# Transcript

**Speaker 1**

For the purpose of this research, I'm not going to ask you any personal information because we have to keep it like. Coat the head like we are going to coat it so there's not going to be like any traces back to you or your company or anything. So, I will ask you a series of questions to basically understand what you expect of us or what you expect of me. Based on that understanding I’ll be able to generate a solution to the actual problem. So, first of all.

**Speaker 1**

We were talking about gender pay, gap analysis and so my question to you is, do you think that your organization has existing gender pay gaps?

**Speaker 2**

So, I don't think my organization does not. OK. However, the organizations that we work with, so we are. And analytics solutions come and they are certain organizations that work with that do so naturally, like, I think the way gender pickup works is this so a lot of times they are companies that might have a gender pay or perceive that they have a.

**Speaker 2**

In the organization, and typically they employ, they basically bring in organizations. Like mine. To do the analysis, partly because.

**Speaker 2**

It's better to have an external sort of vendor to do the analysis, as opposed to do it internally because of discoverability in courts and stuff like that. So typically, what ends up happening is that they do use people like us and so that's what we so our organization, no, I mean. We can't. However, we work with organizations and that's where sort of the story begins. Right. Like, that's sort of how you know, we expect to work with you in that sense because we have certain institutions that do have that or perceive that they have the agenda pick up essentially.

**Speaker 1**

OK. So, from your experience and understanding of the gender pay gaps, why do you think identifying this gap is important to these organizations?

**Speaker 2**

Yeah. I mean, I think it comes down to notion of fairness. So, what I think the, I think the issue the thing about doing gender pay is I mean it starts it starts from just trying to understand. The culture of your organization, right? So essentially. For an organizations culture, you want a place where your employees feel valued. They feel respected. They feel that they can actually have that growth and development that they need. Right. And a lot of this is actually rooted in the concept of fairness and saying, OK, well, look, if someone does a certain job, regardless of who they are, where they're from, if you have a certain job. They said, OK, you, I want you to be a data person. I want you to. Be a lawyer. I want you to do this particular role. Then if there's a market value that you have assigned to that job, that's what the person. Should be paid, right? It shouldn't change whether the person is. A man or woman, whatever black, white, Asian, it doesn't really matter, right? If you have a job and the person is called as you have selected this person as a qualified candidate for that role, then regardless of what it is eventually be paid appropriately to the role. And so. When at some point. Certain organizations feel like culture, like culturally, they have had. They have sort of. Failed in this in the sense that. Pay is given not based off of like setting set preset criteria, but just. You know Willingly, then it introduces the potential of a gap based off of a setting bias and the bias could be anything from gender, race, ethnicity or it could just be as a result of just like honestly just careless planning. But what you don't want is. if you, you. Know if you look at it. At a high level. And you start to see a trend. Now. If there's one of things that I'm not necessarily, let's say, maybe one of things that happen and there isn't a trend to it then you. Can you know? You, you know, you might not say there's a gender or race. Ethnicity or whatever. Pay gap, but once if you start to look at the trend. And visibly and. Statistically, you start to see a trend of men for the exact same job. Women are paying. I mean, sorry, women are working at. You know, I'm making way more than the women. Significantly more. And it starts to become a trend that becomes the issue and that becomes a cultural issue because of course, like it's sort. Of leads to. A lot of like just chaos and if a woman finds that out, then she sues, and you can actually get in trouble for it. And you know, it just leads to a lot of issues and trust degradation in the organization. Right. So, you are absolutely. It's important that like. Again, like that doesn't happen because again, it goes back to that whole culture, which would affect your bottom line or top line Muslim organization essentially.

**Speaker 1**

OK. Thank you for this. You serve these organizations bring these issues to you to identify these pay gap. If they perceive it. So, when it's brought to you. What? How do you identify? If there is a pickup or not, what approach?

