IxDA Sydney Podcast

S02 E05 - Grishma Jena

Audio Transcript

Grishma: [00:00:00] If you have anything wrong with the electrical wires in your house, you call an electrician. So if you have huge amounts of data and you need the plumbing for it, the infrastructure for it, why not call a data site? They'll start another similar data professional.

Sam: Hello and welcome to the IxDA Sydney podcast show where we can't guarantee answers, just better questions. I'm Sam Hancock. And in this episode, Jess and Vinita are chatting with Grishma Jena, a data scientist with the UX research operations team in IBM in San Francisco as an only data scientist.

In her team, she supports a design and research team of over 80 where she uses data to understand user struggles and opportunities to enhance user experiences. Her research in. Are in machine learning and lateral language processing. [00:01:00] She has spoken and facilitated workshops at multiple conferences, including Web Direction Summit in Sydney 2022.

In our conversation, Grishma delves deeper into her role within user research from figuring out best practices and evangelizing research to understand the maturity of an organization from a researching data science perspective. Let's get started.

Vinita: Hi, Grishma. It's so nice to have you here chatting with us all the way from San Francisco.

Thank you so much for taking the time.

Grishma: Thank you so much for inviting me. It's a pleasure.

Vinita: Awesome. So we wanna get started with a little bit of learning just about yourself. What has been your journey and how do you touch design in the way that you do?

Grishma: Sure. I can give a bit context about myself and my background.

So I did my undergrad in computer science engineering, which I know sounds a little weird, but it's a combination of computer science and engineering, and [00:02:00] that made me realize that I wanted to continue learning a bit more and maybe specialize in a few things. So I went ahead. I did a bio grad school with my master's in computer science and after that I just got a job working as a data scientist at ibm.

And two years into my role, I got the opportunity to speak with the vice president of Design. So he was the chief design officer for one portfolio, ibm. And he said, Hey, we have a lot of data and we're looking for a data scientist to help us make sense of the data. I'm not really sure what this job will entail.

We can work on it together. Just know that there's lots of data to analyze, which I don't think we're doing a good job of yet. And it sounded like something interesting, a challenge of course, cuz it was very vague. It was very open-ended, but something that was very exciting and new as well. So I ended up accepting that and joining the team in 2019.

And the way it works at b m is that there's the larger design organization, [00:03:00] and then within that design organization there is the user research organization. So I was put under the user research organization and I wasn't really assigned to any specific team. I was more of a cross portfolio person. So a lot of my first year was just trying to understand what was the user researchers, still trying to have them get an understanding of what a data scientist does, what are the areas I can help, and just brainstorming on what ways we could collaborate.

So I'd say that's kind of the background. And then beginning 2020 are leadership formed, the research operations team. and they collected all of us who were, I like to call Misfits, you know, non researchers working for researchers. We all banded together. We were all put under the centralized team of research operations and since then there's been no looking back.

Vinita: It's awesome. I love your band of misfits as you said that it's a great concept. So just curious, what other roles were under that research operations that [00:04:00] were non-design and then obviously data science, but curious.

Grishma: Yeah, when we started the first, it was just a team of three of us, so I actually ended up doing a lot of tooling helping with recruitment, which actually gave me a good exposure into, you know, the world of research operations.

But today we have a content strategy team. We have people working towards participant recruitment and management. We have a team of developers as well who are helping us with the infrastructure, and then we have some co-ops and interns, and we also have a few project managers who are helping us streamline all of the different operations.

Jessica: I'm curious to know, Grishma, you mentioned that a big part of your role and of being a data scientist is making sense of data. As designers and researchers, we can all relate, like the synthesis part of the process is obviously the most crucial, the kinds of insights we generate from that. But when you say like making sense of data, like can you tell a little bit more about that?

Grishma: Yeah, absolutely. So I can go a little more into detail about what [00:05:00] I consider my prime responsibilities, and then we can take it from there. So, like I said, when they hired me, it was very open-ended, very vague. It was a journey of us understanding what this role is gonna be like. And I think that process still continues to evolve even today.

So the first responsibility for me was creating and maintaining an infrastructure of research repository, which we are now calling the Insights Hub because it's gonna evolve into something. So just trying to understand what kind of data we need to capture, what do those findings, those insights, those atomic nuggets look like, and how do we educate the researchers to start putting data in that format or start doing this?

This is in a particular format. The second responsibility that I have is to look at our different sources of feedback coming in from customers or our users. So those could be surveys, those could be online reviews, it could be a client engagement. And the problem is that all of these pieces of feedback are very disparate and very siloed away, especially with a big company like ibm, which [00:06:00] has I think more than a hundred different products.

So what we're trying to do is aggregate all of that into, again, a central repository or a warehouse, where we can then start to analyze all of that data and look at the board side or the bigger picture of. Hey, this is the kind of trend we're noticing, or this product is not the only product that's having these challenges.

