Novel Cohorts
Podcast Series

Dan Housman, Chief Technology Officer of Graticule, and Jeff Morgan & Nishant Aggarwal from Deloitte showcase a live demo of Deloitte's RWE Agent in action, highlighting the future of real-world evidence with Gen AI

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Dan Housman (Graticule):

Welcome to the Novel Cohorts Podcast. I'm really excited today to be talking with Jeff Morgan and Nishant Aggarwal from Deloitte. We're former colleagues, and it's great to be speaking with you guys. We're going to be talking about agentic cohorts and the future of real world evidence. Today, they've been doing some great stuff at Deloitte that some people have had the privilege of seeing, but many of you haven't, so let's just jump right in. So maybe you can introduce yourself, and we'll jump from there.

Jeff Morgan (Deloitte):

Thanks, Dan, and thanks for inviting us. Good to see you again. So for those of you who don't know me, Jeff Morgan, I'm a managing director in Deloitte life science practice, and I also lead our real world evidence practice. I have about 20 years of experience working with players across the life science industry, helping them kind of build modern capabilities to take advantage of real world data and enable those use cases that span research and development all the way through commercialization.

Nishant Aggarwal (Deloitte):

Hey, thanks Dan for inviting me to the podcast. I'm Nishant Aggarwal and I work for Deloitte in the innovation and technology practice. By title, I'm the VP of innovation and technology, and focus on the disruptive technologies and the life science commercial and R&D domain, and bring this to our clients. And then, in my previous role, I used to lead the real world evidence platform for Deloitte, and work closely with our clients to bring value to real world data sets using this platform. And I'm here happy to talk about the innovations that we are seeing in the real world evidence and especially around the agentic side.

Dan Housman:

So maybe we should jump back and let's hear from both of you about the sort of evolution technologies. What have you seen in the last 20 years? Jeff and Nishant?

Jeff Morgan:

Well, it's been interesting. Evolution, let's just say, over the last 15+years, if you run the clock back, RWE wasn't really the term even used, right? This was essentially Outcomes Research. It was a small function within pharma that did, you know, let's call it, dozens of analyzes a year to support the post launch activities for their drugs, you know, they used the technologies that they had available to them at that point, right? They were basically borrowing other systems from other parts of the organization. But then as real world data and evidence became more and more important to organizations, we saw additional investments start to pour into this space within Pharma. So, you know, probably going back about 10 years ago, we saw significant investments in a couple different areas, building up more internal teams to generate more real world insights and evidence, because the need for it across that whole drug development process was growing. That led to, you know, bigger teams needing to do the work, more mature systems were needed to be put into place. And then we start to see the emergence of self service analytic tools, so tool suites that would allow, you know, either real world scientists or even more business users to be able to access real world data and conduct some of these analyzes for internal decision making by themselves. So where we are today now is, you know, in the era of Gen AI, we're seeing companies now start to modernize these capabilities once again and infuse Gen AI into these various workflows, really all aspects of the lifecycle of a study, starting with how you plan a study, how do you identify the evidence gaps you want to fill, to how you design your studies, to how you execute your studies, and disseminate that evidence. So we're seeing companies down. We're working with them today to embed agentic AI into those workflows to streamline it, because, you know, the demand for real world evidence continues to grow. The resources within any organization you know, they're not going to be able to keep up with the demand, right? The capacity outstrips the demand. So the one way companies are really trying to solve this now is using agentic AI to drive efficiencies into that process.

Dan Housman:

So it's pretty exciting. You guys have actually built real tools, you know? And I guess, what are some of the big pieces that go into those tools that you think are driving them to build them out, like, what's the what's the pain point they're looking to solve?

Jeff Morgan:

So I think the biggest pain point right now, and I mentioned it a few minutes ago, is that the demand is outstripping capacity, right? So how do we make our current real world scientists and analysts who are tasked with executing these studies more efficiently? And that's where generative AI comes in. So that's the one big driver that I'm seeing in the market. The other aspect is that there could be an opportunity to develop higher quality evidence and using and what I mean by that is using generative AI to make sure you're using the most appropriate data set, so helping with the data set selection process to make sure you're developing, you know, high quality evidence that's reproducible and impactful.