**Speaker 2**

Yeah, I mean, I. Think. Yeah. I mean pick up. I mean pig up is. It's just there's so many things you can do. So, I mean, I mean, I think for a purpose of let's say some that you going to do, you're not going to go into all of those things, cause it'll take you a year to do it realistically, right? So, but, you know, I think even. Before you talk about, start to look at pay gap or. If there is. Anything like that? I think it even starts with just trying to understand the organizations. Like I said, culture or trying to understand like their compensation philosophy. Right, right. And in the sense that you? Said, well, how are you paying? Do you have a pay? Do you have a pay? Structure OK for. This role, what is the range of pay? Right. Are you paying 98 percentiles of the market, 75% of the market? There’re so many questions you have to ask, because sometimes like the issue is not because there is an issue from a gender perspective, it could just be like they actually don't have a good compensation philosophy. So, for example, I'll give an example of that. So, let's say you said, hey, you have this junior data analyst role, so they call it, let's say call it we. Call it level. 3 Juno data analyst. And you say for this role your pay is between 30,000 pounds. And £90,000. Do you see the issue with that? It's a wide range. For that one row. Right. So, one person can. Yeah. I'm a junior data. And you know your data analyst, and they pay. They pay per 30K. They're in the range. And someone says I'm $100 and they pay the best 90K. They're in the range. Right. But if you now do that enough times whereby, you're paying people 39. 39 and. Then for some reason most of you are paying 30 are women, and most of you are. Paying 90 are men. Even though in the same range, can you see how that becomes a gender pay gap and that like issue that's even within the within the sort of? Sort of like the within the range, right? There's already an issue, so it starts to even just understand it. Like if there's a two other range like you can just say like is there is too wide of a range. So, when we. Start the analysis. We look at things like that. 1st right. But again, for purpose of what you're trying to do. Right. You come from a place of we've done all that work. And so, we just said, hey. We will look at compensation. I'm sorry, the competition philosophy done all those things and we've sorted that out. This is this is now the analysis.

**Speaker**

To do so.

**Speaker 2**

If we get to the analysis part. We do a few. Things right, we first of all. We trying to understand the population. You know how many men do you have? I mean, women. Do you have? How many? You know how many men you start looking at those kinds of breakouts by different categories, right by level. By job departments, by job family. You know those that different kind of cuts? So, I'm here to understand the sort of the population. Of the actual people we're doing analysis for because let's say you, you do a cut, you look at OK lets. Look at all you know. Engineers in a particular location and then there's like 10 men and one woman, one woman. And guess what? Like your gender here, it tells you all you need to do, like, oh, there's only one woman here, but there's ten men in this particular group. Is there really a guy? Like, it's not when there's a representation issue, not even a pay gap issue. There's a representation issue. So, we start to just start to look at just the people that we have in each category. At the high level, before we even start going into the more of the analysis, part of it, essentially that's sort of how. We start.

**Speaker 1**

OK. So basically, having a general overview.

**Speaker 2**

There's a range issue, compensation policy issue or any other type of issue before considering the gender pay as the last. Yeah, gender is the last thing to do because like I said, you consider even the breakout of the organization because if you're looking at the holistically. So, you say, OK, what is that an organization? Where did your analysis you might look and say, oh well, the high level there is? There's a little bit of OK, but where? So that's kind of why you have to look at the population breakout by department. Let's cut how many women are men? Are each in each department? How many women are men are in each location? Because the general pay is coming from somewhere. OK, so you might look at the whole population and say, hey, there is a gender pay. But when you look at the UK alone, for example, let's just say you're. Losing the whole. The whole you look on the whole of OK, sorry. So you look at the whole of, OK, you look at the whole of, OK, you don't see you see a gender pay gap and you break it down then. Let's look at location and then you look at Sheffield and you don't see anything. But for in Sheffield, the men and women are paying, being paid equal.

Speaker

Right.

**Speaker 2**

It's very equal everything pretty much no statistical difference. And you go, you go to London and you. See the difference? That's probably what it's now. Partly contributed to that overall pay gap, because in London there's probably more people and then for some reason there's that gender inequality. And then you see that.

**Speaker 1**

OK. And considering this approach, what technical do you use?

**Speaker 2**

Methods to be used. Yeah, I mean, I think we look at a few things. So technical methods like, first of all, We take a look at the distribution of men and women. You know and see, OK, trying to understand like well distribution based on distribution, what does that look like? Honestly, most of the time. You know, I don't have normal distribution, I mean normal distribution is like nice is usually happens in theory more often but anyways. But typically I mean historically we've done like OS regression, because that's really the more the more popular one, and it's not necessarily, I don't think it's actually the best one. I mean, that's the point of what we're trying to do like it's not the best one because. The idea is OS assumes that the population is. Normally distributed essentially so we typically what we typically we do that because then you know we use OS regression and it gives you it gives you the you know sort of the. The the high level overview seeing you know, OK, there's a gap. Looking at the charts it gives you it gives you the idea but. I think more and more academics and data scientists are like decide to say, hey, we don't think it's the most accurate of it. I think it solves a lot of problems for the most part, but I think people have to say you don't think is the most accurate of sort of techniques, but that's typically what we have used historically. Or if you look at any gender analysis, you even companies doing it or. Tools that are being built for it is typically. OS regression of the use essentially.

**Speaker 1**

OK. In your opinion, considering what you've said that you use this and you don't think it's the best, but it gets the job done in your opinion, what would you say are the main benefits so far of OS regression and the limitations?