We've got similar use of pain points in this area of the product as well, or this area of the business as well. So just giving that aggregated analysis of the pain points from the users to our researchers. That's a responsible team. Something else that I do is I also like to think of myself as an internal data science consultant.

So a lot of the times researchers will come in and these are very individual one off. So they could come in saying, Hey, we would like to do competitive analysis to under understand the strengths and weaknesses of our products versus the competitors, but we don't really have the data. Can you help us go mine that data and start analyzing it?

So then I'll go maybe look at online reviews, maybe some feedback service that we've gotten. Perhaps our users have mentioned, Hey, your [00:07:00] competitor does X, Y, Z, but you don't do it. That's frustrating to me. So looking at that kind of data, or maybe they can come and say, Hey, we already have a list of feedback surveys, or We have data from AO study.

Can you help us understand these results? Can you help us visualize what's important to the users? Versus, you know, what should not be a priority. So that's more of the data science consulting, where it really depends on the problem, statement and objectives, hand attack. And finally, I do also act as the in-house data scientist in the sense of being a sponsor user for a lot of our data science and design teams.

Cause a lot of the products that IBM builds is actually geared towards developers, data scientists, data profess. So then I'll be sitting in those sessions with them, maybe evaluating UIs or giving them feedback that, Hey, this makes absolute sense as a data scientist. I love this feature. I can't wait for this to be released.

Or maybe the opposite of this is not really what the workflow of data scientist is. This is a little confusing to me. And giving them feedback of their documentation, or the UIs or the [00:08:00] whole user experience for products.

Jessica: I have so many follow up questions. First of all, I think it's interesting what you said about atomic research because it's breaking it down in a way where it makes it easy for consumers of the repo to use.

Do you have a way or format to kind of write out these nuggets? For people to consume?

Grishma: I think that's something we're still working on, but if anyone else listening to this has the formula, please reach out to us, and I think that's the magic sauce. We're all. With jokes aside, the kind of format that we are following is we have given them these buckets of come up with the objective, what is the problem statement come up with the next steps or recommendations, and then the research methodology.

So that's how they are trying to summarize the project. And then the next steps is where we are going more into the insights part of it. And then from there they can link out to additional resources. But now what part of my role is, which I'm trying to also, you know, understand how to take this forward, is [00:09:00] how can we automate and scale up that creation or that finding of the insights?

Because right now we have a lot of recommended steps or next actions. , how do we find those actually actionable insights or the ones that will make the most impact to the product user experience, or to the revenue? So, I wish I had a better answer for you, Jess, but if we talk a year from now, I will.

Jessica: Yeah, definitely.

Actually, I started helping my own organization build out a repo as. Well, and coffee is a huge culture for us, so I'm trying to try to tie coffee beans to it instead of calling it nuggets. We're still, still work in progress, but the repo is called espresso hub at the moment, But very, yeah, very similar philosophy.

And actually what you're saying, like part of generating these insights for different users is. like you said, like how do you automate and scale? Mm-hmm. These insights and yeah. I'd love to hear a little bit more about that. Like when you say automating and scaling, are you imagining like maybe even democratizing some parts of this research and synthesis process to other team members?

Grishma: Yeah, democratizing the [00:10:00] access, definitely democratizing the research and synthesis part of it. I think that's still a bit of a gray area cause different product teams have different levels of comfort with other people coming in. I think some of them are a little protective about their particular framework and the research methodology, and they are concerned that if someone else comes in with maybe not the same amount of experience or context, they.

Use a method incorrectly or come up with some incorrect findings. But I know that there is this initiative coming up where designers are doing a lot of their self-service research. Where they can take small bits and pieces or smaller projects and maybe researchers can come and guide in. So yeah, democratizing access, definitely that's one of our objectives with the resource repository, with any of the insights, because we do want those to go out to the product teams, the managers, the developers, the executives that actually make an impact.

But with the research part, I think we're still trying to find that middle ground while fully realizing that what might be middle ground for me might not [00:11:00] be the same. I think that's something that each of the teams are dealing with in a especially decentralized manner, which, Jessica, coming back to your point about the insights, I think one question that each team or each company needs to answer is, What constitutes an insight for you?

Now, for me it could be maybe to align summary of, Hey, this is what needs to be done. But we were doing this evaluation of different research repositories in the industry, and I think one of the ones that we came across, which is a famous example, is WeWorks Polaris Repository. And for them Insight is more of a snippet of a video recording, kind of like a YouTube playlist where you can just look at Insights one after the other, which I think is very interesting cuz oftentimes we just think of insight as pieces of text.

We can also visualize it as maybe a graph or a video or something totally different that nobody's really thought of. So I think that's probably something that each of the teams should work on. Maybe just for you, it could be bleeding over coffee where [00:12:00] you are talking about, Hey, hey, these are the insights that I discovered, or these are the interesting things that I discovered.

Why can that not be an insight?

