Episode 64: "Understanding & Combatting Data Fraud"

with Dave Hardisty, Associate Professor of Marketing and Behavioural Science at UBC Sauder School of Business.

Fraud has been a big story in the behavioural and decision sciences this summer. Dave Hardisty returns to the podcast to help us understand the incredible story of fraud in research about, well, fraud. We unpack what an accusation of data fraud means and how fraud is different from other bad practices, like p-hacking. We also explore the impacts of fraud and what we can all do about it, whether we're conducting our own research or reading/listening to others' research.

Transcript:

KIRSTIN APPELT, HOST: Welcome to this edition of Calling DIBS. I'm your host, Kirstin Appelt, Research Director with UBC Decision Insights for Business and Society, or DIBS for short. Today, we're once again calling DIBS on David Hardisty.

Dave is an Associate Professor in the Marketing and Behavioural Science division at UBC Sauder School of Business. He's also one of the founding members of UBC DIBS and the Advanced Professional Certificate. He's got a number of interesting research directions I hope he'll tell us a little bit about. And he's recently returned from a six-month sabbatical at Bocconi University in Milan, Italy. So welcome back to Canada and welcome back to Calling DIBS.

DAVID HARDISTY, GUEST: Thanks. Great to be back, Kirstin.

APPELT: So, it's been a few years since you were on the podcast, can you refresh our listeners on who you are and maybe a couple of recent research directions?

HARDISTY: Sure. I'm an Associate Professor of Marketing and Behavioural Science at UBC Sauder School of Business. And so, the biggest part of my job is doing research. I'm doing projects on how to encourage sustainable choices, nudge people to make more sustainable choices, including energy-efficient behaviours in the home, such as laundry and other actions. Looking at protecting biodiversity as well, reducing conflict between humans and bears, for example, I have a green burial project that's new. I have projects also looking at charitable donation and how to encourage people to give more to needy charities. And of course, I teach as well. I teach a class on Ethics and Sustainability for Undergraduates at UBC and a class on Causal Inference and Research Methods. And of course, in the certificate program, I also will be teaching a class this year on behavioural science.

APPELT: Wonderful. So interesting. All the different research directions. We could do several podcasts just on that.

HARDISTY: Yeah. This has been all everybody's talking about in the Twitter, or is it X world lately. So there, I guess let's start with the most exciting, tantalizing example, which is there's a paper about dishonesty and it's famously about signing at the top or the bottom of a document.

For example, if you have to report the mile, how many miles you drove in your car for insurance purposes, or maybe a tax document, there was a study previously, as a series of three studies actually, in a paper published in PNAS, the Proceedings of the National Academy of Sciences. And they reported that people are more honest in their reporting if they signed at the beginning of the document, the idea is saying, “Oh, if you prime people that, hey, your name is on the line here, by signing at the top”, then you're like, “Okay, well, I better report carefully”. Whereas if you were signing at the bottom, you've already filled out the form by the time you get to the bottom, so then the signing is kind of an afterthought, and there's no way that signing could influence your honesty if you're signing at the bottom. That was the idea behind the original paper.

However, people tried to replicate this paper and weren't able to. And so, then that started to kind of question, “Oh, is this a reliable finding or not?”. And there was a published follow-up paper just, I think three years ago, in 2020, a follow-up paper, published with the original authors participating as well as new authors, and they were not able to replicate it, and they posted the data from the original studies. And since then, it's come out that actually two of the studies in that original paper seemed to be fraud. It seemed to be from two different researchers on a paper about dishonesty.

Two of the researchers, seems that they invented the data, so it's not 100% clear exactly who created the data. But certainly, what we do know is that one of the studies Dan Ariely was responsible for, and he was running it, a field study with an insurance company. And maybe we'll dig more into that later. And a second study was run by a professor at Harvard Business School in Organizational Behaviour, Francesca Gino. It was a lab study and the data from that study is also fabricated. That's certainly what the data looks like. Everybody's on Twitter about these fraud cases, how they happened, were they really fraud or not, and various repercussions, how to prevent fraud.

So yeah, these are some of the top people in the field, I guess to also to reiterate, right? Dan Ariely has written a book, Predictably Irrational, influenced a lot of people, gotten them into this field. Francesca Gino has, you know, published hundreds of papers, gives talks. She demands speaking fees of, you know, $50,000 to $100,000 per speaking fee, and is a huge name. These are big names, that are now associated with fraudulent data.