Dan Housman:

So, you know, I'd love to hear what you built. I mean, one of the most exciting things about your team is that you're in the consulting business. You're working with lots of different groups, and you've built some systems, and you guys are leaders in this space. So I'd love to take a look and have you walk through some of the early pieces, because I know we're in, like, day one of Gen AI for our deputy. Like, you know, this is the first peak anyone gets at this stuff.

Jeff Morgan

Yeah. I mean, like our and, you know this, Dan, but our journey into this space started almost 10 years ago at Deloitte, right where we stood up converge health, which you were part of, and the shot was a part of, where we had dedicated engineering teams building out solutions specific to real world evidence. So we built some tools at that stage that weren't leveraging Gen AI because it wasn't available. So what? So those are tools that help our clients better manage their portfolio of evidence, and help them generate insights from the data. And where we are today now is, we're now onto the v2 of some of those solutions, and that's where the Gen AI comes into it. Maybe I'll let Nishant talk a little bit about like one of our most recent solutions that were brought to market called our RWE Agent

Nishant Aggarwal:

Thanks, Jeff, I think this is a great segue, right, like so before, we were using the self service tools to generate insights from this real world data sets, and now we are in this next phase where you can actually use the tools, right, which is a natural language way of building cohorts on these real world data sets, and much more conversational in nature, right? And the reason, since these are natural language, and these are these works on your data sets, these are data format agnostic, what we have seen is the, really, the pain point that we have, it's solving for from the, you know, previously self service tools, right? The self service tools were great. They were able to generate insights, but they're still a learning curve that the researcher would have to translate from that description of cohort, right, or something that the tool understands, and then the tool will generate cohorts and queries and then run against this data set, which has to be, by the way, in one or two common format data models. So there's this problem of transferring or transforming the data to this, these common data sets. So I think when we try to solve this, we want to do a couple of things, right? One, a natural language. We are building the cohort so there's no transformation of these, rebuilding of these four definitions. And then second, it needs to be data format agnostic. It needs to work on your native data sets, right? So those are the things that we solve for. So we lower the barrier for adoption, and the lower the barrier to scale right around in the organization's data sets. So I think with that introduction, I'll go jump into this tool now for a quick demo

Jeff Morgan:

And actually one other pain point that Nishant didn't mention, that we solved with Gen AI, is really around the data management problem in onboarding data sets to these tools. So historically, to load a data set into a self service tool suite, it took weeks and months.

Dan Housman:

You know, it's like, Hey, I mean, there are people who had whole businesses converting data. There were companies.

Jeff Morgan:

So we've enabled Gen AI, to streamline that process from weeks or months down to a few days, which is, you know, a steep change in how data gets enabled into these tools?

Dan Housman:

Yeah, I know you're gonna show in a second. I remember when I was first working with what was kind of a centre core of the group trying to do TranSMART on top of i2b2 and they looked at i2b2, and they're like, Well, what do you want this to do? Because it was that fun front end of the process where you get to ask people, What would you do? And they're like, I just wanted to work like Google. I just want to be talking to the data. And you can see in transplant, actually really tried hard in one of the interfaces to make a command line like Google interface, but the data was so complex, like we were trying to look at RNA data combined with the structured clinical trial and everything, and we had to transform the data for weeks to take a trial and convert it to i2b2 format, I think Nishant may remember, and now I think they probably just, I want to work like, Chat GPT, because everyone's seen it. Their expectation is now at that level. And you know, it's going to be interesting how close we can get to those experiences with the kind of work you guys are doing.