Jessica: Yeah, that's super interesting actually. I think even what you're touching on is like the format of the insight, and I guess that varies for each organization. In your mind with I B M, I'm imagining you have, obviously internally you maintain the repo, but then also you would work with clients as well, which has a completely different format and and process.

In your mind, what constitutes as an insight?

Grishma: Again, I think something we are still trying to discover, but like I mentioned earlier, for me it would be more of an actionable. So maybe a tool line or a three line summary of, here, this is something exciting that we discovered about the product, or this is something we noticed and this is what we recommend to be introduced in the roadmap or to be changed in the product.

Obviously that's an insight for me.

Jessica: I really wanna circle back to your experience as a data scientist then. How do you bring those practices within data science where you have different ways to [00:13:00] organize data and make sense of it, but how do you merge that practice with research ops right now?

Grishma: Yeah, I think that really depends on what level of maturity your organization has with respect to data.

So let's say for instance, and this is something I think I mentioned, right? And my first year, all of the user researchers, the designers I spoke to, were extremely happy, elated. Oh, we have a data scientist, that's amazing, that's awesome. We have so much data. But then they would be like what is it that a data scientist does?

How exactly are you gonna make my life easier? So we had to have a lot of conversations about their pain points and their workflow and all of that. So I would say first one is just analyzing what the majority for data is within your organization. And I've seen a lot of different landscapes because we have so many different product teams.

I've seen product teams that have not much instrumentation in place where it becomes a little difficult because the amount of data that's available to you is not as, [00:14:00] So you can't start analyzing on day one, but you can start planning, okay, if six months down the line we want to answer X extra Z questions, what is the data we need to start collecting today?

Then I've seen people on the other end of the spectrum where they have a huge amount of data. They're instrumenting every possible action on the product, but sometimes it's confusing to understand exactly what has been instrumented. It might be something you think that got instrumented, but actually it's something completely d.

Or just even making sense of what is the quality of this data? Are we getting the right results? Are we getting the right data? Is the data complete? Because that's another thing that happens with data in the wild. You can have a lot of messy data. You can have incomplete, invalid data that doesn't make sense at all, in which case you'll end up with inconclusive results or things that just really don't make sense.

And then of course there's the sweet spot in the middle where you have enough amount of data, which is also complete, which has been well instrumented. People are well aware of exactly how this data is captured, what users are engaging with this kind of metrics. [00:15:00] So from there on, we start to understand what is the problem statement at hand?

Let's look at the metrics. Do we have the right metrics in place? Okay. Assuming we have, let's look at the integrity of the data, the completeness of data, assuming that's well as. Then you go on into seeing, okay, what exactly are we trying to do? Are we trying to predict user behavior? We trying to find different clusters of user segments so we can maybe give them personalized experiences.

We, we just trying to understand what are the top pain points that they're facing. So in that case we'll go more into natural language processing, which is text analytics. So you could look at keywords or frequency of data. What are the top pain points or is it something completely else? So I think that's kind of been my process so far where it's really dependent on what's the problem statement, as well as what is the kind of data that we have at hand.

Jessica: What's a good practice to avoid capturing incomplete or invalid data?

Grishma: This depends on how your products are instrumented. I would say maybe start small so that you're confident of [00:16:00] all of the metrics that you're captured. Maybe you just want to capture two metrics at the start, but as long as you're confident that I know exactly what this number means, as well as what users are interacting with this.

Having a very tight collaboration with the teams actually doing the instrumentation. Maybe those could be your developers or maybe you have an instrumentation team. I think having that ongoing collaboration and communication is very important. And of course before that, in the brainstorming session, make sure that you're capturing only the things that you really need and none of these vanity metrics that actually can't impact your business line or can't actually give you an understanding.

Let's say for instance, maybe you are a social media platform and you're capturing the number of. Is that really something that's gonna impact? Or maybe, do you want to look at conversion? Do you wanna look at number of shares? So being very intentional with what you're deciding to capture. I think that's part of the battle one.

So battle one, is there part two to this ? Yeah. That is making sure that your data is well formatted. I think [00:17:00] that's another issue I've encounted is you might be capturing data. It might be complete, but maybe it's in a very messy format that can make it difficult to transform and analyze. I'm sure we have seen cases where people send you maybe a bunch of CSV files or everything's in a text word format, which is difficult to, you know, take out from that particular tool and analyze it.

So I think that is the other part of the battle probably.

Jessica: Yeah, definitely. And I guess speaking of the whole organization, I think the tools also matter a lot. I guess if you were to describe the ideal research process right now, what kind of tools

Grishma: currently use?.

For me, I rely a lot on open source packages, so my choice of tool is Python because that gives me a lot of flexibility to do what I want to do, whether that's maybe creating dashboards or creating scripts that I can then automate functions on.

I do use some other IBM products as well, which adhere towards Steer side this, which actually I've sat in spots using sessions for. So it's [00:18:00] kind of a nice full circle because I give them feedback and then, you know, I have to use those tools and make my experience. So I use a lot of things called notebooks, which could be Jupyter Notebooks or could be notebooks that are within IBM's product.

