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AI MATURITY FROM EXPERIMENTATION TO IMPLEMENTATION PT. 1

VIDEO TRANSCRIPT

Xiaopeng Li [00:00:00] AI is moving from the age of experimentation into the age of implementation.

Per Österman [00:00:13] Hello, everybody, and welcome to the AI Leaders podcast on Data and AI Maturity. My name is Per Osterman and I'm leading Applied intelligence in the Nordics, helping our clients to become data led. And together with me today, I have a Xiaopeng Li from Microsoft. Please introduce yourself Xiaopeng

Xiaopeng Li [00:00:32] Absolutely and nice to be here with you, Per. So, my name is Xiaopeng, and I lead AI business for Microsoft Across West New York market. Also covering the Nordics. So, my role is really to look into the strategy and go to market for our AI portfolio within this region. So very excited to be here today and talk about AI.

Speaker 3 [00:00:53] Yeah, it will be super interesting topic we will cover is where we will talk about AI maturity and I think AI maturity in my normal work of working with clients across the industry in the Nordics, this has popped up, as a super important topic actually get the value out of AI. From all the investments you do in technology and in creating infrastructure in the company, making data flow freely. And I think the scaling opportunity lies between the people, right? The talent and AI maturity is super important. What is your reflections Xiaopeng on when it comes to touching on this subject? Most likely in many of the different markets you're working in.

Xiaopeng Li [00:01:32] So first, I think, you know, it's becoming increasingly important as a topic, right? Because I think that, you know, we as an industry are progressing, you know, so much when it comes to, you know, how we work with AI. I think some experts within the domain, you know, use the phrase that AI is moving from the age of you know experimentation into the age of implementation. So, in the past years, we see more and more AI projects moved into production. So, I think that's why, you know, it's more important than ever to talk about AI maturity, because now, you know, organizations are now not only thinking about if they should do AI or not, because most organizations think A.I. is a must for them. By some more you know, how they can do AI effectively, how they can scale AI across their entire organization. Right. So that's when we start to think about maturity. So obviously, you know, for organizations looking into this one, they normally start with assessing their maturity where they are. And then of course, they would be looking into how to, you know, enhance their AI maturity and go further in their journey of AI adoption. There are probably, you know, tens or if not hundreds of AI maturity models out there. And there are different frameworks and there are different structures for people to talk about AI maturity. One particular simple framework I tend to use is the three pieces, so people, platform, and process. I think, you know, when it comes to Ai maturity, you have to start by thinking about, you know, if you have the right talents know within your organization, it doesn't necessarily mean you have to hire new people. You could also be reskilling your current employees, right? You know, think about your developers. You know, how to turn your application developers into A.I. developers and how to train your data analyst to become more data scientist and also how to infuse AI knowledge into your leadership. Right? Because quite often, you know, actually in most cases, AI is not only a technology code topic, it's also a cultural topic. It's also a topic when it comes to, you know, improving business processes. So I think the people aspect is, you know, definitely, you know, primary in the conversation when we look at AI maturity and then obviously, you know, we also need to look at the process because, you know, quite often, you know, we use AI to automate the process, to optimize process, you know, in manufacturing, you know, for quality management or in e-retail for personalization recommendation, etc.. So, I think, you know, you need to think about how to, you know, infuse AI into your business process. But at the same time, you also need to think about how you can fine tune your operating model as an organization. So, your organization are actually ready to infuse A.I. into, you know, different parts and different business process and different applications. And the last part would be, you know, platform. So, I think, you know, obviously, you know, A.I. is a technology enabler. So, I mean, at the end of the day, we're trying to solve business problems. But then of course, you'll want to have a, you know, solid and also state of the art platform that can support your development deployment and, you know, optimization of your AI and machine learning solutions.