Nishant Aggarwal:

Yeah, and that is exactly one of the problems to solve for, right? Because of the Gen AI, semantic mapping becomes a lot more easier from the different data sets and different formats, and so enablement of these data sets on these tools becomes a lot more easier and faster as well. It doesn't take months or weeks, right? It's like a day job, right? Or maybe hours to do that. Let me jump into this tool. I think we have done a lot of talking here.

Dan Housman:

We get to the first time everyone's favorite things, a demo

Jeff Morgan

It's probably worth mentioning as Nishant jumping into this demo. So a lot of the tool suites that I'll call the historic self service tools that have been out there, have largely been SAS offerings. And what I mean by that is that they're hosted outside of many pharma companies, which is great. It's turnkey, which is great. But what you have to do is then you have to send all your data to those providers, loaded into the platform. It's tight. You know, you have little to no control over how the software behaves like there's no modifications to it whatsoever. It's all driven by the vendor. So the good thing is, it's turnkey. The bad thing is that you have to ship data outside your organization, and it's a very rigid system. What we're going to show you here is something that gets deployed within our clients' environments and gives them a lot of flexibility to extend and enhance the solution to best meet their unique needs.

Nishant Aggarwal

So what you're seeing on the screen is the RWE agent homepage right? Here you have several options. You can start a new conversation. This is a conversational way to build the cohorts. You can actually go and check out any previous conversations that you have had, right. There are some other links to the cohorts that you have built priorly so you can explore those cohorts. There's a library of analysis that you can perform. There's the projects that help you organize the view, data sets, like all the data sets that it has been enabled in your organization. And the code sets, basically the previous code says that you have created, other users have created, and you want to share and use, reuse in your conversations, right? So let's just jump in and see, like, how do I basically start building the cohort in a conversational way? What you see on the screen is a few starter prompts where we educate the user how to get started. Either you can start by building a cohort, or, you know, access some information about the different coding systems that exist, and then suggestions about studies that have been performed in the past and all that stuff. So for today, I've taken a cohort definition and natural language like I just took this definition, like building a cohort of female patients 18 years of age with histologically confirmed ovarian cancer and fit some exclusion criteria. So what it's doing at the back end is actually interpreting what this definition is and then replaying it back to the researchers. Hey, is my interpretation? Correct, right? So this is our way of having a human in the loop, right? And not just take this and then run it with and then show them account, right? This is slowly building confidence. As we go about building the cohort in a conversational way, we are basically replaying it and saying, saying, These are the inclusion criteria. These are the exclusion criterias, right? That came up by and then the researcher can look at it and say, Yeah, that's probably right. This is what I want to do. What we set this up is actually the relevant studies, right? We also went inside your organization, and you can enable your knowledge bases of where your prior studies are, as well as externally, right, to sites like clinical trials like hey, people with similar cohort definitions, are doing similar type of analysis and work like, do you know that? Right? So this gives them insight into what has happened within their ecosystem, internal and external, right? And then also the prior data sets that were used for these types of studies, right? So this gives them more insights into how they should go about it. And then these, some of some of these suggested criteria as inclusion exclusion criteria is like, although you are starting with this, but, but see what the others have been using in this similar type of cohort definitions, right? So, as you can see that this was interpreted now for the inclusion criteria, we can go ahead and add, like there was a demographics information around age and gender, there's conditions, and then maybe I want to add a treatment, right? I can either add it using one of the statistical criteria, or I can just say, okay, include, let's say carboplatin. After diagnosis, right? So, that just saying this, it will be possible to add that treatment or medication right after, after this. So let's, let's see what it comes back with.

Jeff Morgan

And Nishant mentioned on the right side there, you see, it's starting to provide recommendations of relevant studies or data sets that have been used in prior studies. This is useful for a couple of reasons, and one of the big value adds of this is given the sheer volume of studies now that get conducted at, you know? Or any major pharmaceutical company, they tend to run the risk of duplicating efforts, right? So this, this is a nice way of surfacing similar types of analyzes, so that you may actually not even have to redo or do the analysis that you're planning, because you just discovered that, Hey, someone already did something very similar. Either I could build upon that or just even look at those insights and that suffices, right? That meets my needs. So it's really helping reuse a lot of the knowledge that has been built up in the organization

Dan Housman:

Can I ask a quick question, where did the suggested criteria come from? How does it make these suggestions?