So that helps me analyze all of the data. Yeah, I would say that's pretty much what I use, but again, depending on the particular problem at hand, I could end up using maybe some sort of visualization techniques. Our researchers use a lot of air cable in-house as. Sometimes, not that commonly, but sometimes maybe you start to do a very quick analysis of, okay, let's just look at what data is there, what is the kinda format it's in?

But I would say more or less, I do rely on Python because that gives me a lot of control over doing whatever it is I want to do.

Jessica: Wow. That's very advanced analysis. I just copy and paste my CSV notes from Excel into Figma .But I think, yeah, every, you know, obviously every researcher kind of has their own process.

With these different tools and different processes and notebooks that you can set up. [00:19:00] Then moving into the next step, I think one thing you mentioned was finding clusters of patterns or data and even predicting user behavior. I'm so curious about that. How do you go about predicting user behaviors? Like what are samples and stories that you can share?

Grishma: Yeah. I don't know if I, if there's anything I can share per se, but what I can tell you is what the common Data science pipeline looks. So the way we start off with is, of course we have a question at hand and then hopefully we have some data. If not, then I kind of go on the scavenger hunt of data, which is, which I've done more number of times than I'd like to admit,

Cause sometimes the data is just not there. And once you have that, you kind of go through these different stages where you start off with data clean. Because you need to look at the data, be confident that the data is complete. Then you go through the process of data expiration, which is a very initial investigation of understanding, Hey, are these the kind of segments that we expected?

Is this the kind of user behavior we expected? No, this looks a little strange. [00:20:00] Let's see if we can create some hypothesis around it. And then comes the whole machine learning part of it, which is where you start developing models. Now for user behavior that that could be a regression model where you're trying to predict a particular number, or it could be a classification model, so a regression, maybe you're trying to predict what are the number of conversions you're gonna get from this particular web page, or for a classification model.

It could be, we are trying to predict will this user convert or not? Will this user be a part of the churn on our product or not? So that's having those buckets would be classification. So there are different machine learning techniques that you can use for doing these particular analysis. And then once you get a model in place, there have to be some evaluation metrics.

You look at those. It could be the accuracy. How many answers did the model get? Right? It could be the precision, it could be just looking at the different metrics of the model, how close it was to the correct answer, or does it have any weak points where it's not able to consistently detect a particular type of user?[00:21:00]

And then you go back, maybe you change the model. Maybe you'll combine a few different models. . Once you're happy with the evaluation, the metrics are good. Then you go into the process of data visualization and storytelling, cuz that's really important, right? You could be the best data scientist and you could have the most amazing machine learning model.

But if you're not able to actually interpret and communicate that out to your stakeholders, to the executives, to the people who can actually make a change, it's gonna be pretty much use. So I think that's, again, something that needs to be really focused on. And then finally, hopefully at the end of it, you'll have some actionable insights that you give them saying, Hey, this is kind of the users that we observe these other clusters.

This was something not very obvious to us, or this is the kind of prediction we have in place. Maybe we are confident at the level of 70%, but six months down the line, if we get in more data from X, Y, Z sources, or we can just see if part analysis is correct or not, then we can go back and retune or refine those models.

One particular example, well, not from IBM per se, but [00:22:00] something, one of my favorite examples for data science and user research is actually from Spotify, Australia, if I recollect right? And what happened was that this was back in the day where they were still unveiling the feature of skipping ads. So unlimited number of ads.

And they had these power users that they were testing it and they had six par users. And there was a user researcher, user research team, user research design team that was analyzing, okay, you know, what does this look like? And one of the data scientists who was helping them out noticed that there was this one particular power user who seemed to be hitting some sort of an artificial limit with skipping ads.

And this is Unskipable ads, so this limit should not. So they've worked with e devs to try to understand is there a limitation on technically is this person having some sort of an error, some issue that looked good. So then they went to the user research team and said, Hey, you know, can you help us understand what's happening here?

And then they ended up doing a diary study cuz they wanted to [00:23:00] understand why this is happening, how this is happening with this particular user. And what they realized was that this user actually had this mental model that they could skip only six ads because the number of songs that they could skip was limited to six.

So there was this other limit in the platform that the user thought would apply to skipping ads as well. And they just said, okay, you know, I can't skip more than six ads, so let me not even try. So this was a very interesting example where, you know, user research, design data, scientist Dell, they all came together and they could only see a specific part of the picture.

But then when they all worked cohesively together, we saw the larger. This person has this misconception that they cannot skip unlimited ads. They can only skip six ads. So this is one example I really love cause it shows the power of working together from different disciplines and actually breaking down those silos.

Jessica: That's really powerful. And with that merge [00:24:00] of the practice of research and, and data science, you're also creating efficiencies as a team, right? Because I think going back to the point of automating, getting insights and that whole process, because you're machine learning, creating these models to do this machine learning, and it only gets more and more accurate each time.