Speaker 3 [00:04:49] that's interesting. I read a study a few years ago or couple of years ago, 2020, about the impact you can have, even if you invest heavily in the technology, right? Maybe moving a legacy into a cloud platform and changing some of the way you work within the data and AI organizations. Right? If You could get the full organization, also the business functions, actually understanding the value and how to work with value. Get the insight from the data. You can have a tremendous impact on the overall enterprise value. And some of these companies, the platform companies, superior ones they have reached a stage where they're very mature. Obviously, a lot of other industries, more legacy industries, have the potential to increase maybe 2 to 3%, 4% of the enterprise value doing it right. Getting the people really to scale up. So, I think the potential is really to move the needle of the business functions, which are normally not very deep. They don't have maybe origins in data science or working with data in the way many of the data AI organizations are doing. So, I think the potential is that holistic view on the on the full enterprise and breaking deciders, making data, actually gluing together the functions and from that, creating value, a new way of working. What is, in your view Xiaopeng, the way you can establish the AI maturity, you talk about the three pieces, right? But really, even if you work with people, right. How do you get the people actually upskilled on data and if you prey to the nonbelievers, the business functions, how do you get the needle actually moving in their area? What is...? Do you have any tricks or any experience on how to make them actually become the believers?

Xiaopeng Li [00:06:53] Yeah. So, I think, you know, that's a very interesting question because I think, you know, first of all, it depends on where the organization stands today when it comes to AI maturity and their journey for AI adoption. Right? And then I would offer different advice. So, you know, I think, you know, if an organization is just getting started with adopting A.I., I think it would be really helpful to have a role, either a formal role or an informal role as an AI ambassador or an AI evangelist for the organization. I was recently chatting with the chief digital officer of Telefonica, and he talked about it when they started their AI journey and that's between 5 to 10 years ago. And they actually had a formal role as an AI evangelist within the organization, you know, who is pretty much going around, you know, spreading the knowledge and awareness around the A.I. because, you know, back then AI was still a new topic, and they are just getting started with AI experiments. So, it's so important to have somebody really spearheading, you know, building the knowledge around AI within the organization. And then but for organizations who are a bit more mature, you know, who have started working with experiments, who are looking into scaling A.I., I think, you know, that's where they need to think about how to bring different competencies together. I think, you know, for example, you know, you need to have, you know, your data scientists, your machine learning engineers, your domain experts, your industry experts working together. I was recently chatting way down with the head of AI from Shell as well, Amy, and she talked about, you know, how they actually, you know, embed, you know, different competencies within different business units. So, one way they are doing that is they embed their data scientist into that different business unit within Shell. So, they learn the domain knowledge and they work with the domain experts, you know, on a daily basis. Or they could also do the other way around that they could invite the domain experts to spend, for example, 20 to 30% of their time to work with their data AI team. So that way they make sure all the domain knowledge and industry expertise are actually infused into, you know, the design, development and deployment of AI and machine learning solutions. And I think that's just so important. So that's from a people point of view, right, that you have to, you know, obviously increase the knowledge awareness, but you also need to bring your talents together.

Speaker 3 [00:09:22] Where do you place if you have...? We're talking about the examples who broke up. Sounded like have a spokesmodel More or less. You have a hub of data and AI kind of core, you know, a group level, maybe a function and you also have sub functions in different business areas who actually are the ones closer to the market, closer to the customers, customer, etc... And how did I mention that? That's a common topic we normally are working with clients on. How do you mention? First question could be where do you put actually your data and AI organization? Would it be an I.T. Would it be in between I.T. and Business or a business, right? And then the second question would be, when you create the hub, how big should it be? Should it be big in the beginning and then shrink or, you know, can you reflect on that? Because I think it's really the business you are in. But it's an important question how to get started. What was it to get the adoption working right?

