

Think Ahead – Season 3

Episode 9 – Data-Driven People Management

Khyati Sundaram [00:00:07,680]

We're seeing, I call it the sea of sameness, because every application is looking the same. The cover letters are looking the same. The resumes are looking the same. Answers start feeling and sounding the same. And so, separating the top 10%, or the top 20%, which are the people you want to take in the actual interview room, is becoming really challenging.

Sergei Guriev [00:00:31,920]

Hello, and welcome to Think Ahead, the podcast from London Business School, where we bring together research and real-world insights to help leaders navigate today's most pressing challenges. I'm Sergei Guriev, Professor of Economics and Dean at London Business School. I'm joined by Isabel Fernandez-Mateo, Adecco Professor of Strategy and Entrepreneurship at London Business School, and Khyati Sundaram, founder of Applied, a data-driven hiring platform, built to reduce bias. Today, we are exploring a shift reshaping how organisations make some of their most important decisions. They move from intuition-driven people management to evidence-based, data-supported approaches. Isabel's research delves into people's analytics and performance, and Khyati's experience provides practical insights into how analytics and responsible AI can improve or hinder real-world people decisions. Together, we'll explore what data-driven people management can look like and why judgment and context still matter. Isabel, Khyati, welcome to the podcast.

Khyati Sundaram [00:01:34,720]

Thank you.

Sergei Guriev [00:01:36,360]

Let's start with you, Isabel. Can you tell us a little bit more about your research and teaching at London Business School?

Isabel Fernandez-Mateo [00:01:42,320]

Yes, of course. So, I'm a professor in the Strategy and Entrepreneurship Department. I've been here at London Business School for around 20 years, or 22 years. And I've spent most of my career doing research on how companies make decisions related to people in terms of hiring, promotion, pay, and how those decisions have influence on people's careers and, more generally, on inequality in the labour market. I teach two courses, one on career strategy and another one on people analytics. And in relation to people analytics, I've done some work recently on how generative AI is shaping hiring and recruitment processes.

Sergei Guriev [00:02:20,520]

Yes, Isabel, last year, you published a survey, essay about the impact of generative AI on people decisions, and we'll talk about the main insights from the survey. And now let me ask you, Khyati, you've built and scaled a data-driven hiring platform, Applied. Can you tell us a little bit more about this adventure?

Khyati Sundaram [00:02:41,320]

Yes, of course. So, my background is economics. And I trained as an economist and went into banking. One thing led to another, and then started my first company. And that was also using data, but in a different sphere. And this is my second company, where I brought all of those lessons and challenges of how to use data analytics, but within the people sphere. And the promise of the brand, of Applied is, essentially, how do you add good data and remove bad data? So, how do you make more robust decisions around hiring or any other people-based challenges that organisations have.

Sergei Guriev [00:03:18,240]

We'll delve into this, what good and bad data are, and how you remove bad stuff and remove bias, which, fortunately, can be reproduced with quantitative approaches as well. Let us come back to you, Isabel. Why is it today that we shift from intuition-driven people decisions to data-driven people decisions? In the end of the day, when we think about people decisions, hiring, promotion, retention, that sounds like something that people think about as something with a human touch, really driven by humans, not robots or machines. Why today?

Isabel Fernandez-Mateo [00:03:52,880]

Right. Well, it has been going on for a while. I think there are three main reasons. The first is that we have much better data and much more data than we used to have. Even 20 years ago, it was rare, the companies that had very good, structured data on people. There were some, but not that many. But now we have data on applicants. Everybody who applies, we can trace them. We can also record with HR systems, very small details about people's performance. We have digital data on emails, on people's interactions on Slack, on Zoom. So, we are inundated with a lot of data. That's the first thing. The second is we also have much better models to analyse those data, including machine learning and artificial intelligence. And then I think also people are starting to come to terms with decades of research that suggests that using intuition to make decisions about people, for example, who is going to succeed, is fundamentally flawed.