**Speaker 2**

I mean, I think it. It points out the glaring issues.

**Speaker 1**

OK.

**Speaker 2**

So let's point out the like. If there's a like a glaring like gender pickup, right, but I think what it doesn't do is like the fringes, things that you know, maybe teams that are like. Not a large population. The sort of the way that they. Look at the cuts. And the gaps are maybe not as glaring. You know, so that's sort of where you might not really catch it really like you might just look at it like, oh, it's not a statistical significant, but it's not. So it might just look at that that way. So it might, it doesn't catch the we don't think it catches because again like I said, it assumes that the population is normally distributed and for the most part in the real world, the population is not normally distributed.

**Speaker 1**

OK.

**Speaker 2**

Right. So. So that's sort of what it does. It catches the glaring issues, which is basically when you run a when because when you go to a court of law that's there's an issue of, you know, pick up patients, you sued or something. I don't know if you go to court of law, typically they'll they'll essentially judge it off of like a no LS like they'll probably look call like a external personal para. No L so. I think glaring issues it catches, but I said it goes off to cultures, not just about the glaring issues, but it's about fairness. They actually catch the glitches, the glaring issues or glaring issues. I mean, however. They might be setting up parts of the organization and selling cuts that there is a bit of a gap may not be like as statistically significant, but it's significant enough. That you should maybe fix it. And that's sort of where the the fault, like sort of the disadvantages are? But it's like the. Different like very like sort of. New ones like. Specific cotton mechanization, they kind of maybe tend to miss it because of the assumption up front that is normally distributed essentially.

**Speaker 1**

OK. So, Based off of what you said that OS catches the glaring issues, well then its limitation poses like the ones that are outsize. These assumptions of OS having a normal distribution or like the fringes like you use the word based on these limits. Can you give by chance like a specific example where this instance was a major hindrance?

**Speaker 2**

Yeah, I mean, so like, you know we've ran analysis before where we caught selling issues and we said, hey, listen. With this agenda pay gap here in the organization, it's going. To cost you about. $600,000 to fix. Right. Something like that. And then here is where you need to fix it for this woman. This woman. This because this is the woman that's this particular man is way below. So we will add bunch. We'll add this 30,000 to a salary we have 20,000. So the women's salary you add boom, boom boom boom boom and then they fixed the issue. But if you still look at other women in the organization because so many are getting paid quite, you know, maybe. 10K less and It didn't necessarily catch it, but. Not every 10K or 5K extra who change this person's life like it would be so much better for this person. But but we didn't like it wasn't done because again, we just fixed that major issues and then you run. The analysis again. It tells you you're not. You're not. There's no gender pay gap, and if you take it to a court of law, there is no gender pay gap. But when you look at it. With your eyes, look at every single number. You start to look at the numbers and say OK well. Don't run any algorithm. Let's just look at this team. Let's call it. OK, let's just look at the averages. He starts looking like oh, wow. Is it like A7K difference? You see a nine K, you know 7:00 and 9:00 K difference. Since statistically significant, but. I'm sure this woman will will love. To get that extra 7K in. The salaries right on average, right? Yeah, that's sort of all you start to see and you're like, OK, like culture like, you know, and those sort of things is. What really kind? Of you know, you ask of oh, OK, well, like what? What is longevity? How you think about? Good culture. How? Do you sort of beautiful? Those are the. Things that that go just beyond sort of. What the statistical? Significance gives, but you look at the. Actual human person. So this is sort of that's kind of why we see this limitation and then we'll then we'll OK well well there's a limitation with the algorithm because you want the algorithm that. Catches even those you. Know exactly.

**Speaker 1**

OK. And the purpose of this is to actually come up? With a solution. To this limitation, however, have you tried any other approaches? I mean, yeah, I mean we.