Xiaopeng Li [00:10:21] Absolutely. I think that's a very, very good question. And again, you know, it depends, right. I mean, which is the answer to everything. But to simply put, I think, you know, for organizations who are early in their journey of adopting AI, I think it would be more practical and also faster if they establish an AI center of excellence, which is a centralized organization for them to really create competence an AI community of practitioners who understand, you know, how to prepare data, how to train models, how to deploy A.I. solutions. I know, of course, that they would serve as a, you know, centralize the unit to work with different business functions. So, I think that's a good starting point because you need to build your companies from somewhere. And if you're early it doesn't make sense to have eight individual data scientists in every business unit where you know, they have silos, they won't be able to share knowledge, they won't be able to help each other and co-develop solutions. So, I think, you know, a center of excellence is a great starting point for, you know, organizations who are, you know, slightly early in their adoption journey. But then again, I think if you look at organizations who are quite a mature are quite advanced in their journey, then, you know, they would have a more probably hub and spoke, you know, operating model, as you mentioned. So that means they will still have a centralized unit somehow as a competence unit and they have a pool of data scientists and, you know, machine learning engineers which they can leverage to support different business unit. But then they also start to embed even more specialized, more, you know, domain experts. So, data scientist way the specialization and domain expertise within business unit. Let's take the example of a oil and gas company, right? There you probably want to embed a data scientist, Way of understanding of geology in your unit for exploration, right? Because that's where they not only need to understand data science, but also how you know, how you investigate the different landscape, but how you identify opportunities for drilling for all your platform etc. So, I would say, you know, that's for more mature organizations, you can have a hub and spoke approach. You can have a centralized of the unit while embedding resources into different, you know, business divisions.

Speaker 3 [00:12:48] And I guess one common problem, because there are scarce resources who are really if you have the combination of deep industries like subsurface exploration in the oil and gas industry, that's very rare, very narrow. If you don't, you know, get your team together, you're probably are risking a flight risk or there is an attrition risk of your most valuable data scientist because there will be no... They will not be able to expand on their competencies and solve the most difficult problems, if they are alone. As a team you'll probably be much more effective in finding the real problems and teaming up on solving them. You need a number of data engineers per data scientists, etc., etc. So, you need to have a team together.

Xiaopeng Li [00:13:35] Exactly. Exactly. So, I would say, you know, it's always a balance of, you know, speed and also, you know, sort of scale, right? Because of course, you know, if you embed, you know, those resources within individual business unit, they are closer to the business, they are closer to the decision makers and they make things happen faster. But if you want to do things consistently, effectively and at scale across your organization, that's where you need to centralize the competence, centralize the way of working and the tools and platforms they use. But then of course, I think regardless, as you pointed out, it's very important to foster internal community. So, when I say community, it's not a formal organization, right? It's basically a group of professionals who, you know, practice similar technologies. It could be a community for AI, a community for, you know, data platform, data analytics, etc... And those resources could be sitting in the same team or embedded into different business unit. I think, you know, either way, that community building is so important, especially given how fast, you know, AI technology is developing nowadays.

Per Österman [00:14:47] And I think silos in a way is a typical problem of legacy company, right? You have a lot of silos and maybe optimize your AI solutions for one specific function, but you leave others you know untouched. And if you can enable this community, you probably have it easier to go through the silos and actually expand. Data is the Common denominator between the silos and get more value out of that. So, I think it's a good reflection. And many clients I'm working with right now they're talking about self-service, democratization of data and how to enable democratization. We talk a lot about data products as well as being the, you know, the outcome from a data & analytics and data and AI practice, right? Really To have these data, data domains, the data models in a place where it can expand maybe multiple data use cases based on the data progress into a specific area. What is your reflection on that? Is that something you come across Cross-industry or...?

Xiaopeng Li [00:15:53] Yeah, absolutely. I think, you know, data as a product is more and more, you know, embraced as a design principle, if you like, you know, for many organizations, because I think, you know, more and more they realize, you know, data analytics, you know, should be something that is almost considered as an internal provider for the rest of the organization. Right. And you're not only providing technologies, solutions, but you're actually providing products which are, you know, which can be, you know, integrated into other solutions. Well, you know, other business processes. So, I think it makes a lot of sense when you trade your, you know, outcomes of your data analytics process as products. And then of course, you also establish a certain level of SLA within your organization. So now that you know your internal, you know, data products can be trusted by different teams, and they build on top of each other. And I would say, you know, I see similar things from AI and a machine learning point of view as well, because, you know, as organizations mature, they will start to deliver, if I may, AI products within the organization as well. By that I mean they might have trained a let's say, a machine learning model for demand forecasting, or they have a trained machine learning model for, you know, personalization. And maybe the training process happened within one business unit, but then the outcome can be reused by another or the rest of the unit, business units, right? So that's the scaling we want to see. So, I think, you know, data as a product or machine learning model as a product, that's definitely a trend that we're seeing more and more, especially for more mature organizations. And that's definitely, you know, a practice we should embrace because that means, you know, we are making our solutions repeatable, reusable. And that's of course, you know, helping us to, you know, keep the costs relatively low and making sure we maximize the impact.