And with the metrics that you might have defined, you're only getting better at predicting some of the behavior. And as a result, you can create better solutions or, you know, find better ways to solve these problem.

Grishma: Completely agree. I cannot tell you the number of times I've seen researchers painstakingly manually copy data, transform the data.

Jessica: That's me. That's me today.

Grishma: It breaks my heart, and that's what I'm trying to do is I'm coming up with these automated scripts that I can hopefully hand over to them. You don't need to come to me. You don't need to wait for my reply. Here's the script. Give it your file as an input. Get this as the output, and just run ahead with it.

There is just so much opportunity for increasing the efficiency and a lot of that is even low [00:25:00] hanging. I noticed some data scientists and to some engineers might not seem like the exciting problems cause you don't have like machine learning ai and you know, all of those fancy things come again. But just imagine the amount of relief you are offering to your peers in research and design, right?

How much, how many rs are they saving on average in a day, in a week in a. And think about what they can use that time for. Maybe they can use that time to speak to more users or to get better buy-in from our executives or from our product managers, or try to convince product managers that, Hey, this feature already needs to go into the roadmap because we've heard so many pain points from our users.

I think it's, it's definitely a huge, huge opportunity fear there, and hopefully more and more people come across to doing, Yeah, for sure. Maybe the metric for the research team is the number of minutes or hours you've saved. researching the researchers. That's something our team says. No, we are very meta.

We're researching the researchers like, [00:26:00] yeah.

Jessica: Yeah. Right. So for teams without the luxury of a data scientist like yourself, what are some steps you would recommend for them to kind of get started to move into that direct? .

Grishma: Honestly, I would say if they do have the interest in the bandwidth to start picking up some sort of a programming language, that would be the ideal case scenario.

That could be R, that could be Python, that could be Java. Anything what you feel comfortable with, cuz the amount of time that you can save by, you know, automating something, or you write one line of code and have it iterate over 50 different documents. You're saving time, you're scaling that. But if you're not that comfortable, I would say a lot of these tools out there in the market like Airtable Dub deal, Coda, so many of those give you that no-code, low-code introduction where you can start using some of their automation workflows, some of their Synthes tools I know our researchers use Enjoy HG for tagging purposes.

So I'd say just [00:27:00] starting to introduce yourself and getting familiar with having a tool that's helping you do the analysis that's helping you do these Synthes. If you don't have access, so you can even start off in an Excel spreadsheet. You can use macros or you can use those visualizations and get a little comfortable with that, and then slowly build your way up to a programming language.

I would say that would be my biggest recommendation. And also think of it from your career perspective. People who have quant skills, they are definitely needed. Right? And they, that's a hard skill on the job market. It makes you a lot more attractive as a candidate to the companies, to the industry that you're working in.

Apart from that, I would say something that everyone can do is just collaborating. Going a little outside of your comfort zones. Maybe your team doesn't have a data scientist, but maybe some other product theme or some other part of the company has a data scientist or a data analyst, or maybe even an engineer.

Go and talk to them, see what tools are they using, what is their workflow [00:28:00] like? Is there something that you can reuse them? Is there something you can collaborate with them on? And if in the event that your company doesn't have maybe a work for a really small company, talk to someone in the. Everybody's just so willing to share their experiences and their journeys with you.

Maybe they already have something that you can, you know, latch onto, you can start using. So I'd say those would be my top two recommendations.

Jessica: Yeah. And exactly why we're talking to you as well. Right. There's so many nuggets here that you're sharing with us, and it's super helpful.

Vinita: Grishma. I actually work on a data science team as the only designer.

So maybe we're soul sisters in a completely opposite way. But one of the things I emphasize in the kind of research and design work that I do is that we need to bring the human aspect to data science. So curious to hear about where do you see data science not being the be all, end all, and us not living in a automated [00:29:00] world with robots that have already predestined each of our actions and behaviors.

Grishma: I'm so glad you brought that up. Cause I think even working as a data scientist myself, it's so easy to forget that human aspect of it. The human element of it. And there was this quote I was reading the other day that said, Behind a data, behind every number is a user like you or me is a human generating that number.

Of course, unless you know it's sensitive data, which we'll not talk about to date, but it's so hard to forget, you know, that there are people like you and me, there are humans behind each of those numbers, each of data points that we are analyzing. And in terms of that, I feel like one things that I have learned while working with designers and research.

They've taught me how to be more empathetic towards the users. But that just comes with your job role, like trying to get into the shoes of the users, the heads of the users understand how they feel, why they're feeling this way, what can we do to make it better for them? So that's something I think developers and data scientists, people on the other [00:30:00] side can learn from.

Just try to be more humane, more empathetic around their experiences. The users, experie. Another thing is that at the end of the day, you do need someone to understand if what the analysis is saying, is it right, is it drug? Is it missing something? So that interpretation part of it, you definitely need someone to be there.