**Speaker 2**

Yeah, I mean we've, we've. You know, we've tried. I mean, there's some, you know, there's some algorithms out there and that that and. That sort. Of where we you know what, you guys, what you are potentially, you know, going to do comes in. We've tried different things. Right, like we even tried like you know. Just looking at sort of. Sit like back. They're like sort of averages, weighted averages and looking at that and you know that you know like that's also a technique you you will catch certain things and that's also very like sort of time consuming, right. And so can we create something that? Accounts for all of. That, and it's not time consuming, but it's also not limited in terms of the distribution of the employees. So we've tried a few of that. So I mean, I'm aware of all. That sort of techniques, right? Which we have not tried yet, but we are proposing that that would be a good a better technique to try to see. What it will will, how that would work? So the techniques that people use, like there's some techniques that have been more proposed and more in academia. And decide to. Sort of take a foothold in the industry a bit more, but by some simple and I say no, actually it's no. Less. There's actually a better sort of regression techniques, so some people have proposed things like GLS regression. Some people are proposing. Like some like doing a bit of. A bit of more of that nuance, like sort of clustering sort of proposed even that the one that's sort of taking a big a better a big foothold now is like that WLS. Regression, right? So. So, so now we're saying, OK, well, if that's the case, if we know that OS and looking at where the average is is not really doesn't really account for some of this. Variation and distribution for organizations. So why don't we then take a look at proposed proposed techniques that would work right? And so one of the biggest ones, you know talking with. Our data scientists and. Some people that really understand, like, you know, this sort of, you know, statistical methods. They're like, well, we think WLS would account for. Yes, because it's WLS. Takes into account the distribution. And you're able to. Sort of. Yeah. So it takes. That's the biggest thing. So we want, we want, we want to do the analysis using WLS and then and then we can even try out and. Then an additional sort of. Because I think a lot of times the the the thing about. Statistics is I always say you. You tried in threes and see. So if you're going to know less regression, you see what you. You want WLS regression? You see what your outcome is? Maybe you run a cluster analysis or something or whatever. That is, you see what? The outcome is. And then you see sort of, oh, well, the hypothesis is like the LS should give you. The most accurate results. And how you know it tells you where the issues are and tell you know you can look at, OK. Well, how much it takes is going to take to sort of. Close that gap and then that we can come back to us and say, hey, I'm gonna say it's going to cost you $1,000,000 and here's here, here the places that you're going to put the money to, you have to add X amount to special salary X amount to salary and then that will close the gap. That's what we want to do, right? That's sort of the angle. So that's sort of the the idea we're looking at sort of bringing in those techniques that are. Proposed because we have not run it yet, but they. Have proposed and the. Hypothesis is it will do better. So that's sort of how we're. Thinking about it.

**Speaker 1**

In terms of these proposed solutions, if you were to like strictly look out for what you're going to keep using among these proposed solutions, what specific criteria would you watch out for?

**Speaker 2**

Among the proposed solution, yes. I mean, of course we want to take into account the fact that you Know like first of all I want to see what the distribution is Right?

**Speaker 2**

So if you come to tell me, look, it's normally distributed then or less might just work. But I don't think it is. Most companies are not. So that's the first. Thing like, yeah, we understand what? The distribution looks like. And then. We need to understand like we need to. I need to see kind of overall what the gap is at the top level, then also in the cuts, right. So by by the department, by location, and then I only to understand like. Sort of led to what level is your. Output like so what's your error? Error error? Level like you know error level is and stuff like that. So using regression, what like we're talking about like. The value and all that stuff on the R ^2. So just running those things, you just need to understand obviously the typical techniques of I don't invalidate all that stuff, whatever. Right, but I think. Yeah, I think it's just like just. I would love to just. Understand. OK, signal distributed. Yeah, like just. What does it look like at a high level? What does look like in the cuts? Yeah. And that's it. And then I think I think one thing people. Don't do is. Well, is. Just then use your eye to look. At things as well. Right. So if you do run 3 three different more burdens and then you just. You just do some averages and then you start to see. OK, well, one of few averages I've done the averages by. Cards and this model catches this. This this model says this model says this and you know maybe this one model does not catch a gap, but another mother catches a gap and sees this. And you look at your you use your eyes to see. OK well it. Does look like it's a bit of a gap here. Woman doesn't catch it. Another model like assigns it as a gap. Then you start to see that OK. But this model is a bit more going a. Bit more in that and. The other model, so those are. Things we're going to. Look out for. Just like kind of like kind of doing the. Just like with the eye test as well.

**Speaker 1**

You mentioned a few models like cluster. WLS and stuff but like just curious, you said you've not tried and why haven't you tried these models?