Per Österman [00:17:53] And I guess that has to do with maturity, right? Because if you are starting the journey, you cannot just go directly, you know, you cannot jump into that area directly. You need to mature up to that level. I guess if you have a center of excellence or a hub, it's easier and it's well established that you don't need to push all the time. You get the pull from the business functions, then it's much easier to get that working right. The way we did in Accenture and AI maturity started, we found, you know, four different categories of companies in terms of maturity. So, one is the really AI high achievers. These are the ones who actually have the C level of the company actually establish themselves as we should become data driven, and we should fuel that across the whole company, work across our silos to really get data to bloom together. And we need to measure value and outputs right from AI. And 12% of the companies we actually did research on have become AI achievers. 12% were also AI builders, so they invested heavily in creating infrastructure, a data foundation platform, but they have not actually come up to C level to say this is a promise for the whole business. And that is not a promise for the market either that we should become data led. It's just very good infrastructure, 30% are AI innovators. So, then you have the opposite, right? You have the leadership of the company saying we should be data led this is super important. AI will be the promise of the future. We could create a lot of value from it. But there is no data platform, no infrastructure really, which can taken away. And as many as 63% of the companies we did research on are experimenters and that's the bigger number. Right? And the reason why they are experimenter is that they have both from a leadership position said that we would like to become AI and data led and we should create much more business on it. We are starting to build the infrastructure, but really, they are not scaling as they want, right? So, they don't see the value from all the investments. They don't see a proof of concept to actually be scaled out to something that can be used by business and as a new way of working. And that's quite a big number if you look at the investments done. So of course, everybody would like to become an achiever which only 12% are. But the majority is actually experimenters. And I think one reason is that the infrastructure, the data foundation has been a super big topic, right, to create. It's very easy to be seduced by technology and you have a program that will implement the cloud environment or a multi-cloud environment. It could take a year or maybe two. You need to commissioning the legacy. the belief is to save a lot of money on the commissioning. But I think the real problem for many of these companies is actually to scale out based on the this that they're investing in infrastructure and focusing only on that and not on the value creation. Any reflection of that, the outcome from this research which you can give?

Xiaopeng Li [00:21:18] Yeah, no, I think that that's very interesting insights that you have shared. I think obviously, you know, different surveys and different research, they have different sort of methodology, how they categorize. But I think, you know, I you know resonate a lot you know with what you shared. so, from my point of view I think this actually touches upon the last P. So, the platform, right? For me, that means two things.

One thing is really the data foundation, which you talked about, because obviously, you know, to train AI you know and machine learning solutions. We need quality data, right? Here I'm really emphasizing on quality data because, you know, the amount of data matters, but also the quality matters even more because obviously, you know, all the biases and errors you have potentially in the data sets will be inherited by your AI and machine learning solutions. So, we want to make sure the data are of, you know, best quality possible. So, and of course, to achieve this data foundation, it's actually quite a journey for many organizations, as you mentioned, because they might have, you know, data residing in different systems or, you know, some, some, some, um, from something in the cloud and or within different geolocation as well. So, it can be quite messy, you know, to start with. So that's why, you know, I think, you know, for organizations, especially the innovators as you you're referring to, who have high ambitions for A.I. and machine learning, they should also be pragmatic and realistic in, you know, assessing themself. Do we have a strong data foundation in place? Because to support your AI ambition, you might need to start a way at data warehouse or data lake to have a centralized repository where you can actually have quality data for your data scientist to work with. Because I think, you know, for a lot of data scientists, you know, what frustrates them the most is when they have been hired into an organization to do data science just to find out there's no quality data for them to work with. And they end up starting to work on things like the engineering data preparation, which, you know, it's not really of their expertise, right? So, I think that data foundation really comes first. And the second part I want to emphasize is that, you know, for organizations who do have such a data foundation in place, and that means they have, you know, modern data warehouse, they have, you know, you know, modern data lake in place. You know, you need to think about how you can, you know, operationalize and professionalize your, you know, lifecycle management for AI and machine learning. And by that, I mean you know, obviously you can have your data scientist training models on their laptop individually. But you also want to ensure they work together you know a collaborative environment. They share their code, they shared their models, and they also work with machine learning engineers. So, they can, you know, effectively put the models into production and they integrate those machine learning solutions with your business process and existing applications. And that's why, you know, you also need a platform to scale your AI development and deployment. And quite often, you know, especially in the past two years, a lot of customers and partners come to us to discuss about ML Ops. So essentially you can consider ML ops as the DevOps for AI and machine learning, right? So, I think as organizations mature on their journey, more and more of them started looking into how to leverage the practice of ML Ops to really, you know, bring the different processes and different roles together in a streamlined way to scale AI, so to speak.