The human in the loop, and a lot of the things that I've mentioned and I know so far have mentioned, okay, I have these scripts and I have these tools, open source packages. . But what I fail to mention is that I collaborate very frequently with our designers, with our user researchers, and they're the ones who come in and tell me, oh, you know, this data actually means this.

That is similar to what you're already capturing here. Let's not do that duplicate thing or, oh, actually for this particular product and interaction for a user is this, or you know, this is what a web page is like, or these are the different product terms we're using. So this is what is important to us, because for me, I'm not the subject matter expert.

I rely on the expertise of [00:31:00] our researchers, our designers, to tell me, okay, these are the different sub-products. These are the terminologies that we're using. These are the specific keywords. This is what a user means when they say a dialogue or a floor or an attraction. So definitely very important to have that human in the loop element.

And this reminds me of another case study. This was from AB and amro where I think they had some sort of meta tagging system for their customer service. Something like a customer service organization where they wanted to come up with different tags for user questions or providing support. Whenever they have support tickets opened up.

What they did was why not have machine learning, cuz we can. So much data. Let's go ahead. Let's see if the machine learning model can predict the tax for it. And went through all of the different process of data science that I mentioned, like exploration, creating those models, validating all of that, and the metrics.

These course came out to be really great. Everyone was super excited. Everyone knew it was gonna be a [00:32:00] success cause they had 90% accuracy and off the charts numbers. And then the user researchers go and test the model in the wild with the support. and what happens was that it was a complete disaster.

Terrible scores, the time on tasks, shut up. Nobody knew what was happening, and that wasn't what was supposed to happen, right? Because the model had such good scores. And what they realized was that initially when the support agents, they were using their own brains, right? To think, okay, what are the tags that could be responsible for this support ticket?

But now when the machine learning model was introduced, the model was really good at suggesting tags. Also was really good at suggesting a huge number of tags. So now the model is suggesting 20, 30 tags that the agents had to manually scroll and think, oh, is this tag relevant or is this appropriate? Or is this what support?

So that actually increased their time on task because now the model was giving them that information overload. [00:33:00] The agents were now spending more time on that, going through that list. So then only because the user researchers stepped in and conducted that usability study, they came in, they went back to the data centers and said, okay, this actually is a failure, even though it looks really good on paper, because this isn't the experience that we are hoping for.

So then finally, I think they came to, you know, a good understanding of, okay, the, let's suggest maybe five tags or 10 tags. But that was one very interesting example for me because like I said, it's not that data science is the be all and the end all. We definitely need those humans in the loop, whether it's in terms of making good models or in terms of understanding of these models are actually doing what they promised to do or what they set out to do in the first place.

Vinita: Yeah, I think that's a really good point, and I love the example that you shared with us too. I'll speak from a design perspective. I think we can forecast that this is something that would happen, but I think sometimes, for lack of a better term, shit needs to hit the fan before we can see [00:34:00] those examples actually play out and see where and why we need both design and data science one the same page.

So it's really, really great examples. I wanted to shift gears just a little bit and talk a little bit about org structure. You talked a bit about how, because you're researching the researchers, you sit at a platform level is what I'll call it, and I'm using air quotes at the moment because that's maybe not the right exact term, but where do you see the work that you do starting and ending?

I think one of the biggest things with some of. Teams that we work on is also being able to say no to certain kinds of work. So where is that happening for your team?

Grishma: I can give a slightly more in-depth explanation of the org structure. So like I mentioned, we have the design team, the design organization, and within that is the user research organization.

Within the user research organization, we have about six, seven different. Where one of the teams is the research operations team that I'm on, but all of the other [00:35:00] teams are different product to business units. So we have one business unit for security, one for automation, one for cloud, and so on and so forth.

And then all of these are comprised of researchers, user researchers, who then interact with their design counterparts, their dev counterparts, their PM counterparts. I would say a lot of the work I've done in the past has been mainly focused with user researchers, but occasionally also working with.

Designers with product managers. So sometimes they have the need to do competitive evaluation or gain a better understanding of, you know, the data that we're capturing, maybe from feedback surveys. What I do see in the future happening is that, especially when we talked about having those insights, democratizing access to those insights and making sure that you know, the people who are actually in charge of making that change happen, listen to it.

I feel like we are gonna start impacting all the different aspects of the product. So that could be product manager in terms of actually [00:36:00] telling them, Hey, these are the sort of pain points that we listened to. Here are the researchers who have worked on this. And combining with the researchers, we go up to the product manager and say, okay, we propose that in your upcoming roadmap, X, Y, Z should be prioritized.

This particular thing, is it as important? Or maybe you're only listening to that one really loud, high paying customer, but actually here are 50 other customers who have a completely different experience or expectation. So I think kind of just level setting with the product managers. I know what some researchers and our company have started doing a bit is.

Opening issues within the dev environment. So developers use GitHub to track their issues. So maybe there are certain errors or bugs that users are consistently facing. So researchers find that they're hearing that from their user interviews, and then they go and tell the developers. So I think that's again, another avenue where we can have some sort of collaboration with the developers, where we say, Hey, this is what we're seeing.