**Speaker 2**

Time I mean it's. It's yeah, if you're having a lot of. You know, takes time to because you know the idea with this regression for paying pay gap it. Is it's very iterative. You run a model, you test out, you check. You take a look at the. You look at the employees, you. I mean, you talk about. It internally you take a look. And see and see why there's a gap for sometimes, like there's a gap. Because maybe it's supposed to be. Yeah, they're the same job, but oh, actually this this other person has 10 years, way more, 10 years more experience. You know, so there's a new variable that I didn't. Even think about, there's not ten year more experience than this other person, so even if they're the same job we're paying this person, that gap is assigned to the experience. So if there's a gap and it's explainable. Then that makes sense. So it's. Oh, there's. A gap but. We're like, oh, actually, we're paying this person 20,000 percent, £20,000 more. $2000 more because actually this person has 10 years more experience or some like, Oh yeah, they didn't take any sort of. Stock they just took, you know, they took, they just took more cash. Right. And you. Oh, yeah, we didn't. We didn't add that to that you. Know stuff like that so. If it's explainable as to why, then yeah. So it really is just really time because it's very iterative like you, you want the other analysis you have to probably run it like 3 to 4 \* a year, especially if you're growing. Right. So typically I mean we are motion has done with a lot of work, so. So typically that's sort of why we haven't, you know, because you once you set the OS regression. There's new data comes in new companies coming. You just take the same code right? Like you just run the and you work on the relative process that takes a long time. So the reason why you've not invested a lot of time is just you know that because really just time and that's something we want to do. And then of course we're doing a lot more. Research thinking about. Like, OK, well, what's the better way? To do this. And so yeah. You know, when you talk about like you want to do the analysis. This makes sense. Like. OK, well, let's have you try it. You know, as part of your project. And then if you can come back to us and give us the break and then that's actually going to be very helpful for us as a foundation to try and build on top. To sort of see how we can implement it in this. Company as well.

**Speaker 1**

OK. Speaking of the time that you mentioned you, from your experience like how long does the standard like pick up analysis?

**Speaker 2**

Take I mean the the analysis is like the to run the model itself can take you 5 minutes, right? Like it's not the actual model. Once you put the data in then just you just write you have the code then you run it. That's. Is the process around the gender pay right? So prepare your data right, the clean the data, the structure you want, what fields are you going to use? You know like OK, we have a line on the field line on you know the definitions of the fields that the the the you know how they're mapped. And then I don't forget I mentioned to you beginning of the conversation during the pre work of like composition like you know like your your composition like policies and all of those things and stuff. So all they know from begin to end they can take as much as nine months a year.

Speaker

Right.

**Speaker 2**

But what for purposes of this project? Like a lot? Of those pre work. Has been done so you are most starting from a data point. You have this. You know you're going to be given this data. And you're gonna start to do the analysis off of that. So you have to do. The cleaning the structure, the mapping, all of those things. So, but typically end to end from initial conversation could take as much as. Nine months. A. Year, but the analysis itself can be, you know within like within like I get, you know, technical analysis itself, you know, because you going to do some analysis, you going to work on it, you're going to test, you know all those things. So we'll take you maybe like weeks a month you know to really do run but end to end the full process is about. Nine months. OK.

**Speaker 1**

Earlier you mentioned part of the. Background of the study for the pay gap analysis that looking into maybe the ethnicity or the different departments or things like that. For the purpose of this research, are there any specific areas that you want to be more focused on regarding the pig?

**Speaker 2**

Pick up. Yeah, we don't. We're not. We're not in ethnicity. So we're we're not gonna do that, right? We just. Look at the agenda for. This OK, so as a focus looking at gender. Looking at high level, I think for this data set we're giving only the US population of this company. So I think everyone will see you might see some other companies, but I think I mean some some other locations I have to I have to remember that I have to look at the data set, but I think we're most looking at at least either US based or at least us paid like. In dollars, because if you start to break out like. They're being paid in pounds, they're being paid in yen. That's a whole new complication, because again, you know, you start to bring in sort of. The pay structures for the countries. US will pay naturally more than UK, so if your data scientist in in the UK data science in the US the same job you guys pay more because again standard of living is very different. Some of doing business is very you know cost of. Doing business is also. Very different as well. So we're all looking at, I think just I think it's mostly. If I'm not mistaken, at least for the data set. That we are. Looking at, we want to focus on at least the US population. And then we also want to look at things like, I think we look at it by department. And then you know call center.

**Speaker 1**

OK.

**Speaker 2**

As well. I think that sort of.

Speaker 1

And considering a proposed solution now when when this solution has been brought up, how do you expect it to be delivered to you?

Speaker 2

Yeah, so, so we don't expect you to to give us a fully. Polish solution now and that's not that's not the expectation, because again, we're still not to go talk to companies like iterate because we can come to a. Solution a lot of times. You can iterate 25. Times for it kind of. So just like give. Us a solution? Because we might go and say, hey, there's a gap. Here, here they cannot give us. Sort of some like. Rationale as to. Why that we don't necessarily know. It's not shown in the data. So typically what I would want from you is. Is there a gap? OK. How much is the gap? Like what like what percentage? So for every dollar demand makes, how much does the woman pay, right. So the percentage gap? OK. And then? Then the breakouts by the cuts, so by the apartment, so is they got by the apartments they got by level is they got. By cost center. I just. See that then? Where are the gaps? Who are the? People that are causing the gaps. Right. So if all the men on average, there's ten men, 10 women for some reason, I. Know it's not. It's hardly ever like that, but let's say it's. Ten men, 10 women in the team. And they all do the same rule. And on average, the men is they pay 90. They on average of 90K on average. Two men. Are maybe 80K. Which of the women are bringing that that down? Which would mean if we pay. Them more it would. Bring it up, because maybe so we already, on average we paid maybe like 100 hundred and then you have one person that paid 40 and that brings the average to like 80 or something like that. So if you pay that person 80 that spend that's paying getting paid 40 maybe increase it to 70 or 80. With that kind of bring it up. So you know. I need to. See sort of The Who. The people that. Are that are being underpaid? And then I need to understand. OK, well, based on your analysis, so how much? So that's also thing OK statistically, how much statistically can we pay them? To eliminate the gap.