There are a lot of cognitive biases that we have of many different types. For example, a very classic one is, we make up our mind about a person in the first few seconds when we meet them. And then we spend the rest of the conversation justifying to ourselves why this person will be good or will not be good. Or we tend to like people who are very similar to ourselves, and then we believe these are the ones who are going to succeed. So, intuition is fundamentally flawed, and that has become more obvious to more people over the years. So, I think those three things are the reasons. However, as you say, we tend to think that this is about people. So, I know what is good. For managers, often, it feels more of a sense of control to be able to say that they are following their experience. Often, we say that being able to read people is almost a characteristic of leadership or wisdom. So, therefore, it's very hard to let go of that, I think.

Sergei Guriev [00:05:52,760]

Thank you, Isabel. And indeed, there are many subconscious biases and prejudices and stereotypes that people don't want to let go of. And you're thinking that, "I'm a leader. I know better. I'm in this job exactly because I've made so many great people decisions. And my boss selected me to be in this chair exactly because I've done a good job so far without any data, without relying on modern research methodology." So, turning into you Khyati, which people decision, as you saw in your work, in your company, are more likely to be shifting from intuition-driven to data-driven?

Khyati Sundaram [00:06:31,240]

I think all of them, depending on the context of the team and the size of the company. For us, we used to do a lot of hiring decisions, but our customers were working on analytics within employee sentiment, engagement, retention. And all of them are quite related. So, if I made a bad hiring decision, you will see downstream effects later in retention or culture. So, I always talk to customers about, are you mapping the data throughout? The holy grail for my product was always, look at the person you're hiring. Can you confidently argue that this person will be in the job six months later, 12 months later, will they thrive in your team? That is the problem I was trying to solve. We have all the data, as Isabel said. We're inundated with data, but people don't know how to stitch them together. With AI, I think there's a little bit of more confidence around. Yes, we may be able to stitch these data together, but equally, is adoption there, are people able to understand what is good data, what is bad data? So, there's a lot of burden of education on practitioners like myself saying, "This is the type of model you should trust," or, "These are the types of data you should use." But people are, I think, more open to using data across the different people analytics spectrum now.

Sergei Guriev [00:07:42,000]

Yes, but the adventure of an employee in the term, indeed, starts from hiring, And, indeed, Isabel, you worked on funnels, how people get pulled into funnels, go from stage to stage, and initially get to the most important event, which is interview. And we still see a lot of unstructured interviews, even though we are inundated with data, we have new methodology to analyse the data, including machine learning, gen AI. Isabel, despite having all this data that organisations now have, on all stages of the employee trajectory before and after joining the organisation that Khyati has mentioned, why companies are still using intuition-driven methods, such as, for example, unstructured interviews?

Isabel Fernandez-Mateo [00:08:32,840]

Right, so you're correct, in most of the hiring process in many organisations, they focus on unstructured interviews, which are mostly like chats. Why are we still relying on that, when we know that the structure methods are much better at predicting performance? And I think there are a number of reasons. The first is related to what we just discussed about

manager's intuition and feeling of control. Very often, for example, you would hear managers saying, "But I have to have these interviews, these chats, because it gives me a sense of the chemistry. Chemistry is very important in hiring. I know who's going to fit, I know what I'm looking for." And that sounds very rigorous, but in fact, we do know that chemistry is another word for liking, whether you like somebody or not. And that is an important thing, but it's not necessarily predictive of performance. So, that's the main reason, but it's also the case that unstructured interviews are cheaper to run. When you have a very structured processing, which you have to have clearly defined competencies, scoring systems, multiple evaluators, that requires a lot of resources that not all organisations are prepared to spend. And finally, it is the case that in most organisations, even very big, sophisticated ones, there is not really a check of whether the methods that you use actually correspond to performance later on. Nobody really follows up. I think that's related to what you were saying. Were these methods actually accurate, do we check? So, if you don't check, you basically are perpetuating the status quo.

Sergei Guriev [00:09:57,480]

Thank you. I really liked the word chemistry you used, because chemistry sounds like science, but as you correctly said, we use this word when we don't have data to back it up. We, kind of, say it's something subjective. That particular person clicks with me and my understanding of what the organisation needs, but that also means I don't have data to back it up. But you also mentioned that this may be the case even in large, sophisticated organisations. Khyati, when you work with clients, large organisations, do you see a qualitative shift to data-driven approaches where organisations actually do follow up, as you said, on whether this recruitment technique pays off in terms of this person staying in role six months later, performing well a year later, or not?