This is a technical [00:37:00] challenge that we are facing. Or maybe we have another feature in mind. Is this technically feasible or, So again, that's the depth angle for it. Executives leadership, of course, you always need their buy-in. A lot of times. The other stakeholders, they need to see the kinda work you're doing, the impact of it.

And actually just overall establishing research as something that's not just nice to have, but something that's really needed to have that seamless user experience. Cause what's gonna happen at the end of the day, if your users don't like being on your product, don't like interacting with your product, they're gonna leave your product.

And that's gonna impact your bottom line, that's gonna impact your revenue. And I feel that is so easy to overlook. A lot of people don't really realize that research design that's so crucial to your users staying on the platform. I mean, think of it, I'm sure in our day-to-day life, we interact with so many different products that just leave us very frustrated.

I know for sure I have had interactions. Maybe the buttons is supposed to be clicked, but it doesn't get [00:38:00] clicked or some popup shows up. That error is completely understandable. And it makes me so frustrated. I don't feel like using that product, but I also don't feel like countrying with my day. After that.

I just wanna go, you know, either hit the punching bag or just take a nice walk, take some nap, maybe drink something that'll calm me down. We really fail to realize the impact on our emotions and on our lives, on our mental health. Maybe that the products that we interact with every day. And of course I'm not saying that this is, I personally don't work on a product that's saving lives of people.

No, not that. But it does make some sort of a change in your life, for better or for worse. I think I went off on a tangent there, but I just wanna underline how important it is for companies to understand the value of, to use research. And I'm saying this as a data scientist who had been, you know, in the devil, in the data science world.

And that's definitely something I've come to appreciate over the years, and I've been very. To have had that exposure to understand the kind of work that designers and [00:39:00] user researchers are doing that you know, this is something really important and we absolutely must do this as part of every initiative.

It's not just a box that we need to check.

Jessica: That is so true. And actually I think speaking of communicating and conveying the importance of doing research, I think a lot of it is what you touched on earlier about storytelling and especially with organizations who aren't quite there yet in terms of embracing research as a regular practice.

What are some things that you have tried to bring others onto this journey and being able to story tell the importance of research?

Grishma: I think what we have tried doing that and we are definitely seeing different levels of accepting that research is crucial, the design is crucial, so we've gone to parts of the company that have been very successful in that collaboration, in that tighten it, working together with PMs and devs and we've taken some successful case studies from there.

And gone to the people who are maybe not as convinced and told them, Hey, you know, actually doing [00:40:00] this particular redesign or research, it led to a conversion of maybe 10% and the users that we received, or it led to a lowering of number of support tickets that were opened on average, which of course at the end of the day saved us money because both cost a lot of money.

So I think just having those successful examples, again, they don't have to be from within your company. They could be from within the industry. They could be from maybe a peer of yours. But taking those successful examples and actually showing the impact in numbers, I think is really valuable. Cause a lot of times, a lot of people want to just.

See those business metrics being impacted, whether in terms of the amount of money you are saving or the number of users you're increasing, or the increase in revenue that you have, just tying that sort of metric or that financial value to certain research activities, that could be very interesting. And just last week actually, I met Claudia, Natasha, I hope I'm pronouncing her name right, who is the director of Insights at HighSpot, which is under the [00:41:00] unicorn startup.

She came up with this Uxr valuation model, and she was telling that how as researchers, designers, we feel uncomfortable assigning that monetary value. Everybody else does that. Product managers do it, devs do it, executives do it. And if we wanna survive in the industry and we need to really show our impact, we need to show our impact in terms of those financial figures.

Jessica: What are some examples of some of these metrics that we could define, especially in terms of how it impacts the bottom line?

Grishma: Again, I think it really depends on your particular project, but what I've seen some people do is see if there is a decrease in the number of support tickets or the number of issues that were open.

See if there's an increase in the number of users, decrease in the time on tasks spent. I know some people also just look at revenue as an aggregate and then just divide that to see how much value per user is contributing towards the product. So if you're increasing, if you have maybe let's say five users that signed up last month, then you can see, okay, [00:42:00] what is the average revenue that we get from a user?

And then multiply that by five and say, okay, you know, this is the kind of increase we have seen. I would say those are the sort of metrics, but really it's definitely an open-ended question and something that we all should come up with better numbers for. Cause one of the challenges is that research can often take a long time to do, and by the time it actually goes into the product and impacts maybe the user who suggested the initial idea or who complained about that, we don't know if they're still on the platform or not.

Or you know, maybe a lot of things have changed. Maybe a product has undergone some sort of a revamp. How do you know that this is tied to that particular activity that you did? So I would say that there are certain assumptions, some best yeses that you need to employ. But again, at the end of the day, maybe something is better than nothing.