Nishant Aggarwal:

Yeah, these suggestions are being made from the studies, right? That has surfaced up here, right? Because they were using similar types of cohorts, right? And they were using some additional cohort criteria. So those are the suggestions that it's surfacing up.

Dan Housman:

That's great, because I get asked this all the time, you know, like, well, you should be able to know what things we care about based on our Phase III clinical trial. And then I have to have an analyst go in, read the trial, look for all the endpoints, see if they match to real world data endpoints. It's a lot of work, yeah, and even then, we don't know, like, how to convert it, because it's like, code set mapping could take a week. I think it's easy, but it's not so easy.

Nishant Aggarwal:

It's not easy, yeah, but this is, this gives you a starting point, right? Rather than going in and doing your research on the web right and running through different papers like this gives you upfront like, what information will be available. So again, going back to the demo, like the medication, I added carboplatin even after the diagnosis, to see if it got added, right? Like, so this is great. Like this, at this point, I'm satisfied. This is the cohort I want. So I clicked on that button retrieve medical codes, because how do you define carboplatin or ovarian cancer or peritoneal cancer, right, like so that's still, to me, as a researcher, I want to use specific codes when defining that right, either ICD 10, SNOMED or CPTs, right, or whatever. So it's what it's doing is that the back and going back and retrieving for all these elements, right data, elements like the right codes, and then we'll surface it up for the researcher to look at it and see again, gain back confidence that these are the right codes, right that I want to use, for example, like this peritoneal cancer. I click on it and they can see, okay, so the ICD 10, they're using these codes. C48, C56 they want, if they want to remove some codes, they can do that right there. If they don't feel like this is the right terminology to be used, but in SNOMED, it will be used like this. So I think they give them a lot of control.

Dan Housman:

Did those code sets get pre-generated? Or were they generated by Gen AI?

Nishant Aggarwal:

This is an existing code. These codes are not pre generated. These are, of course, like codes from the vocabularies. So Gen AI is not generating these codes, but like, it's using those codes, like hey for peritoneal cancer. These are the right ones to use right by, by crawling the database and all the sites right now. So now, since I have all this information, and I'm pretty confident, like this is the board I want, I can go ahead and execute the criteria, right? But in execution, they basically, by the way, the relevant data sets, based on all the conditions and criteria that you have selected are these four, right? I'll select one of them, the Medicare data set, and then I'll say, okay, run on it, right? So what it's doing, it's at runtime. It's basically based on what that data set format is. It's generating the queries right, based on our criterias and running it against this data set, right? And it's generating it in a way, that attrition table. So you know where the patient population has dropped. It's not just a single number at the end, right? So you have, basically, you will see that waterfall view of where you're losing patients like so right? I can see half of this population, or more than half, is basically female patients. So that was my first criteria, and then it will basically go ahead and generate all this, and then in the meantime, like there's View SQL. So every code that gets generated right there, we basically researchers would be able to hit the View SQL button and see the different steps and the different SQLs that were generated, they can copy them. And then, you know, if somebody is interested in or validating this tool, they can even take this and run, run this in their own SQL Editor to regenerate this population, right? This is where, or even, like, you know, sometimes people use it to change certain things over there. So, because they want to, at that time, get into, you know, modifying this themselves, so you can see this cohort. This definition is now executed. Eventually we got 2000 patients. But out of the 2 million patients, you can click on your SQL. You can see on the SQL that was generated. You can click on copy and copy them to your SQL Editor and run them. If you want to validate it, you can also click on this View Cohort Statistics panel. So what we cohort statistics do is basically now, now that you have created this cohort of patients, right, I want to pull in that data for those cohort of patients and then plot it. And then I want to see some descriptive statistics about that patients right, like whether this has the right age distribution, whether, and then from the index days, of course, and the right until, whether it has the right gender distribution or ethnicity. By the way, all this is being generated by Gen AI, or agentic AI right? It's the day. There's a data pipeline. It pulls the right elements, right, and then it uses Gen AI to plot these visualizations, right? So that's what it's doing behind the scenes, when I say, like, review the key cohort characteristics. So it's pulling all that data so it is able to generate now, right? Like I said, the age of this group is 41 and above, right? There is race distribution, you know, and then there's ethnicities distribution, where we want to take this is basically, now you can prompt for further if there are things that you want to further investigate, like, Hey, what is the comorbidity and what is the medication distribution for this cohort of patients, of ovarian cancer? So, so at this point we can, we can basically see right, like they can prompt a different way that that's, that's where we want to take it, like something that's not there in the tool, but we are working on it, but that's, that's how we have, you know, positioned this tool, and then clients are using it for I'll take a pause here. Back to you. Dan, Jeff, anything else?