Per Österman [00:24:57] No I think you're absolutely right. It's important not to wait to create value while you do the heavy lifting of creating your data foundation and bringing your legacy systems data into a modern environment. But really, we call it double velocity, right? And if you look at the AI achievers in this study, what was common with these achievers, they did the heavy lifting. They are maybe also ongoing with the heavy lifting of creating the data foundation, which by the way, is never ending. It's always continuing. Right. But they are actually not waiting long before they start looking into what data should be lifted or transformed into the new environment. And that data should also be targeted for a specific data product or a specific use case. Right? So, you really get started just within months instead of years to start creating adoption in the business and show me the business that is not just the cost program. It is actually a value program, and it can free up value very quickly. I think that's a good point you make there actually to do this with envelopes and other ways of working right to get it right from the early beginning.

Per Österman [00:26:12] Thank you very much for listening in on our podcast on Data and AI

Maturity. This is the first podcast out of two, and I hope you enjoyed our talk here together with Xiaopeng. And stay tuned for the next part.

100% Josh. Great points. And you mentioned about reorganization, but I won't touch that one yet. We're definitely going to come up at that point. We will have a quick discussion on that probably in about 5 minutes. Now leading practice is, as we see across our client groups when we execute cloud data transformation initiatives, is because organizations run a business, it's not the shiny new tool that we have. You can boast that you have you have your data in the cloud and you're in the new. We always talk about value and benefits. So, leading practice is to define expected benefits and then maybe update them as you go along because things do change. Another leading practice is to track how they are being realized during the execution, because sometimes what people do is they define these benefits upfront and never actually revisit them and or track if they're being realized. I think one thing is very, very important in these data initiative, this transformation initiative is to keep the business wanting more, so early business benefits realized during initial phases are extremely important to continue the momentum on a program like this. Could you elaborate on how and if and when NFCU defined benefits, and also how you tracked them and created momentum as you go along, as you went along?