APPELT: Big names, and also one of the results that's often mentioned when people are introduced to this field. So, now that we know a little bit about the recent news, maybe we can back up and just talk about what is fraud in the behavioural decision sciences. What does that mean? What is fraud in the scientific context?

HARDISTY: I mean, broadly, fraud is when you're misrepresenting yourself. It's kind of professional lying is maybe the way I would put it, lying for professional purposes. And, in this case, within behavioural science, we're usually talking about data fabrication, in other words, making up data. If you want particular results, and you're not getting them, maybe you just make up the data and enter it in an Excel spreadsheet, for example. That's a common version of fraud.

There might be other versions as well. For example, if you claim that you ran a study, but actually somebody else ran that study and then you're taking credit for it and lying about who actually did the study, that would be fraud as well. That's not so common, though. Usually when we talk about fraud in behavioural sciences, it means making up data.

APPELT: And for folks who are newer to the topic, maybe we should distinguish fraud and p-hacking. So maybe we'll start with defining p-hacking and then compare and contrast hacking and data fraud.

HARDISTY: Yeah, so, p-hacking, the 'p' comes from p value, which is how you know, if a finding is statistically significant or not or you know, if a difference is statistically significant, for example. And often, if the p value is less than 0.05, then we say it's a "significant" difference, if it's greater than 0.05, we say it's "not significant". And so, people, including many you know, researchers often have an incentive to want to find 'p' less than 0.05. And sometimes we will analyze the data in a way that makes it more likely we'll find 'p' less than 0.05 like and this can happen for perfectly innocent reasons, right? You're poking around. You're trying to find the best way to analyze the data, and you know you're looking at "Okay, what do we do with these outliers? Do we exclude them or not, or is this real data or not?". Maybe this is somebody answered randomly and by accident, they just, you know, put down their finger on the zero key by accident and said $10 trillion instead of $10.

Sometimes it makes sense to remove data. But in other cases, that can be done, you know, strategically and give you what ends up being reported as a reliable result but in fact is not so reliable, not so significant. And so, we call it p-hacking when people are collecting data or analyzing data in a way that makes it more likely to get 'p' less than 0.05 than they should.

APPELT: I think it also helps if you understand that a 'p' value has a nuanced meaning in terms of it doesn't mean that this is categorically a true result. It means that 95% of the time-- maybe we don't go deep down.

HARDISTY: What is the p value? We could do a podcast episode on just what is a p value. The correct, the definition of a p value would be let's say you have p equals 0.05. It means that if in fact there's no difference, let's say you're comparing control group and a treatment group, right? A control group versus a "nudge", and you find p equals 0.05, it means that there's only a 5% chance that you would see this difference that you observed if actually there's no difference between the groups.

APPELT: And so, yeah, so if we use that definition, you can see that it's not that this is categorically true, it's that 95% of the time, blah, blah, blah. It also can be the case that if you were to run 100 analyses, you'd get some that seem significant just through random chance. And so, another common form of p-hacking that is often unintentional, is that people run a bunch of analyses, a few are significant and they report those, which makes it seem like those are very true results when you're not showing that, "Oh, we actually also ran all these other results that weren't significant".

I think that is one that shows how it can be, you could do that intentionally by only reporting certain results, but you might not have realized that your results were due to chance.

HARDISTY: Yeah, that's a great point. P-hacking can be intentional or unintentional, right? And as you said, if you run 20 different analyses and you find that 19 of the ways give you null results and one way gives you a significant result, and then you only report the one way, and it's p less than 0.05, well just by the definition of kind of p-value, you'll you know, you'll find something significant if you look at 20 different things just by chance.

So, p-hacking is something we all try to avoid, to do good science, and it's something we're always looking about, and we're learning as a field. Personally, I used to do p-hacking all the time, and I still do, to some extent, I'm sure, because it happens unconsciously. I'm always trying to minimize it. And one of the best ways to avoid p-hacking is through preregistration, because that way you're making sure you're not being overly flexible in your reporting later.

So, p-hacking is just about, to put it another way, p-hacking is mostly about how you interpret the data you have, right? And that's very different from fraud, which is where you are making up data, right? That's always intentional, you know? You're never accidentally, but you know, fraud kind of by definition is intentional and it means you are purposefully being deceptive, purposely being untrue.

While we want to certainly reduce p-hacking and we want to reduce fraud, we tend to see fraud as a bigger moral violation, right? If somebody is accused of fraud or if data is found to be fraudulent, that's pretty serious.