Khyati Sundaram [00:10:44,720]

I think there is intention, but it doesn't happen in reality. I think the bigger problem is the cost. There is a monetary cost to it, but also a time lag. You have to wait six months, 12 months to understand whether the process you did six months ago has worked, and people have moved on. Nobody is being tracked for KPIs on whether this person is still in the organisation six months later. You were tracked on time to hire, which was, "Yes, I closed the role in three weeks. I'm done, I've got my remuneration there." So, I think the incentives are not in line, but also there is a cost to it. While you were talking, I reflected to myself, I had a very interesting conversation with an employer because we always do the aeroplane

test, which is, if I was delayed in an aeroplane, can I spend 25 hours at an airport with them? And I was like, yes, you could use that, but do it in structured way. Put every candidate through the same test, with the same rubrics and the same objectives, and then you might be able to get a more structured answer from that. So, I think it's hard because that test tells me people have this inertia. They won't necessarily use any other systems compared to what they are used to, but you could still add guardrails to the systems you're very comfortable using, for example, the aeroplane test.

Isabel Fernandez-Mateo [00:11:58,160]

I mean, you have to also make sure that whatever you are testing in the aeroplane or airport test is correlated with the job criteria, because if it is not, then what's the point?

Khyati Sundaram [00:12:07,200]

Yes, but it quite often happens that you're testing for chemistry in the aeroplane test, because can you spend 25 hours? "Yes, I can, because I can have a great chat, I can have a meal with you, and I can sit in the same room and work with you." I think that's what it ends up being, but a lot of the work we've done over the last seven, eight years is about adding more data. Even if that's the context you want to use, we want to add more data to allow you to make a better decision. And a lot of organisations want to do that, it's just hard to do in practice.

Sergei Guriev [00:12:36,560]

It is hard, and you, Isabel, mentioned this word correlated. Correlation is not causation, and we researchers think about counterfactuals all the time, so you mentioned, I apply the aeroplane/airport test and think this person, I like this person, I can spend 24 hours, 25 hours at the airport. Recruit this person, this person, half a year later, does well. But what about the other person who didn't pass this test? Can we actually trace this person's career trajectory outside of the organisation, because we've not hired this person? Maybe this person who could have been hired, not passing this test, could have done much better. And this is the situation where superficial approach to correlations may actually be misleading, right? What do we teach, Isabel, to students when we talk about, don't take correlation as evidence of causation?

Isabel Fernandez-Mateo [00:13:29,680]

I think you answered the question very, very well already, because this is a very used sentence, "Correlation is not causation," but actually, it's one of the most important issues when we're thinking, for example, about hiring, really to keep this in mind. What I often tell the students is, we see a pattern in the data. Even like a very rigorous machine-learning model, you see in the data that say people with this degree are better performers. And then you immediately jump to action, let's hire people with this degree. This is pretty obvious, a lot of people do it. But you have to start thinking about, what are the reasons why that might not be the case? And one of them is there could be something confounding, some confounding factor in which there's something else that is driving, but the fact that these people have this degree, and also that they're good performers, but we don't see it.

So, it's not a causal relationship. But I think the most important one in hiring is precisely what you mentioned, which is, in statistic terms, selection bias. We only see the people we hired, and let's say, for example, that we see that in the people we have in the organisation, programming skills are uncorrelated with performance. And we come to the conclusion that we don't need to hire for programming skills because they don't predict performance. But of course, we've already selected people who are very good at programming skills. We don't see the people who we didn't hire. And not seeing the people who we didn't hire, in many, many different ways, has consequences for how we decide what are the factors that are important when hiring.

And of course, we are going to be in a very difficult spot trying to find those data and those counterfactuals, but the solutions are not very complicated statistical fixes. It's really interrogating the evidence. Where are these data coming from? What am I not seeing? What is the sample? Asking all these questions as managers is very important. And paradoxically, I think with LLMs and generative AI, it is becoming harder to ask those questions, because we get these answers, and they sound very good, and they are very plausible, and we might not go and actually answer, what are you not seeing?