**Speaker 1**

OK, so basically you're requesting a research information based on the data set insight information you're not like looking forward to like a working model. I mean like I would love to see, would love to see like at least like the the idea is we want to see the final output.

**Speaker 2**

Give us the model like in the back end like in the written thing in the back end. So that way as we read it, if you want to ever if you want to go back and review and say, well, how did he get to this, we can at least see what you wrote. We need to just see at least your model, you know add comments. And this is what this does. What this does so that way at least we can always go back and take a look at that.

**Speaker 2**

Because, ideally, what's gonna happen is if you once you iterate, iterate and then we finally have gone to the answer we want to now implement, we're going to take that code as the at least as the guide OK.

**Speaker 1**

It's actually. Just for further understanding, when you say A trait, are you saying like that's a way to evaluate the model or?

**Speaker 2**

No, it's more. It's not about that. That's not about availability.

**Speaker 1**

Best model, OK.

**Speaker 2**

Model, right? That's more of just an internal conversation.

**Speaker 1**

Myself a team.

**Speaker 2**

With your team. Because we can just say, hey, there's there is a guy, but they come up to us and just say it's not to do with your model, right. It's more about hey, like, yes we we yeah we see. That's a guy. Yes, of course there is. But actually we are fine with that gap. Well, why? Well, like this person was a consultant for us before he joined. So he he negotiate like we are going to pay more or the person took a little bit more salary and then didn't take more as much equity. Or this person actually. Yes. They are in the same. Role as this woman, however. His businessman has 20 more years experience with this woman, so I'm paying him for the experience. And so it's fine. We have that gap, OK, that we can say, OK, but not gonna change anything. We see. There's a gap there, but we can explain it. So if ever it comes up and the woman says, oh, there's a gap. There is a thing of the company telling woman, actually I'm getting paid. Let's listen. Well, actually. This game because more because he has 20 years more experience and we're paying for the experience. And then so as long as the gap is explainable and it's not just solely. Because of gender, that's what we. Want to get to essentially. So we could run, we couldn't analysis and see there is a gap, but they can explain that. Let's say we see, oh, there's a gap and the gap is in these two, three teams and it's these few people and we look at those people and we look at that and we say yes, actually makes sense because these people are way more expense than this other people. That's what they. Is that guy then? Then that's fine. We might need to do anything else. And then was like more has done his job. We had a conversation and we are fine with it because then now if there's anything that comes up, they can always just say, oh, actually, no, we can it's explainable because. Of this, this this reasons.

**Speaker 1**

Essentially just to go back a little to what you said earlier that you've done some of this analysis using OS regressions. Is like most commonly used, and now you're requesting this same analysis should be done. With a different model. So basically, are you looking at it like a comparative analysis wherever you are comparing the output of what a new model is done? Or are you trying to address a specific problem or limitations of your own?

**Speaker 2**

To address the issues of not just our own model, but just the. Industry as a whole, right? You're saying hey? Look, yeah, OS is the facto. But it doesn't mean it's the best one. Because it is not just about people. A lot of times economists or data scientists run this sort of models, and they. Have this answer. And they're like, yeah, it works. We did it. We sold the gap, but it's like, did you really solve it because they might be selling people that you missed and? Your model did. Not catch as far as not just about solving. And right, having a good model, but it's actually about having making sure that your employees have a good user experience. So for us, it's really trying to address a limitation that we see based on prior experience. And second, we're moving. For me, find models that are adaptive regardless of. Sort of your population, if it's normally distributed or not, this model actually will work. You know and sort.

**Speaker 1**

Of and show what it is to capture. OK. Thank you. So I have this question though, so if you're provided with a potential solution that meets your criteria, how do you intend to evaluate this?

