human-to-human

interaction, and that's what the platform is intended to facilitate in ways that a platform wasn't originally intended for video conferencing just doesn't have those capabilities as part of it, the instrumentation of students, the ability to readily move people into small working groups or pairs and have them work on a problem together. A platform that was a video conferencing platform isn't really geared for that type of interaction.

Beena Ammanath: Daphne, this is fascinating for me because I have two teenage boys and I've seen them. It's very similar to you. It is very easy to turn off the camera and explore the rest of the world that's at their fingertips. It's very hard. So, is this now available? Is this being used by schools?

Daphne Koller: Yes, absolutely. So actually, it took a while to build out the platform, but it's mostly intended at higher education because a lot of the lower schools and high schools are moving back to face to face as they should, but for universities, there is actually a lot of interest among students to have some, maybe not all, but some of their courses in an online format because these are oftentimes, well, they are older people, some of them are actually like post that 18 to 25 year range, they have jobs, they have dependents, they have a mortgage to pay. They can't just put their life on hold and spend their entire time sitting in a dorm room somewhere and then going to classes. So, providing people with an opportunity to take some of their classes in a much more flexible format is a huge equalizer, especially for people that aren't among the privileged, whatever 1%, 10% that can really just go and have a wonderful college experience with green lawns and discussions in small seminar classrooms with 12 peers and a professor. How do you create a great learning experience for those students? That's what the focus of this platform is.

Beena Ammanath: That's amazing! I am definitely going to learn more about it. I am also a huge believer in what machine learning and AI can enable as more personalized education, because everybody learns differently and I see that difference just between my sons as well. One is very much he learns by reading, by listening; the other one needs more visual. He learns more from videos or some whiteboarding. So, there are different ways that students learn, no matter what age. Is this going to expand into more of that personalized education realm, where you can reach students where they are in their learning type?

Daphne Koller: Oh, 100%. I think the challenge with personalizing the learning experience in more traditional settings is always started with, we don't have enough data on what students are actually doing. So, if you think about the data points that we have on a student in traditional face-to-face classes, you get their four assignments that are turned in in a semester and they're graded on the final exam or the final project. That's really not enough to learn from. And you get one per course, so by the time you've learned anything, that student is off in the world and it's not possible for you to really apply those learnings.

Nice thing about a platform like Engageli is that you have a constant stream of data around every student. And we're not talking about invasive data like gaze tracking or something like that, but every time they raise their hands, it's recorded; every time they take notes on the platform, it's recorded. They can vote the instructor up or down in a given segment of the class, that's recorded. And so in ways that are not invasive, because they don't infringe on the privacy, they're all about the interaction with the class, you get a tremendous amount of information about what students are actually doing, and that enables a huge range of things.

First of all, it enables the instructor to just track who's not raised their hand in the last 45 minutes or not taking notes and then just call on them and say, "Hey, Daphne, I noticed that you seem quiet today. What's going on? Do you have a question?" So, first of all, just pure data collection enables much greater interaction and then of course you can start feeding that data stream into predictive models to say, which students are likely to need more attention, who's likely to benefit from a different reading or a different

type of assignment. Because you have that rich data stream, that is really what enables this machine learning and the personalization to take place. So, I think this is a huge opportunity for us to both engage our students better, but also to learn about what works both for individual students as well as at the meta level. The amount of educational research that you see that's been published on classes of 30, 50 people and then, how much statistical confidence do you get from limited data collection about such a small group? Here, all of a sudden you have the opportunity to generate massive amounts of data around large numbers of students, which can really reshape the way in which we teach broadly.

Beena Ammanath: You touched on this briefly, but making education more accessible, that is the other factor that comes into play. As you know, there's a lack of women in AI. There's a lack of diversity in general, and it's on top of mind for a lot of companies, and a platform like this can help us reach these communities of women or underrepresented minorities and get them more engaged and make that education more accessible to them who might otherwise not have had access.