Sergei Guriev [00:15:29,840]

Yes, one of the features of generative AI is, of course, generative AI tries to be liked and persuasive. And this is one of the objective functions of those models. They like to be used,

they like to be loved by the customer, and they're very good in formulating answers in ways that are very convincing. While we know and we teach, and you study that as well, Khyati, both in your master's degree in LBS MBA, that the golden standard is eventually in randomised controlled trials. So, eventually, what you want to do in the company is to say, you, hiring managers, you apply this technique to a randomly assigned group of applicants. You, the other group of managers, apply a different technique, and then we can pair the results of these two randomly selected sub-samples so we avoid this problem of selection bias. And do you see that happening, Khyati?

Khyati Sundaram [00:16:22,520]

It's very interesting you said that, so we did that at Applied internally. So, we put a small sample through a regular status quo approach, say CVs, two interviews, meet-the-boss chat, and we put a different sample through a completely Applied approach, which is take anonymised resume, and then add structured interviews or structured formats of assessments to it. And then we did double-blind RCT, and we looked at their performance over three months, six months, nine months. So, we wanted to correlate it and also try and build the causation over time. And we saw that the Applied pathway predicted performance for certain types of roles. And so, this doesn't really happen at a large organisation. It cannot happen because they don't have time, and they don't have money. But it was Applied's promise to the brands that we've done that R&D, we've done it for you. So, we know what works in certain jobs and certain contexts, and that's what we were helping organisations do. So, that's really, really important as a concept to do, but I think applying RCT instead of hiring is not going to scale well in organisations.

Sergei Guriev [00:17:28,040]

That was actually my question. So, you also observe organisations where people don't have time, don't have money, but sometimes, you probably also see organisations where leaders, senior leaders, override your model's predictive recommendations with their judgments. Is that hubris, overconfidence, unawareness of research methodology?

Khyati Sundaram [00:17:54,280]

For us, I think the biggest problem was confirmation bias. They were using the data to confirm what they already knew. "So, I like this person. I've hired for 30 years in this role. I know exactly what good looks like. I'll pick and choose the data to suit my narrative." I think

that becomes the norm, that's what I've seen. And also change management's been really hard. Our problem was never selling the product. It was, "Why should I change this process for something that has worked for me?" And I think "worked for me" is what Applied is trying to solve, is, "It worked for you, but you don't know whether this person will be in the job six months later. How much does firing cost you? How much does restructuring cost you? All of these are downstream problems because you've hired incorrectly." And those are the problems that we were trying to stitch the data together and give you a better insight into all of those angles. And I think that's doable, but it is challenging. And it just needs a lot of resource, a lot of time, a lot of commitment from different stakeholders. But for us, it was confirmation bias and change management that was a problem.

Sergei Guriev [00:19:03,120]

Thank you. Now, these things also were a problem before generative AI. So, what does GenAI change for employers and for the candidates, Isabel?

Isabel Fernandez-Mateo [00:19:14,560]

In terms of how generative AI shapes the hiring process, so to speak? Yes, I think it's interesting because we tend to think of generative AI affecting the selection stage, when you are screening for CVs or perhaps AI-driven interviews. But I actually think that the impact of generative AI is broader than that. It affects the whole selection, the whole recruitment process. If you think of the recruitment process as a funnel with different stages, the first one is defining the job in the first place. And some organisations now can start using generative AI to define those jobs, searching for data on market trends, internal trends. What capabilities are we needing? So, it's not only for hiring for jobs, but also for defining the job. You can also think about generative AI affecting which kind of candidates we attract. Even before they are applying, you could use data, with generative AI and models, to target specific candidates or specific types of candidates that will see exactly what you want them to see in order to attract them to the jobs that you have. Which, of course, is great in the sense that it can broaden access, but it can also, depending on the data you've used to train those models, keep hiring exactly the same people that we have always hired.