Dan Housman:

It's great. I mean, I can tell that there's going to be so many places to insert new features, and I imagine it's pretty quick to develop them too. I mean, obviously I know I'm not, I don't have to build them, but they're going to be quicker than what we used to do when we were coding forms, and we had to agonize over the structure of every screen down to the labels on every graph. It could take us months to respond to a customer inquiry of a feature. This sounds like, you know, the next step will just say, Well, let's look at a distribution of meds or line switches or things that hopefully the Gen AI can sort through and write the queries for

Nishant Aggarwal:

I mean, we don't have to wait weeks or months for the coding to complete and testing to release, right? So that whole process is compressed, I would say, right now

Dan Housman:

So I'm curious what reactions you've gotten from the clients, the pharma sponsors, and other groups so far, because you must have shown it to a few groups

Jeff Morgan:

Yeah, it's a good question. So feedback has been very positive, and some of the key differentiators that we've heard from the market are that they really like the multi data format capabilities, so not having to conform to a common data model, the data in its native format. They really like transparency, right? Nishant showed you that you can see the SQLs. That's kind of building some trust in the application. They really like how they can handle very complex inclusion, exclusion criteria, including temporality, and the intelligence suggestions piece is also something that's we've been told, as a differentiator of our solution, and then just kind of the overall design of having the human in the loop of it, is something we've heard kind of loud and clear when we were developing this solution from some of the, you know, pharma companies we were collaborating with, is, you know, we need to have human in a loop. Here. Nobody wants a push button solution that just spits out an answer. You need to have those kind of purposeful checkpoints throughout the process to make sure that the solution is being accurate right, and then the user can finally tune it without having to re prompt things. So Nishant showed you how you can delete some codes if you don't like them. That's another nice feature where you could just click on a code to delete it, as opposed to having to re-prompt it to delete a code. So, you know, we were very thoughtful in how we designed the overall experience, to ensure one that it kind of fits into the existing workflows of RWA scientists, and then two, it kind of builds trust in the application. Because, I mean, I think we could all agree that everyone's excited about Gen AI, but there's also a lot of skeptics about the accuracy of it, so we needed to do something to ensure that we could instill trust in the solution.

Nishant Aggarwal:

Yeah. And then just one more thing to mention, I think what Jeff said, what all the great points, right? When we approached our clients, they have seen at that point so many talk to your data tools, right? So they have thought like, Oh, this is another one of those, right? But, the things that Jeff talked about really differentiated. This is a verticalized talk to your data tool, right for real world evidence, users and community, right? We understand their pain points, and this is like that interpretation that's going on behind the scene, like, hey, now you need to extract the right medical codes which could be relevant, right? And those workflows are built into these agents right behind the scenes. So that intelligence is there, if that's why it differentiates from the other talk to the data tools, because this is more verticalized for this so, so, so that also resonated very well with our clients