APPELT: Yeah. But then something that's similar between p-hacking and data fraud is that they both tend to have the end goal of getting to 'p' less than 0.05. Just the means that you're doing it are, like you said, more or less of a moral violation. And in the case of data fraud, stretches the imagination to figure out a way that data fraud could be done unintentionally, whereas p-hacking can be very easily done intentionally or unintentionally.

Yeah, and they share in common that they both lead to unreliable findings, right? They both lead to maybe published papers that aren't what you think they are. Both contribute to the replication crisis. So that actually is a good segue to my next question. So, why does it matter if there is fraud in the behavioural and decision sciences? What are the impacts and who does it impact?

HARDISTY: Well, there are many and wide-ranging impacts of fraud. The first one is what we were just talking about: "Do you end up with unreliable findings and why does that matter?". Well, it may be, I mean, the whole reason we're excited about behavioural science is the science part, that it's based on evidence, right? And without that evidence that we're leading people astray, governments might implement a policy such as signing at the top of a form. They have to spend resources, maybe to change their forms, right? Changing systems, we know, takes time and energy. And so, it leads to waste of resources in that way. It can also lead to problems for other researchers who are trying to extend and follow up on those findings.

There is a story about, it was the Behavioural Insights Team running a study in Guatemala with the Guatemalan government, and they said: "Hey, we want to do a behavioural science study, one of the problems we have is people not paying, not reporting their taxes accurately for VAT taxes, and we're willing to do a big study". They did a huge study in Guatemala with hundreds of thousands of participants. I mean, as people in the country, changing the tax forms between signing at the top or the bottom, and found indeed null result. No effect of signing at the top of the bottom because it was based on the original paper, was based on fraud. And so, they wasted the time of the researchers, they wasted the government's resources that could have been spent on many other things that might have been more promising.

So, and that's on a kind of a social level. It also impacts people on a personal level in that, I mean, the fraudsters are getting ahead, right? They are finding things that are supposedly exciting and then publishing them. And that's keeping back other real findings from being published, right? So, it hurts others who might have been able to publish other findings that might have been able to get out there. It hurts people who they may be a student and you're wondering "Why can't I get this result to happen?", right? "I'm doing the same thing as this famous people at Harvard or Duke, and it's not working. I must be the problem". That leads people to doubt themselves when they can't do the same thing as what's been published. What, supposedly, has the stamp of science on it.

And so, I think that leads some people to discouragement, maybe, you know, dropping out, changing a career. And a lot of those are not publicized very widely. People don't make a lot of noise when that happens. I think there are countless unknown people who have been impacted by this fraud. Really, really wide-ranging and negative impacts, as well as it undermines our trust in each other, right? It undermines the credibility of the field. When there is fraud, it will lead people to not trust other results. It leads people to not trust each other, right? You're wondering, “Oh, like who else is maybe doing fraud?”. I think that it has numerous wide-ranging negative impacts.

APPELT: Yeah. And like you said, some of them are quite direct and some of them are quite indirect. And we are perhaps a bit more able to measure the direct effects and the indirect effects on, you know, societal trust in science or peer trust of colleagues. And people abandoning the field are hard to quantify, which is a good segue to my next question is how big of an issue is fraud? How common do you think it is? Is it a really big issue in the behavioural decision science, or is this a small issue?

HARDISTY: Well, it's certainly very important, so in that way, it's definitely a big issue. How common is it? Is hard to know, as certainly I mean, these are recent cases of, these are cases of fraud that were detected, it's been found before in history as well. There are some other names people may know, like Diederik Stapel and Dirk Smeesters. This isn't the first time fraud has been discovered. There are a lot of people working on trying to find fraud, but you don't know how big it is. One sign that this field is taking it seriously, is there was actually Francesca Gino, she's the one of the researchers on the paper I mentioned that had fraud in it, she has a lawsuit now for defamation against the people who found the fraud.

And from my perspective, this lawsuit is quite spurious. It's just trying to save her reputation. But there's been a huge backlash or support, show of support from the community to support those working against fraud. There's a fundraiser. They raised over $250,000 in three days and from I'm not sure exactly how many, but hundreds and hundreds of researchers contributing to this, including Nobel Prize winners, right? Names you would know, like Richard Thaler, Daniel Kahneman, other big names in the field, all contributing and putting their name on these anti-fraud efforts. It's something that the field is taking seriously. And I mean, my current belief is that it's only a small minority of people doing fraud.