And then, at the end of the day, we also have the selection process, which is what we are used to, screening CVs, AI interviews. All this is for the companies. But then there is the

side of the candidates. Candidates are also using generative AI. They are using generative AI to write their applications, to write their CVs, to send 100 applications to each job every day, with the result that we have companies inundated with very nice looking CVs. And they are finding it very difficult to distinguish the high quality versus the low quality. I think that one of the consequences of this, that we're starting to see, is that we are going to end up coming back to some "old-fashioned" ways of hiring. So, relying on networks, relying on the status of the school these people went to, because those things are harder to "fake" with generative AI. So, that's a development that we have to keep watching for.

Sergei Guriev [00:21:17,400]

Yes. If I use AI to write a job description and job ad, you can use AI to shape the application exactly custom-tailored for this particular job. And indeed, I'll be inundated with hundreds of thousands of identical applications, by definition.

Isabel Fernandez-Mateo [00:21:34,513]

Everybody's using AI, and everybody's getting rejected.

Sergei Guriev [00:21:38,600]

Khyati, did you observe that as well?

Khyati Sundaram [00:21:40,360]

Yes, well, I often call Applied a rejection machine, because we've had millions of applications through, and we've rejected, or 90% of the candidates have been unsuccessful. I think that's going to be the bigger challenge now with AI. We're seeing, I call it the sea of sameness, because every application is looking the same, the cover letters are looking the same, the resumes are looking the same, answers start feeling and sounding the same. And so, separating the top 10%, or the top 20%, which are the people you want to take in the actual interview room, is becoming really challenging. And what I see employers doing is some of it is old school. Can you call people into an interview room? But you can't do 5,000 interviews, because nobody has the time, or there's a cost associated. So, there's a layering effect going on, as I might add additional assessments, I might give them a work sample, I might get additional reference checks, I might do a video interview. And there's all these layers being added to actually test for authenticity, which we didn't

have three or four years ago. And so, it's created a different problem. And there's lots of different solutions to that problem, which we did not have before.

Sergei Guriev [00:22:50,280]

Yes, this all sounds scary. We talked about the stage of application. We talked about the stage of interview. Let's assume the person is hired. We need to measure performance. Isabel, is it easier or harder to measure performance today? With all this data that Khyati was talking about, do we get finally to solve this problem and measure performance exactly? Which will help us eventually to develop the optimal predictive tool.

Isabel Fernandez-Mateo [00:23:18,360]

Yes, I think measuring performance is one of the hardest things that we can possibly do in organisations. It's almost a structural problem, because no matter which measure you use, it's going to have advantages and disadvantages. So, you might have a lot of data, but you also want to have a subjective measure of performance. So, I'm not saying that intuition and knowing the context doesn't matter. They still matter. So, subjective measures of performance, like 360s or the manager's evaluation, all these are still important, but of course, then again, subject to biases. So, then we say, okay, we have all this data. Then let's just use the data to have objective measures of performance, things that we can count, output, or whatever other things that sell, something like that. But we also know that once a measure becomes a target, it stops being a good measure. And people can game it, and they will try to game it. So, if you are measuring for these very specific dimensions of performance in a very good way, people might compromise on quality, or they might compromise on other things. So, at the end of the day, you have all these complications. No measure is perfect. Individual performance is not completely individual. It depends on the context. It depends on things that have happened to that person. It depends on the team. So, we need to have a system in which we actually have a combination, a robust combination of these objective and subjective measures of performance. And I think that good data and very good models can help us with that, but we have to be very careful not to fall in love with those data and these methods, because they're not perfect either.

Sergei Guriev [00:24:52,120]

Yes, they're not perfect. And you, Khyati, mentioned good data and bad data. We train GenAI models on past decisions. As Isabel's mentioned, some of these past decisions are

subjective and not immune from biases. So, how do you differentiate between good and bad data when you measure and predict performance?