**Speaker 2**

I mean, what we're going to do is, I mean, we're going to what, what we will do is if we get the solution, we'll typically do what we also do. We'll run a nowhere else against it as well. So one over SNC. Did they? Did they capture right? So if you come and just say, OK, yeah, we've seen this yesterday that is normally distributed, you run anywhere else we got. This these are the people. These are the gap. Then, naturally, if you're, if you're any data science is what your weight is going to run the the de facto to check. So if we don't run the de facto, we're going to compare it side by side, right and see, right, it's not. This is not about like oh, what models like what is the no this is more about you just run the model and just see you have to just compare it. And just see. So it's just like, OK, well. What did they catch you that they did not catch you? And immediately if you start? To see that, oh. Wow, it's the same. It's the same that there's a gap here and here and there isn't here in the OS. Then we'll just we'll just bring pull the population of people and we just do like basic averages. Let's just see. Oh well in OS. The women are 90,000. The men are 93,000, he says. There is no gap statistically significant. It's just fine in the WLS, he says. There's 1993.5 or whatever, 93. Oh, it's in. There's a gap. We they think this.

**Speaker 1**

That's the gap.

**Speaker 2**

OK, then. So it tells you what you. Need to know. Right. So it just tells me one one more list counting for a lot more and it's more. Sensitive than the other one. Right, so we're. Going to take a look at those things. So it's just that simple, it's not. It's nothing like, oh, yes, you can run them all and look at all what is the. R-squared, this that, and the third. But it's just that simple, we're. Going to run. The defacto we take the model that. We take the solution and we run. It and then. We see what it catches. The other one doesn't catch it. It's pretty much similar. It catches in. OK then we know. OK, well, fine. It's called it. But if it's catching more than the other one, it's just a thing of that. Comparing it to the base and then going from there.

**Speaker 1**

OK. You said. You see if it catches it. If it doesn't catch anything like there's no more difference. Does that mean you would stick to your current approach if there is no difference?

**Speaker 2**

Think going forward we have to change anyways, right? I don't think it will have even won. And then we see how much difference will never do it again. No, we we do it. We do it. I think it's important to sort of I think The thing is the thing. What what has historically been the issue is? People just want one OS region and that's it. They just want to waste the region and see and masses. They see the outcome and boom. OK. That's all really good. Boom. Boom, boom. Yeah, that's what it's been. Now we are saying. We think they're better models. Therefore, he should run us more. So now for every gender pay analysis, you should actually. Maybe run multiple model? One first of all maybe to see what the best mobile is.

**Speaker 1**

But it's it's.

**Speaker 2**

It's the second thing is also to have a frame of reference as well, because you run nowhere less. You want to be less run then you can start having frame of reference, say well, where do I? Where does it say there's a gap where they say there's a gap? OK, wow. OK. What does it? Say there's a gap, right? So you see those. Things and you sort of go from there, right? So moving forward, I think. I think also that even for organizations, I think negotiations to ensure pay gaps should run multiple. Not just multiple analysis. When you iterate, however, but multiple marbles, multiple different kinds of algorithms. Cash, because now all this good work, all this works mostly doesn't like you could find it. A data set like a company that is normally distributed and then oh, that's my soft for that. But still doesn't mean should run. Of you, unless you still. Want to see there might be. Things that you think you know they might be missing. So again, all this is a hypothesis. But moving forward, we're going to have to run multiple. So I think this is a good thing to get because when we get that, I mean it's going to enable us to sort of say, OK, we have this thing, we know we already have OS, we're seeing this sort of proposal for the BLS, OK, this is great. And then we can see the. Comparison and then moving forward then it. Sort of becomes almost like our. You know, like ammo, right? Around the whereby it's like we just operate that way. So OK, yeah, this is what we do, we. Run this model. Run this model. This whole comparison, which I'll understand, and then we go from there. So I think I think for the purposes of your, if you're going to. Do this. I think it's I think. You should still want I think. To to to for you to be actually great. I think you should run OS against the model because then. That's your, that's your base. You have that now. That's your frame of reference. You should run OLS. See what that is. And you run it. WS you start and you start to compare. And then that will give us now that way if. You come to us and say. Hey, here's this proposed solution. We found the gap. Here's the cuts where the gaps are. We run these three marbles. Here's what we got. Here's what we saw. And here's not. That's why we're going to. Go with the WLS. And that's that's essentially perfect. That's essentially what we want.

**Speaker 1**

And while considering this you've mentioned WLS has one of the options and then.

**Speaker 2**

Again, and by the way. You could try different. It does not to be. You can do some research and see the other things that we other models that we don't know like we have. Not gone into.

**Speaker 1**

Talk about. So you mentioned the. Few but like. From your experience with a few models that you know and mentioned and the OS, you can currently using, are there any like cost implications of these models?