Daphne Koller: Absolutely, and we saw that in the Coursera days where there were many women who didn't have access to education. Women in countries unfortunately like Afghanistan and others, where it's not easy for them to leave the home, were benefiting from access to this education. But even here in the United States, coming back to people, oftentimes women, who are supporting a family and need to do their learning in the evenings and over the weekend, and if you don't give them this type of learning platform, they won't have anything. The other thing that we saw with a beautiful study that was written by one of our female data scientists at Coursera, who's now a faculty member in her own right and an incredibly smart young woman called Emma Pearson. She did this study about the importance of female role models in terms of your teachers and how does that affect women's interest in engaging with the material. And she was able to show that women who are exposed to a woman instructor are more likely to go into a field, and what was beautiful in some of the work that she did was she was able to do what I think is one of the very first controlled experiments in this regard, because we had one class, it was a machine learning class at University of Washington. It was taught by a man and a woman who, as it happens, are married to each other, and one of them is my former PhD students, Carlos Guestrin and Emily Fox, incredibly talented, both of them. She was able to show that if you flipped the names of the instructors and the prominence in how they were displayed, if you put the woman first, more women were likely to take the class than the same class if you put the man's name first. And this is really a very powerful demonstration of how a female role model can actually directly play a role with this kind of really carefully controlled experiment that is so difficult to do in education and social sciences more broadly.

Beena Ammanath: That is absolutely fascinating. I did not know about this study, but we do focus a lot about getting more women in AI ,featuring women role models, but we also need platforms like what you're doing to make that education more accessible. I know you have personally seen this at Insitro, the need to be able to understand the subject matter expertise or the domain expertise while also understanding the computer science and machine learning side of things. You've called yourself bilingual, but it's also an opportunity for the two groups to come together and build something more powerful, but in a way get more diversity to the table, get more women involved. There are more women in health care than in computer sciences, so if we can team up, that way the overall team is going to be more diverse.

Daphne Koller: One hundred percent, and also what we found, even in my time at Stanford and also at Coursera, that women oftentimes get drawn into machine learning or computer science when that is in service of goals that they consider to be societally good. There is a disproportionate representation of women in machine learning in the specific subareas of application, the health, to the environment, to other things, and so those interdisciplinary interactions are a great way of bringing more women into the field from both sides.

Beena Ammanath: So true! So, in your experience now having done several companies, what are some of the good things that biopharma companies can learn from tech companies, whether it's from a cultural, operational, or any other perspective? What do you see some of those positive things that tech companies can teach biopharma and vice versa?

Daphne Koller: So, I think one thing that is an interesting tension is the pace at which tech moves versus the pace at which biology or biotech moves. And one shouldn't stretch this too far because something like the Facebook model of move fast, break things, that might be fine if you're building a social networking app, but if what you're building is a health care device or a drug, you don't want to move fast and break things because what you're breaking is people's health. You have to be careful. But even with that I think there is a real opportunity for biopharma to learn from the tech world how to think about things from a systems level. So, how to build platforms and systems that just instrument and systematize, and thereby accelerate processes that you do again and again. In biopharma oftentimes every program is a snowflake, every one that you basically start from scratch and the only thing that transfers is the knowledge in people's minds, which is great, but it's not really a system. What we're building in Insitro is really something that's intended to be a flywheel for performing tasks within drug-discovering developments that are repeatable and systematizable. So, when you do it the first time, it may actually take longer because you're building out all this infrastructure, but the second time you do it is faster, and the third time, by the time you do it the fifth time, it actually is moving much, much faster because machine learning also learns from its previous experience and so the platform gets better, but also the machine learning models keep getting better, and that's something that is not part of the operating norms of most biopharma companies, and I would say that is a big thing that they need to learn from tech.