Josh Reese [00:19:47] Yeah. So, I really like the approach that that we took with this because a lot of what we're building is those capabilities that have a ton of potential value and a ton of potential uses. So, your value that you're going to realize from that over time can be quite substantial, but it will take time to realize that that value. So, I agree with you, right? The last thing we wanted to do was work for three years and say, okay, now we're ready to start using this thing. Let's see what value we can provide or obtain from it. What we what we did instead was really take that MVP approach where every quarter there's something tangible that we are delivering to our members and to the business. That's has value, that's meaningful that we can point to and say, look at the value of these data management capabilities. So, every quarter, we're still building those capabilities, but we're doing that in a way that also yields tangible results every single quarter by solving specific business use cases that were actually proposed by the business, so we're getting there by and at every step of the way as well. I think it was a very unique way of approaching it, and because of that, there's no question as to the value that we've already been able to achieve. We're seeing it. We're watching it unfold as we go. And we're building that rapport with the business and the adoption at the same time, because they're seeing the benefits, they're seeing the things that are tangible in terms of real-world examples, had a couple of examples of things we actually delivered. You know, I mentioned we're very passionate about helping our members better manage their finances. One of the things that we were able to achieve was delivering personalized balance notifications to our members to help them prevent overdrafts. This is really helping them avoid fees, avoid situations where their balance is getting too low, and we were able to personalize that with some really cool AI machine learning that we were able to deliver. And what we found was, as we personalized, it's one thing to target individuals who are susceptible to these types of things, but then to communicate that to them in an even more personalized manner is really critical. So, we were actually able to identify that each individual has a different threshold that makes sense to them in terms of when their balance is getting to a place where they need to take action to keep it above a certain level, so that was really cool. We were able to demonstrate the power of the platform and the power of personalization to do that, and we saw tremendous benefits. Our members loved it. They took action. They actually corrected, changed their behavior in many cases where they were spending less. They were increasing transfers from other accounts elsewhere to offset that, and we saw an incredible ability for us to help them manage that cash flow. So that was just one example. We've also been delivering some personalized savings recommendations to our members to help them build up more savings to offset against any future needs. So just some really, really cool real world use cases that we've seen have been yielding tangible results, and the more of those things that you that you generate, the more goodwill and the organization, it gains you, right? People can start to say, oh, yeah, you know, this is this isn't just, you know, a bunch of servers that we’re installing or a bunch of technology that we're building up. There's real world value that we're getting from it. And that's important because a lot of this is new for folks, right? Not only is cloud data new, but AI and machine learning is certainly new for a lot of people. And so, it's helpful to demonstrate the value that you obtained from some of these modern analytics capabilities, because people can be skeptical, and people think it's all just buzzwords, and is it really any different? And so, it's important to kind of gain meaning, build up that credibility with folks as well.

Lascelles Forrester [00:24:59] That's fantastic. And you're definitely speaking from experience. But did I hear you're right? Did you say quarterly MVPs and seeing values quarterly? When I'm hearing that and doing data transformation on premise, you're thinking 12 to 18 months to get your foundational component ready and up to speed, and then after that, six months to get your first MVP through. I'm sure the folks who are listening are going to be asking, how long did it take for you to actually get to you initiating benefits, to start receiving the benefits that you were getting now on a quarterly basis?

Josh Reese [00:25:41] Yeah. Yeah. So, you know, I can answer that in a number of different ways. We did some foundational work. We had a quarter or so, quarter or two of some foundational work with some tangible value. But really, I mean, we now have a world class AI engine that we've built and in a matter of weeks we can go from the build of the insight, the build of the model to deploying it to pushing it all the way into our channels and to delivery literally in a matter of weeks, which is just so remarkable for us, given that, you know, before all of this, I mean, a lot of this wasn't even feasible, to be honest with you. We just didn't have those the capabilities to deploy these kind of model outputs into channels in any sort of industrialized fashion. It would have been an ad hoc one-off project to do that. We weren't able to do these kinds of things at scale, but now it's all industrialized. So now that you've established kind of that repeatable pattern of building the model, doing all the model validation steps and all of the governance around that, deploying that into production and getting it ready, kind of hardening it for operationalization, it's just amazing. We've got a repeatable pattern. Once you kind of get that foundational layer stood up, you can in a matter of weeks spin up these new things, and that's really, I think, power of, in a lot of ways, the cloud, but it's just the power of the modern way of doing the stuff, too. You know, in the old days it was you'd have some data scientist somewhere in some corner of the organization on their PC building a model, and then it was like, okay, what do we do next with this? We don't know. There was no way to actually make it actionable, and we now have that that capability. And I think a lot of these cloud capabilities have really made that a reality.