**Speaker 2**

No, I mean, I think I think the biggest thing is. The cost implication is maybe more on. Because like if you want to model and tell you there's no gap and you go pay people and you solve the gap, OK, fine. If they take, if the gap is solved. But is it really? So the cost of the implications is you have to weigh how much your culture and the longevity is important to you. It's that simple. On one hand. If all always could tell you, hey, look. You need to. Pay $600,000 to close the gap. You paid the. Salaries and you. Close the gap. And then that's fine. But you run another model that's more in depth. I mean, as actually saying no you. Actually, to pay 750,000. You cannot be like, Oh well the OR. Less is the de facto ah. I don't pay an extra 150, so I'm gonna do that. I'm not gonna do that and. And and and you and you wouldn't get in. Trouble because the Oilers, you know? Accounts for the all the major stuff. But you missed. You missed out an opportunity to make more employees happy and. You know, just culture really kind of make sure that things are so you misunderstanding intangibles that way. So their cost you know maybe you end. Up paying more because it's. More accurate but. But again, it's, you know. Is it? I don't know. You know what is what is legal is not always the right. Thing right, like. So yeah, it's legal. Yeah, it's fine. Legal legally. You can get away like it's fine. You basically is the high level. They run analysis, they'll see. OK. Well, that's there's no God. But it's not the right thing. Can you actually look better and deeper and understand? Oh, actually, there are things that we can have people that we can pay here and here and here a bit more. And actually it would be better. It really is a kind of comes down. To sort of the culture. And what the perfect people want.

**Speaker 1**

OK. And whatever solution that is being come up with, I know so far it sounds like just identifying if these gaps exist or like also trying to like know how to solve them. But then how will these solutions be incorporated into your organization as a whole?

**Speaker 2**

That's I'm saying like if there's a gap, we say this is how much? We then we pay them. It's that simple. Right ?

**Speaker 1**

So if you choose this, if you choose a specific solution, will you be like, OK? Probably just just thinking, is it like? Auditing process or hiring process you keep using these models or something to like check.

**Speaker 2**

Yeah. I mean, you're gonna have to always. That's something you run. You have to run. That's asset to you. You have to check from early on. It's like you have to run it 3:00 to. 4 \* a year. So if you find the issue. You solve for it. But but again, it goes back to that initial thing I said. And you should we should also solve. If we see. That the other issues that are causing the pickup such as. Like hiring and offering. Like, what do you hire when you're hiring? People like why are you offering the men that retraining your your? For managers having like very more narrow ranges, you can't have a range of 30 to 90. It should be like 30 to 40 or 30 to 38 right? Things like that. So you you have to change a few. So you're gonna have to change a few things if you say, OK, well, we realize, OK, well, this is the issue causing that like so we retrain managers we we train recruiters. We we have a stronger competition philosophy. And then you have to run the gender pay gender pay. Once you implement it you something you. Have to run like once 1/4. Maybe twice a twice a year, 3 \* a year maybe, depending on your growth, but that's something you absolutely have to just keep running. So you run it once you know as you grow you you solve the problem in this and you in over the next quarter you grow by 100 people, you run it again next quarter just to see. Because then that way you make you're constantly maintaining and making sure that people are not getting on the page.

**Speaker 1**

OK. Thank you very much for this information. It's there like anything you think that you would like to bring to limelight that will probably be beneficial to the research as well.

**Speaker 2**

Yeah, I mean, I I don't think, look, sometimes you might see gap, but it's not. It's not always because there is. Bias or because they just careless sometimes just because there's not good planning and. So again, the idea for gender payers to make sure that. That that if there is a disparity. It's not. Because of a specific, it's not because of a specific. Thing which is gender. Right. Because if you basically the idea. Of gender pay is. If you if, all things being equal. If you bring a man and a woman. Is my making more everything being equal? And if everything being equal, the man's become more than it's gonna pay because everything else is equal. But if you look at and you say, oh, there is actually some disparity, but it's because of these other factors. And not just about you then. There's no gender pain. Becomes an issue where you're paying someone more because of their gender. That's what the issue is, and so you, the job that we're trying to get and what? We want from you is to. Do the analysis to show us if. Men are getting paid more because they are men. That's it. And it's not because the men because of. Other things like maybe experience tenure, I think that. Then then that will be fine.

**Speaker 1**

Thank you very much for this. I really appreciate your contribution. Towards this and at any time of the projects in the research, we can always reach out to you and if you have any concerns in regards to how the data is being used, you can also reach out to the research team as well.

**Speaker 2**

Think it's something we would absolutely use? And we inform a lot of things for us, I think, yeah, I think we're very useful for us. So, yeah, I'm looking forward to this. So thanks.

**Speaker 1**

Thank you very much.