The other thing I would say, which is not so much learning from tech, but really creating that hybrid culture in which, oftentimes if you're a tech person going into a biopharma company, you don't have a seat at the table. You are more kind of like the receiving end of a dataset, where someone already decided on the strategy, defined the question, created the dataset, and you are stuck with a little paragraph blurb explaining what the dataset is and supposed to analyze the results. That's not a super empowering role to be in, and I think if biopharma companies really want to create something that is more of a hybrid tech company, you have to give the tech people a voice at the table so that they feel like they too have a sense of ownership on the strategy and direction and so that their input can actually help create some of those systematic processes we just talked about.

Beena Ammanath: Most companies are now using some version of AI in their businesses, and then there are number of AI-focused product companies. What are some of the lessons that you've learned from other AI-focused companies that you hope to avoid those mistakes that they might have made.

Daphne Koller: So, there is a couple. First, I think is that data quality is paramount and when you read some of the failures that have happened, especially in some of the companies that have tried to apply machine learning to health care data and discovered that the machine learning algorithm latches onto artifacts that have nothing to do with the underlying biology, like some watermark in the X-ray image or some population difference between one hospital and the other that they neglected to test for and correct for. I think that is a mistake that a lot of companies and also academic institutions have made. And so we place a huge emphasis at Insitro on data quality, both in our externally acquired datasets and certainly in anything we generate in-house. The second one, I think, is that it's important to make sure your methods are fit for purpose. You want not to err on the side of, we're just going to throw this really simple whatever classifier at this, because that neglects all the advancements that have been made in machine learning, but at the same time, you also don't want to come into this with, "I'm going to throw my fanciest, best, most

amazing adversarial neural network with graphs and transformers and stuff," unless it's actually useful. So, you really want to make sure that you're solving the right problem, and that your model is fit to purpose for that problem, and it's really easy to get stuck at one extreme or the other. Then the third one, I think, kind of elevating data methods and then there's people. And one of the things that I would say I've seen as a failure in a lot of AI-centric companies is the tendency toward hubris and exaggeration. It comes in both in like, "Oh, we're tech people, we're going to solve everything because we've seen tech like, solve every problem and we're going to have 100 drugs in three years." It's like, no, you're not. It's really hard. What we're doing is really hard, and those unrealistic promises you alluded earlier to the AI winters that we've lived through, these are dangerous to the field because, first of all, they create rightfully skepticism, and then when one doesn't deliver on what were unrealistic expectations to begin with, then you end up with people saying, "See, I told you it was all a bunch of hooey and there's nothing there." What's sad, I think, is that in earlier incarnations of AI winters, which had this breaking of the bubble and people saying, see, we told you there was nothing there. There probably wasn't all that much value that had been delivered. It was just hype. This time, there's actually real value that's coming out of this type of work, and if we end up because of an excess of hype having people lose sight of the value, I think that would be a real, real shame for the field. At Insitro, we all try very hard to be very balanced about what we say. We say, look there's a tremendous opportunity. It feels like the time is right, but it's a really hard problem and it's going to take us a while to get it right. We're going to work as hard as we can toward achieving ambitious goals, but it's not the same as saying we're going to have 100 drugs in three years.

Beena Ammanath: Love it. Daphne, how can people stay connected with you? Where can our audience follow you to keep up with all the amazing work that you're doing?

Daphne Koller: So, we have a website www.insitro.com. We have a Twitter feed. There's also my personal Twitter feed and LinkedIn page, and so, we definitely post exciting news there, like when we closed our series C earlier this year. When we make major hires as we recently did, we hired a really remarkable executive from Google and Facebook, who then went into drug discovery and really helps us bring together those two worlds with a true deep-tech perspective, but yet in a drug discovery company. So those are some of the news that we announced, and so we would love for people to stay connected with us.

Beena Ammanath: Daphne, thank you so much for joining the show!

Daphne Koller: Thank you very much, Beena, and it was a great pleasure to be here.

Beena Ammanath: Daphne, thanks again for being with us on the show and thanks to our audience for tuning into AI ignition. Be sure to stay connected with the Deloitte AI Institute for more AI research and insights. Thank you and take care!