Dan Housman:

So, you know, I'll talk about that now that I'm data. You guys know, I wrote, like, a blog piece I put out last week or so about agentic AI and cohort building. One of the things at least, I've experienced in even like presenting these things to pharma, has been the heart attack you hear from compliance or safety or epi with the what ifs like, what if someone just self services their way into a publication that launches a safety signal we have, and I've been hearing this since the beginning of time, and I'm sure you guys have too on self service tools, which is, these people aren't epidemiologists. We don't know what their training is, and they could put anything out there, and the damage control could be ridiculous. So I'm curious, what, whether you've had some of those constraints, and if that's going to become a big blocker to getting this stuff through?

Jeff Morgan:

Yeah, I mean, like, like you said, it's, it's been a chat, you know, a cited pain point for not such, just for when Gen AI came about, like it's everyone's been talking about that for, like, forever, right? 10 years, like, in a self service tool like Jeff stumbles across something that could be construed as a safety signal. Now that's going to trigger a whole bunch of SOPs that need to be followed to investigate that. So what we've done within our W E agent is to build in some guardrails based on your role within the organization, what you can and can't do within the solution to help minimize the risk of doing that people could game the system. But we're trying to put guardrails eventually, you know, it all comes down to people. Need to trust their people. But we've also put guardrails within the application to make sure that things like that don't inadvertently happen

Nishant Aggarwal

Yeah, yeah. And I would say the guardrails could be like, you know, before it was, like, pretty limited, right? People can game the system and then say, okay, they still get to the stuff. But with Gen AI, the guardrails, we are putting it at the pace, right, like so you can be very smart, right, like you blocking some kind of a safety signal that the end user is trying to generate which he's not authorized, or trying to compare outcomes of two of two medications, things like that. You can be upfront about it, and then put those guardrails at the base. And then, you know, the tool takes care of itself, the agent, right? So that's where compliance comes into picture.

Dan Housman:

Yeah, I love the idea of and I think it's always gone over well, because it's some of the first place people play with Gen AI is, can we use it for compliance? Can we use it to check things? Because I think it's a great utility, and because you can do it all in the same call it a code base with a bunch of prompts, but they can keep adapting it as they learn. So, you know, I'm hopeful at least, that a lot of those challenges can be answered with the same technology we're using to build the new capabilities for the users. So hopefully adoption won't be as long as some of the prior cycles. Like, do you think this will get adopted fast, compared to cohort building with a, you know, a web app, which is really where we've been for a long time?

Jeff Morgan:

Yeah, it is. It's, I mean, we're already seeing it because the barriers are so low, the challenge with the previous version of self service tools, like we had a Solution Suite, and there's a bunch of other ones out there on the market, they just required a lot of training, right? And a lot of hand holding, all that has been removed, right? It is pretty intuitive how to use these applications now, and it's going to get even more intuitive over time, right? Like, what you're seeing is essentially v1 of what this solution looks like, you know, in 12 months from now, right? It's going to be even slicker and easier and more intuitive to use

Dan Housman:

It's certainly my hope. And we can start talking a little bit like, Hey, what are we going to do in 2026 which is where we're coming into that we're starting to do projects with these tools, and that we're starting to, you know, put them against new data sets and take on sort of second order kind of uses of them. And I think one of the things we're excited at gratitude working with Deloitte on is we have a lot of relationships with different data sources, and maybe we can just move the tool to the data source, or come up with interesting cloud strategies so that we can not have to move the whole data source over for folks to evaluate data, because the fit for purpose problems there, and maybe health systems can start putting this on top of their data and keep the data behind their walls, but let folks chat with it for a reasonable cost.