Khyati Sundaram [00:25:14,000]

Well, you have to have data throughout the funnel and connect it to the outcome. So if you don't have that data, so, let's say, pick a salesperson hire. You've done that hire. You've looked at what a good sales pipeline looked like, how much they've generated, how much revenue they've generated. You know what's happening for three, six, 10 months after they've hired. So, if you connect that data, you can then predict whether, "Okay, I asked these questions in my sales hiring interview. I know these questions predicted a good hire, these questions did not predict a bad hire. You need to deprecate those questions and deprecate those things. But that means you're collecting the data throughout the funnel and constantly stitching the data back up and down the stream, which doesn't happen normally. And so, that's the big challenge, is with AI, you can have the ability to do that. Not everyone needs to be data scientists now. You could tell AI where you want to go. AI, if trained on good data and sitting on top of good workflows, could lead you there confidently. But the question is, do most people know what data they're collecting, where they're collecting it from, what good objectives look like? And that's the challenge. I think many organisations are still in a place where job descriptions are sitting in a hard drive from five years ago, which is not going to be helpful in any kind of AI or predictive model.

Sergei Guriev [00:26:31,600]

You can still ask GenAI to rewrite those job descriptions. Yes. And everybody can do that. Now, what you said is very important. In order to go back to the hiring methodology, hiring approaches, you need to have the ultimate objective measures of success, of performance, which, Isabel's mentioned, is hard to establish. But you mentioned sales data, output data, staying in role or being fired. This, of course, helps you to produce an objective predicting tool. So, eventually, you do need some kind of metric, however crude it is, to stitch this data and come back to the application and interview stage.

Khyati Sundaram [00:27:17,280]

Yes. So, if you pick the wrong data, for example, let's take the salesperson again. And we did this mistake, and I see this, again, in organisations. If you use sales calls as a metric, a salesperson will always find enough time in the diary to make 20 calls, 30 calls, 50 calls a

week. If that's your performance measure, it's not accurate. You can build an AI on top and say, "This is my salesperson. They do 50 calls a week. I need to hire another salesperson who does 500 calls a week," because you're indexing on that benchmark. That is the incorrect model, because it's no longer a metric. That is a useful target. People will just find that system to game it. So, it's what kind of underlying data is there? You actually need to look at, did this person generate revenue? And how much revenue? And with what resources? And then connect that to, "Yes, I actually tested 500 people. These are the questions I asked. This is the person I hired. This is the objectives of this person." And with Applied, we could do a little bit of that. We haven't solved it entirely, because as I said, we collected the sample for the people who are hired, and also not hired. And everyone who did not get hired through Applied, on average, they would come back two more times to apply through Applied. So, I have this history of data sitting across what they were good at, what they were bad at. So, now I can start stitching samples across different outcomes and make a more predictive decision. That is challenging because it needs longitudinal data over a long period of time. So, I think that's the real challenge with hiring and performance, because you're not connecting the two pieces of information, even though you should.

Sergei Guriev [00:28:55,920]

Despite all this convincing, I would say, pitch for Applied and Applied methodology, I heard that Khyati did say that not all problems are resolved, Isabel. What remains for humans to do in people decisions? Even with all the data around, with all the methodological progress, with all the RCTs and machine learning, are there areas where humans are still in demand?

Isabel Fernandez-Mateo [00:29:19,320]

Yes, we hope so. We hope so, definitely. So, I mean, with these models, AI or otherwise, or other types of data analytics, what they are very good at is spotting patterns, finding patterns at a scale. But there are still a few things that there is the room for humans. First of all, the context. I have to understand the context. The model might tell you, a very simplistic example, that this person is the perfect one for the job. But you might actually also know that perhaps there is something in the context in how they did the interview or whether your team needs something else. So, whatever it is that the situation rather than the pattern, the manager might be in a better position to examine that. The manager also might be better at making trade-offs. So, I might pick the person who doesn't tick all the boxes, even though there is one that does, perhaps because I'm trying to broaden the

different backgrounds of the team, or perhaps because I want to send a signal to my other employees. So, understanding those trade-offs is also something that the humans are there for. And then there is also the judgment, the fact that we are talking about decisions that really affect real people in organisations. And at the end of the day, you need to be able to explain those decisions in a way that it doesn't look like the models are taking over, but we are using them to support our judgment, to increase the confidence in our decisions, rather than to substitute for our decisions.