Lascelles Forrester [00:27:59] That's fantastic. Again, great insight, Josh, and I'm even more thrilled to be having this conversation. You did mention a while ago about organization and hardening the solution and making it ready for production. It leads us into the next topic I would like to discuss, and it's around your talent, your organization, how to get prepared for a cloud data transformation, and you lived it so definitely would love some of your insight there. As I think through many of my client engagements, some of our clients have been focused on technology, you know? What's the IT required to implement the solution? Others were focused on the business and the benefits and making sure that business was involved. But some have done both but overlook the need for both business and IT, because it's not just IT or business. Both need to understand it requires skills that's needed to execute, to extend and to run a solution. I've seen for my experience that our clients need to think about required skills even from the strategy phase and at every single step of this data transformation journey, because it's very, very important, because if you wait until the end, you're going to have to catch up and you're not able to maintain a solution. And some examples of the skills and how they organize, and, how they're executing are one of them. An easy one to identify is required skills to implement, right? Are they the skills gap that you need early on not just to implement, but also you want to think about skills to transition from a development perspective into production perspective, skills to maintain from a technology perspective, the skills required to keep the lights on, for lack of a better word and also the skills to enhance, to actually continue the momentum, as you actually go into production. And a key one that I see clients completely forget about is the skills required to use the solution, right? Business users out there require some kind of change management for them to become data literate, for them to become analytics literate, to understand how to use this really good and powerful solution, because if it's not utilized by the business and by every single person in your organization, it could be seen as a failure. And I would think that you would agree with that, Josh So what was your approach to talent and overall adoption of the solution and overall thinking through making sure that the organization is ready for the solution?

Josh Reese [00:30:48] Yeah. So, I'm glad you brought this up because it's probably one of the biggest learnings for me in this journey was really just the importance of skill sets and the mindset and the people capabilities aspect of all of this. We invested very heavily in the technological capabilities, right? The data management, the AI/ML all of that stuff. But one of the things we did right in this initiative was really focus from day one on talent and organization. We knew that there is skill set gaps and challenges across the board. Basically, what you just laid out. There are gaps in terms of the build phase, the actual transformation phase, the stuff that you needed to stand up and the foundations to get things going, and then there's obviously in the maintenance phase and the ongoing management, their skill sets, different skill sets, to your point, that are involved in that. And then the usage of the platform is a whole other ballgame there. We knew that we had skills gaps across the board on all three of those categories going into this, and we needed to have a strategy for how to address those. a lot for that insight, Josh. Very, very Otherwise, the danger was we'd build all this fancy technology using a third-party integrator, but we wouldn't have any of the knowledge or skill in-house to maintain it ongoing and manage that. Let alone that, we wouldn't be driving the value from it that we really wanted to get. So, we knew we had to make talent and organization crucial to the strategy on an equal playing field with all the things we needed to do from a technology perspective and obviously the business side as well. So, I think we've done a lot there. We've really focused on our talent acquisition. We've did a lot of skills assessments early on. We've run the gamut of it. We've done a lot of upskilling programs and training that are really having a big impact, and what we're seeing now is because we invested early on that it's paying us benefits now. So now as we're looking to fill roles to maintain these platforms going forward or to use them, given that the talent market is pretty challenging right now, we've built up a lot of internal talent who are actually filling those roles. And if we hadn't invested there early on, we'd be really in a tough spot in trying to source some of this talent. But we essentially invested in our own internal talent pool from day one. That's really been a benefit to us, I think. We really laid the groundwork for, as the technology matured, we also had our talent and our organization maturing in a parallel path so that when the time came for when we wanted to tap into that and really leverage those people capabilities, we were already there as well. So that was crucial. And I honestly would say probably the most important part of a cloud native transformation is your talent and organization.

Lascelles Forrester [00:34:35] I agree. I agree 100%. I'm glad to say that at the end it's the most important because I do believe that even if you build a Rolls Royce of a data repository in the cloud, if you don't have the right skills and organization and talents around it, the benefits will not come. So thanks a lot for that insight, Josh. Very, very insightful. Josh, this has been a fantastic conversation. I thoroughly enjoyed it and I really appreciate the time you took from your very busy schedule to share some of your lessons learned your expertise in cloud transformation. And to all those listening to the

I couldn´t agree more, because otherwise you have a grasp fruits effort where everyone is having their own little shop, doing automation in their own little place versus really having a COE or some type of a model that you are leveraging, so that you have a common platform, common tools being used across the enterprise. There you start to have greater efficiency and you also have some governance on what types of initiative you want to pursuit and you make sure that there is actually value in them.

I agree. It goes without saying that all of this is underpinned by a value case and an investment strategy that needs to be executed, but if you don´t have clarity on what those initiatives are, specifically how each one of those are going to drive value, then there is no foundation.

That's right and I think Alex, you and I, have seen in some of our engagements, how hard it is for an organization, to really capture that value, if they do not have those operating models and organizational structures in place