Vinita: I love that there's always baby steps, right? And I think you've done a really great job of talking and adding that caveat that it's really dependent on the maturity of the organization, how they're looking at the data, how they're looking at design, how they're looking [00:43:00] at research. Because sometimes, we push too hard because we think we're at a certain place and sometimes we don't have enough and we have to go out and build a business case to bring those people and those resources and those tools to us because we've grown too quickly potentially.

And IBM obviously is a large organization, but we can start to see that there's similar struggles in different ways just based on the team. Rolling into that. How do you see your role growing or what kind of next steps that you see? I know you touched a little bit on things that need to still be figured out in terms of how we define insights and those specifics, but on a higher level in the organization that's quite mature, how do you see your role growing and the team growing?

Grishma: That's definitely something I'm wondering and having conversations with my leadership about as well. So I'll say T B D is the shorter version. With the longer version is that what I would love to see happening across the industry, not just at ibm, across [00:44:00] at IBM too, is maybe we need to start having a group of data scientists that cater to our researchers and designers specifically for, you know, tasks in this.

Sure there are people who help you with instrumentation and analyzing the data, but can we have data scientists that do this full-time so you don't have to, you know, beg, borrow steel.

So I would say maybe, let's say a few years down the line, I would love if there is an organization of data science within research and design that I don't know if I'll be leading or I'll be supporting.

That would be nice. Definitely a stronger collaboration with our product managers and developers. That's something I'm starting to see in bits and pieces around the organization, but I think having a better education of what research adds, how design contributes across the entire company and with product managers, developers, engineers, executives coming on board and really understanding the value and importance.

I think that would be definitely [00:45:00] something I would love. I like to think of myself as a bit of a middle person right now because I come from data science and engineering background, but at the same time I've been working with user researchers, so I feel like I can help bridge that gap, come with that common language and start some talks around that.

Otherwise, definitely see me focusing a lot on insights management. Trying to think of how do we come up with that architecture. It doesn't have to be just a repository, but it could be insights. And now again, we can go into what those insights mean, but just looking at different streams of data and acting as a connection for all of those teams of data.

And that's something I've been doing since 2020. I've been having conversations with different parts of the organization or different. Across the company because there's data that sales teams are selecting. Maybe a proposal went through or maybe they had a loss. Why? What were the concerns? Having a conversation with product managers cause they're the ones who are engaging with our clients, having conversations with our user researchers.

Because they are the ones who are talking about the user experiences. So having all of these disparate sources of [00:46:00] data, but how can we actually centralize that and operationalize all of that so that not just our design and research teams have access to it, but also anyone else in the company that has a business need for it, has access to it.

I would hopefully like to see my role evolving towards that as well. And the kind of analogy I like to give is that if you have anything wrong with the electrical wires in your house, you call it electric. So if you have huge amounts of data and you need the plumbing for it, the infrastructure for it, why not call it data science? Or another similar data professional.

Vinita: I love that. That's such a great analogy. Kind of our final question that we always end on is any resources, books, media. Would you recommend just to start off, just to start learning or as Sam says, things you hang your hat on. Sam wear as a hat all the time.

Grishma: Very cool way of saying that. I was wondering what that meant. I would say I personally like [00:47:00] reading blog and articles a lot, so I kind of veer a little towards that. There are a lot of articles, well, Nielson, Norman, user interviews, user testing, they're coming out, discard. They're coming out with all these amazing conferences and blogs they published on a periodic basis.

Those are really. Kate Towsey has been writing quite a bit as well, and she was the one who actually came up with the term of research operations and is one of the, you know, founding figures in the field. Definitely look at her work. Jake Burghardt is also writing a lot about insights management and insights platform, and he's publishing on Medium and his own blog, so that's something I'd already like looking at in terms of books.

I do know that there is one book in the works, but I'm not sure if I'm allowed to say that it's in the works. By someone known in the field. So I guess we'll wait for. What I really like doing is looking at case studies of how different companies are dealing with these different problems and looking at conference stocks, and I feel like that gives you a good breadth of, hey, maybe someone in a completely different industry has those same problems.

Just [00:48:00] that sense of kinship that, okay, whether you're a small or large organization, whether you're a tech company or a healthcare industry, We are still having those same limitations, the same issues, and I believe there's also a research ops Slack community that a lot of people are part. So if you wanna get started with research ops in general, and of course if you wanna get started with anything related to data analytics, you have Coursera, you have edX to start with, any of those foundational courses, a lot of great books on Python as well.

Just honestly pick up something that you are comfortable with and then from there, just go.

Vinita: Awesome. Thank you so much, Grishma. It's been so good to hear all of your insight nuggets through our recording today.

Grishma: Thank you so much for inviting me. It was absolutely delightful to have this conversation with you all.

Sam: And that concludes our latest episode of the Sydney IxDA podcast. Grishma's wonderful case studies, including one about Google AI and qualitative analytics [00:49:00] can be found at ixdasydney.org alongside the audio transcript for this episode.

Grishma: Hi, this is Grishma Jena, and you've been listening to the IxDA Sydney podcast.