Sergei Guriev [00:30:50,160]

Khyati, what do you think? I know that your job is to say that data and models are taking over. Is there space for humans, for leaders here?

Khyati Sundaram [00:30:57,480]

Absolutely. There is always space for humans. And people analytics is a human-driven function. And I think there should be space for humans. For Applied, we have always told our customers to use data as a prompt conversation for conversations. So, you would look at the data and say, sometimes, "Okay, I think the data says X, but I believe in Y." And you should use that as a prompt and have a conversation to understand why the data says that particular thing. I think that's done really well in terms of managing change within organisations. I have a very interesting anecdote about a customer who looks at it very rigorously. And what they do is when they override any decisions given by a data or an algorithmic system, they note down every time that's happening. And so, over a period of a year, they can assess whether they're overridden it 75 times or 25 times, and they build a percentage. And I think what they're getting is a bell curve. And that will allow them to take a more robust decision on, okay, let's say the decision is overridden 75% of the time in performance or pay situation, then they would argue that the model is not producing the right results, or there isn't enough buy-in in the senior leaders about using that model. So, you would then recalibrate, and the confidence around that model would change. Equally, if they had never overridden any decision, then you would have an argument about, oh, are people just using that decision without any accountability, without any judgment? Are the right decisions not being surfaced? So, those are the kinds of questions we can start digging into once you have that kind of data. But it was very interesting for me to see that customer doing that.

Sergei Guriev [00:32:40,080]

Yes, this is, kind of, evaluating the model, but also, you can use this experience for evaluating the human themselves. If this human always follows the model's advice, probably this job can be actually automated and eliminated, and there is no need for this human.

Isabel Fernandez-Mateo [00:32:56,120]

You're giving people ideas.

Sergei Guriev [00:32:59,680]

But seriously, if you think about old-fashioned leadership, you have advisor A giving you advice to do this, advisor B giving you advice to do that. And you need to make an executive decision. And you need to be held accountable for your decision. Now, the difference is you follow your intuition, you follow a human advisor, you also follow an AI agent telling you to do this, this, and that. And then as a leader, you are held accountable for going left or right in this particular situation. So, we are back to basics where leaders need to make decisions and be accountable for the implications of those decisions. If they don't make decisions, we don't need them. So, we are coming to an end of our podcast. And in the end of our podcast, we always ask a short question, a signature question. Thinking ahead, what should business leaders be thinking about when using data and analytics to make decisions about people? Which principles should they follow?

Isabel Fernandez-Mateo [00:34:00,120]

So, I think the most important principle is what we have just mentioned, which is that use the data and the analytics to increase the confidence in your decisions rather than to make the decisions for you. Before you collect any data, be very aware of what is the problem you are trying to solve, what are the right data to analyse that problem, and transparency is very important, and accountability. It most often falls on the culture of the organisation, really.

Sergei Guriev [00:34:23,120]

Thank you, Isabel. Khyati?

Khyati Sundaram [00:34:24,520]

I don't think this is a very economist thing to say, but don't use data instead of conversation. So, I quite often see some leaders doing what I call algorithmic confidence laundering. So, you'll make a decision. You'll then say the data said that, but even though the data didn't say that, or you have just made a decision. So, it's hiding behind the data. So, I always say, just have the conversation, understand what the data is saying, and then choose to override it if you want to.

Sergei Guriev [00:34:51,000]

Thank you, Khyati. This is completely aligned with what Isabel said about transparency and accountability. You should not hide behind data to arrive at the decision you've already made. So that's all for now. Thank you very much, Isabel and Khyati. Today's conversation highlights both the promise and the limits of data and models in people decisions. We have heard how analytics can bring greater consistency and transparency to hiring, performance, and promotion, but we have also seen why numbers themselves are never enough, and why prediction must be paired with explanation and judgment. The takeaway is clear. Using data in people management is not just a technical exercise. It is also a leadership decision. Thank you for listening to Think Ahead. To explore more insights, please visit [London.edu/think](https://london.edu/think). And until next time, keep thinking ahead.