Jeff Morgan:

I think the data market, or the landscape of data vendors and accessing data is going to continue to evolve. So obviously, in the US, it's pretty mature. Outside the US, you've been focusing on Dan quite heavily and graticule. A lot of those organizations want to maintain control of their data. So we're seeing the emergence of, you know, the term you hear a lot is trusted research environments, TREs, meaning, I'm not going to send you my data, but if you want to use it, you have to come to my, you know, to my platform or in my environment to do it. So what that becomes, what that challenge creates for Pharma is for me to do feasibility for a study. I not only have to do it against the data I have internally. Now I have to go into a bunch of external systems and do it. Maybe I don't know how to use it, everyone's tools are a little bit different. So my queries, you know, my feasibilities, might not be apples to apples. So you know what you know our vision and how we could potentially work with gratitude is, like you said, this could be like a federated network, where within pharma, you have a single pane of glass to do your feasibility, whether the data is both internal to your organization or external to your organization, but it's a seamless experience where You're able to do those feasibilities and light analyzes across a network, and not having to log into multiple systems and learning different different technologies

Dan Housman:

Yeah, it's super exciting. And I also think the hopefully the volume of studies can go up, and I don't mean in a bad way, like, Oh, we're flooded with garbage, real world data studies, but there is a productivity problem to how much it costs us and other groups to go end to end with the study, right? Because there's just so many steps. So we know, I know, I'll say this is still a bit of an infant compared to running a full EPI study. I don't think people are ready to hand the keys of an epidemiologist over, I'll call it chat, GPT, RWE, whatever it is. But if they can be able to do it five times faster, then we can have five different segments of HEOR, or five different segments of, you know, the market, be covered at the same amount of time, instead of, like, manually walking through six months per study to publication.

Jeff Morgan:

Yeah. I mean, we're like, there's an opportunity to compress the time for segments of the life cycle of generating study. So we're talking about feasibility execution here. But then there's a whole set of capabilities that we've been building around protocol authoring for our RWE studies. So compressing the time it takes to generate the protocol and the sap, right? So just trying to take that, what's probably a four to six month timeline at best of executing the study, end to end, right? We could save a couple weeks on protocol. We could save a couple weeks on feasibility. We could save a couple weeks on execution. So when you stack all that time savings up, you're going to get pretty significant savings.

Dan Housman:

And maybe another big thing that is just turning the corner, although I feel like we've been hammering it up for six years at Graticule, at least, is getting into these unstructured data sets that I think have been locked up because they're just so risky to play with, like the full free text of an entire EMR images that are related. Probably the first thing to go is we've been able to at least solve for using some version of these AI tools to do di D but at the same time, we can use these tools to interrogate a big free text data set, and no humans? Well, I wouldn't say no humans. Humans today use abstraction to solve that problem, like Flatiron. When they first set out, I imagine they had all this technology, and then they hired, you know, an army of nurses, because there was no way to do it with the technology. When they started to be able to abstract oncology data reliably off of all the data sets that we're looking at. But, you know, and we're somewhere in between, I think right now, right we can play with it. We can get data out. We might not trust it enough. We're gonna use abstraction at times, but the auto abstractor is like an agent, and it's coming, and that's that's a huge shift for the whole industry on research, because so much in even clinical trials is abstraction.

Jeff Morgan:

Yeah, I remember in my previous life at a data aggregator, just to pull out a single variable using NLP, that was months of work on our data set to do it and structure it and get it to our customers, right? Yeah, like, that's going to change.

Dan Housman:

So I think we're going to have a lot of fun in the next few years. Hopefully it's great to see Deloitte, you know, still innovating like you guys always are, with this gen AI stack and the agentic stack and all that, all that stuff has already come into play. Looking forward to seeing where we can take things together next year, hopefully we'll get some clients who want to test out some innovative stuff, because, because that's what kind of powers it up

Jeff Morgan:

Looking forward to working with you and doing some pretty cool stuff.

Dan Housman:

Great. Well, thanks for taking the time, and thanks to everyone who listened. I'm so glad you guys could provide a demo, because it's so hard to sometimes get, like, the real software on the screen. So I think everyone's, you know, I'm thinking a lot of people will find this a fascinating little discussion we had. Thank you