Most people are not in behavioural sciences for the money. They're doing it because they care about truth and evidence. That's why people are doing this and not something else like investment banking or something. I think fraud is rare in our field, but certainly there are a few people doing it, and we need to remain vigilant, and we need to set up institutions and incentives to check and to promote good behaviour. So yeah.

APPELT: And do you think there's any reason to believe that fraud is more common in the behavioural and decision sciences than in other parts of the scientific world?

HARDISTY: Well, I mean, fraud happens across all scientific fields. So certainly, we're no exception in that regard. It's quite, unfortunately, also quite common in medical research, drug trial research, many other fields. I think fraud is going to be more common when something cannot be easily, independently replicated and verified. So, a case where you're not going to get any fraud is if you know, you're analyzing an existing real-world data set that happens to be out there, like you're analyzing census data, right?

Maybe it's a, you know, an economics study, then, you know, it's impossible to have fraud for the most part unless the original data for some reason was tampered with. But you have other economic studies where it's based on private data, where they say, “Oh, this company shared this data with us” or “This government shared this data with us, but we can't share the data with you. It's secret”. Any time you can't double-check and verify, that's where fraud is more likely. So that's where I think fraud is becoming less common now in our field over time because of the open science movement, which I think we'll probably be talking about more in a bit. The more we have data sharing and methods sharing, transparency, the less fraud there will be.

APPELT: Yeah, that's a good point that it depends on the surrounding systems and incentives that make it easier or harder. So, much like behavioural science, can make things in the real world easier, attractive, social, timely, we can make good practices in our own field easier or harder.

Well, pulling on this idea, I think we are saying and agreeing that bad actors and bad practices aren't unique to our field of behavioural and decision sciences, and certainly neither of us thinks that the whole field is invalid or that people should stop practicing behavioural insights.

What does this mean? What are the implications of fraud? And I think maybe you’re going there already with some of what you're saying.

HARDISTY: Yeah. So, as we were just talking about, we want to develop institutions to prevent it, such as sharing data. Another direction is what should you do as an individual consumer of research, right? If you're reading research, what do you think about it, knowing that there is some small amount of fraud out there? I would say don't trust any one study or any one researcher too much, right?

The most reliable findings such as default effect, just to pick one of the standards that we know is very powerful, very reliable, or anchoring, you know, I do it in my class projects all the time. They've been replicated over and over again by many different people, in many different places, right? So don't take too much away, if you see one study that's exciting “Oh, that's cool. That's a great idea.” It's great, you know, but don't take any one study as gospel, right? Just because one study found something doesn't necessarily mean it's true, it needs to be replicated by others.

And the second thing I would say is any findings that seem incredible, like, you know, too good to be true. Maybe just squint at them a bit harder if it's like all it takes is this like one little trick and you'll fix everything. Like “Hmmm”, you know, take a closer look at the data there and look again. Look for replication.

APPELT: Yeah. The burden of proof is still very true. One study is not enough. And anything else we can do to be better consumers of research to detect and avoid it, when we're consuming research, reading, learning, listening?

HARDISTY: There are some resources online if you're interested in fraud specifically, as well as p-hacking. Data Colada is a great resource. It's a website where they publish a lot of methods and findings, this is the group that broke the current fraud scandal that we're discussing. There's also Retraction Watch, which is not just behavioural science, but across all sciences, because as I mentioned, unfortunately, you get fraud in other fields as well, such as, you know, medicine, biology, etc. And so, Retraction Watch is a source to find out about fraud in the field.

You can also find retraction notices. Make sure you're on the lookout for that, because occasionally, papers are retracted later once the fraud is found. Like, in fact, just today, one of the Francesca Gino papers in Journal of Personality and Social Psychology was officially retracted by the Journal. And so then now if you go and find that journal online, it will have that retraction notice. But unfortunately, sometimes people don't know about that. And so, they continue citing and relying on papers even after they're retracted. So, I guess I would say if you're unsure, you can always go back and double check the article online. Make sure it hasn't been retracted.

APPELT: Yeah, but it speaks to the importance of staying current, whether it's re-accessing or just being plugged into the community and so that you can have someone you can check in with to just say, you know, “Is it still considered state of the art?”. Because like we said with the insurance case it's in textbooks. It's in, you know, almost any resource that's covering behavioural science, that mentions the study.

And so, a lot of students, when they take an introductory course, it's one of the findings that they think is really neat. And then you don't know, it hasn't been supported unless you check in.

HARDISTY: Yeah.

APPELT: Well, turning to the field, how can we do better? What can we do better in our own research? What are some of the best practices with our own data? What should we do? What should we avoid?

HARDISTY: So, one is in our own research is always try to keep the raw data around. Sometimes, we end up with multiple data files because you have to be known as part of good data analysis, you do need to do a fair amount of data processing often, especially if you're combining data from multiple sources.

It's key to keep the original data, and it's also good to have more than one person involved in the data. Fraud is, I think, much more likely if you only have a single person working on data, because then if they do something shady, nobody else will have any idea. And by the way, this issue of fraud is not just for published research. This also serves, I think, for internal research, even that never gets out to the public. That's just within a company or an organization. There's often pressure to show good results. And this isn't just for behavioural research studies. This is like anything, you know. “Was your product launch a success or did your new program get enough involvement from the public” or whatever, right? Any time you only have one person working on it, there's some incentive to make things look better and some possibility for fraud.

APPELT: And also, just for error, like going back to p-hacking, having multiple people involved reduces unintentional mistakes as well.

HARDISTY: Yeah, certainly unintentional mistakes are much more common than fraud. And the unintentional mistakes do tend to lean in a certain direction as well because if you make a mistake and then you look at the results and you don't realize you made a mistake, but you look at the results, they didn't come out the way you thought you would, then you go back and double check and you're like “Hey, did I do something wrong? I thought this was going to work and it didn't” and then you find your mistake and you fix it, right?

But what if it happens the other way where you make a mistake but you didn't realize it and the results came out looking good? Are you going to go back and double check and make sure, probably not you're just going to run, be like, “Oh, we got the result. Awesome.”. And so, in fact, even just accidents can lead to data looking the way you want it to. And as you're saying, that's another great reason to have somebody else double check, run the analysis as well on the data, to catch mistakes or find maybe there's a better way of analyzing the data.

That's a good step. Another method, I'll say that's good for p-hacking, as I mentioned, is preregistration. Of course, that doesn't deal with fraud at all, because you can preregister and then still just make up any data you want. So, while preregistration is certainly good for reliability that doesn't stop fraud.

APPELT: Although it's possible that some of these techniques like preregistration, may discourage fraud because people feel like there's more chance of scrutiny. And so the fraud would have to be more sophisticated to avoid detection. So maybe it increases the friction costs of fraud in some ways.

HARDISTY: Yeah. I think preregistration also sends a signal that people care about good research practices and truth. And so, it creates a social norm that we’re not going to tolerate shady business. And so, I think that may also discourage fraud.

APPELT: Yeah. So, making sure we keep original data that we preregister, that we make materials and data available for sharing, are all important. If we circle back to the idea of research with partners, which is part of the study with the Ariely study, where they had a research partner, sometimes we're not responsible for our own data collection. A partner organization may be the one managing the data collection and sharing a data set with us.

What can we do to make sure that the data is high quality? And again, it may be that there is fraud, but it could be that there's just some unintentional error. How can we, once we get data checked for things, to make sure that there's high quality data?

HARDISTY: One thing you should always be doing, whether it's your data or especially from partners, is look at the data. What I mean by that is look at it in many different ways. So even just looking over the data file, right?

One of the studies that was fraudulent in that 'sign at the top versus the bottom' paper actually had much of the data was in a different font. Believe it or not, the data was in two different fonts and the fraudulent data was in one font, and the real data was in a different font, which sounds like almost ridiculous. But somebody had entered it and not been that careful with the fonts. As well as, sometimes you'll just notice things will jump out at you, right? You'll see a strange pattern and usually it's not fraud, usually it's just some kind of mistake. But you'll see like another thing that did catch fraud in one of the other papers by Francesca Gino is that there was a question that asked "What year are you in school?" and something like 20 people in a row answered 'Harvard,' for “What year are you in school?”.

You can understand how maybe one person might misread the question 'What year are you in school?' They just see the word school and they answer 'Harvard,' But like 20 people in a row making that mistake. And then also those 20 people happened to confirm the beliefs of the researcher. This is a bit odd, right? It's a clue something's wrong. Maybe it's not fraud. You know, you can't conclude just from something weird in a data that it's fraud, but at least something's off. So that's kind of the first step I would take is just looking at your file in that way. And then looking at your data in other ways as well, like descriptive.

You look at the distribution, histograms, running or doing a few what we call sanity checks. Just to make sure, for example, if you happen to have gender and you happen to have height, then you could see like, okay, you know, do men tend to be taller in this sample, right? You'd hope so. Just doing a few just basic checks of things that ought to be true, even if they're not going to be reported in your paper, just to make sure it seems like everything's okay.

APPELT: Yeah. And I think, again, this goes to the point that this isn't only combating fraud, but it's improving data quality. If you find that everyone is answering 'Harvard' to a question about what year are you in school, maybe the question was worded so confusingly that people couldn't understand. And so it can be that it helps you detect problems in the materials you used, or the way the data was collected, or the way people interpreted questions.

HARDISTY: Yeah, kind of a beginner mistake I see often from students is they get their data and the first thing they want to look at is the p-value, right? And I've even had cases where a student came to me and they said, 'Oh, we got a significant result. There's a difference between the two groups, it’s significant.' I'd say, okay, well, which one's higher? Which one was higher than the other? 'I don't know.’. Right.

APPELT: Yeah.

HARDISTY: So definitely start with understanding the pattern of the data, what's going on overall. And then you should only move to p-values later on to know how reliable findings are. It should not be your first step.

APPELT: Yeah, absolutely. Well, as we start to wrap up, what are some of the takeaways for you from this whole news cycle over the summer about fraud?

HARDISTY: I mean, biggest takeaway for me is just it's reinforced the importance of open science. Open science being, you know, pre-registration, sharing methods, sharing data, and ideally sharing data analysis code as well for those that are up for that, if you have code from SPSS or R or whatever stars software you're using, that's something that the field has been advocating for a while for reducing p-hacking.

But that's also how the recent fraud was caught, right? Because the researchers shared the data for their studies and then people could look at that data and discovered irregularities and discovered the fraud. So, I'd say it's more important than ever to share your data, share your methods, and, you know, full transparency, that's my, I guess, my biggest take away.

APPELT: And what do you think this means in terms of the idea of replication and the importance of science? Not always just reaching for the shiny new idea, but also replicating and building on other studies?

HARDISTY: Yeah, indeed. I mean, good science is cumulative science, right? We, more so than ever, we need to replicate not just exact replication, also extending into different areas of application. See what works when, how often, how reliable.

And I think there's a lot of pressure to do something that's brand new and really interesting, exciting and that's fun. But that's only one part of science. And those things that seem very shiny, new, are probably less likely to be reliable. So, I think it means we need more such as pre-registered replications. That's, that's great because sometimes you have a registered replication report where the journal will actually agree to publish something before you even have the results, which is awesome, right? The journal will say, “Okay, what's your study methods, your data analysis plan”, and then they'll accept it for publication and then you collect the data. That's kind of a gold standard for replication.

APPELT: Yeah. And I think more broadly, it's interesting how things around fraud and p-hacking often speak to other issues in the field. So, if we're doing more cumulative science, we're also testing the boundary conditions. So, does something replicate if we use a non-WEIRD population, for example? So, it gets into some of the ways that the field has traditionally not been as diverse, inclusive, and not promoting equity.

So good practices don't just help with fraud detection or reducing p-hacking. They have other important benefits as well. Well, as we finish our podcast here, I'll ask you my traditional last questions, which are “Do you have a message for our new BI practitioners in training, whether it's related to the topics of today or just more generally?”.

HARDISTY: Sure. I mean, number one, look at your data, as I said. Number two is that it's fine to explore your data and analyze it in different ways, right? Just, you know, we've been talking about how there's this danger of p-hacking, but it's also you often learn a lot through analyzing your data.

And I don't want you to be scared to do that. You just have to be clear then, that the results are exploratory, right? And so, you can say, “Okay, we have our pre-registered hypotheses and ways of analyzing it”. You report those, and then you're still free to analyze it in other ways. You can say, “Oh, we also did this other analysis that we figured out after the fact. But they're just a little new, a little exploratory. So, you know, take them with a grain of salt”. So, you know, go ahead and have fun analyzing your data. Don't be scared. Just don't over claim that you predicted it all along.

APPELT: Awesome. Well, thank you, Dave. We get to talk a lot, but it's fun to have a dedicated conversation on a topic we both care about. So, thank you for joining us today.

HARDISTY: Thanks for having me. It's been a great discussion.

APPELT: And thanks to our listeners for joining another episode of Calling DIBS.