[Calling DIBS](#)

Episode 10: "Energy-Efficient Lightbulbs and Lightbulb Moments in Data Analysis"

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

As a co-founding member of UBC Decision Insights for Business & Society (UBC-DIBS), Dave Hardisty is a great example of the intersection that we call BI — he conducts Behavioural and Decision Science research using rigorous experimental methods and data analysis to tackle pressing problems, like the climate crisis. Dave and I chat about one of his recent projects encouraging energy-efficient purchases; Dave also discusses the challenges, rewards, and ethical considerations of working with data.

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 Calling DIBS on Dave Hardisty, one of the founding faculty members of DIBS. I'm really pleased we're able to have Dave on the podcast today.

Dave is an Associate Professor of Marketing and Behavioural Science, as well as being the current chair of the Marketing and Behavioural Science Division at UBC. And Dave does really neat research about decisions about the future, which is an important topic. He also has a passion for using behavioural and decision science to improve challenges like the climate crisis. And on a personal note, I'm always impressed with Dave's research ideas and his way of combining innovative theory with real world impact and positive change. So, Dave, welcome to the podcast.

DAVE HARDISTY, GUEST: Thanks for having me on, Kirstin.

APPELT: Can you start by telling us a little bit about yourself?

HARDISTY: I mean, that was a great introduction. Not too much more to add. I teach. I do research. I like hiking and long walks on the beach with my dog.

APPELT: Excellent. And maybe tell us a little bit about what led you to a career using behavioural insights?

HARDISTY: My background is in Psychology, and I've always been interested in making the world a better place, and specifically nature, I love hiking. I realized that actually you can use science to help people make better decisions and hopefully make a big impact on the world. And yeah, that's what I'm doing now.

APPELT: Excellent. And so, as I said in the introduction, your main area of research focusses on decisions about the future. And for those not coming from an academic background, can you explain what that means?

HARDISTY: Some examples of decisions about the future are decisions about sustainability, about the environment where those have impacts for a long time. Could be decisions about financial future things such as saving for retirement. It often involves trade-offs between now and later. Do we have instant gratification or do we make a good choice that's good for us and for the world in the long term.

APPELT: It sounds like there's a lot of trade-offs there. Is that the main challenge with decisions about the future?

HARDISTY: There's a lot of challenges. Partly it's the trade-offs. Partly it's that it's difficult. The future is uncertain and abstract. And so even if you were a perfectly self-controlled person, it's still not always clear what's the right choice about the future. And so, I try to study both. How should people make choices about the future, how people actually do make choices, and then how do we move them in the right direction from what they're doing to what they should be doing?

APPELT: 2020 seems like an interesting year for that research. Since you and I are partners not only in research but in life, I obviously know your research quite well. And it was hard for me to choose one or two studies to ask you about today. But I thought that maybe we talk about one of my favourites, which is your Ten-Year Cost project, encouraging people to buy energy-efficient light bulbs. Can you tell us a little bit about what you were looking for, what you were testing in that project?

HARDISTY: Sure. And first, I'll clarify in case it isn't clear, Ten-Year Cost is about 10 years, not about getting tenure, although there is a little relationship there, the project had to be backburner for a little while I focused on tenure. So now it's back on the front burner. We are interested in how do we nudge people to choose more energy efficient products.

So, for example, when you're buying a light bulb or any other thing that uses electricity, such as washers, dryers, vacuum cleaners, home energy heaters, things like that, often there might be a cheaper one. But that uses only a little energy, that uses a lot of energy or a more expensive one upfront, but actually, in the long run, it uses a lot less energy.

And mostly people, including myself, often just get the cheaper one. When you're shopping, you're usually not even thinking about energy like when I bought a computer recently, I got a new computer and I was worrying about the hard drive and the RAM, and even though I study energy efficiency and environmental decision-making, that's my life, even for me, I forgot about it. And I have no idea how energy efficient my computer is actually still to this day. I'm looking at it on my desk and I have no idea. And so, what we did is we came up with a label where we put the cost of energy over 10 years for that product.

For an inefficient light bulb here in Vancouver, for an average household, it might be $200 on average that you'd spend on energy over 10 years, whereas for a more efficient light bulb, it might be more like $60 only that you'd spend on energy. By putting that 10-year energy cost underneath the price tag, it reminds people about, “Hey, I should think about energy and it matters”. And it nudges people, then people tend to choose the efficient product much more often. We did a field study; shall I dive into that?

APPELT: Yeah, I think it'd be great to hear about how you were able to partner with "insert brand name".

HARDISTY: Yeah, we actually partnered with a couple of different organizations on this project. One we started with was BC Hydro, our local utility company, and we ran some just user surveys of residents in BC. These were hypothetical surveys about different types of products, as I mentioned, like vacuum cleaners, lightbulbs, washer dryers, lots of different products.

And for each one, we randomly assigned people to one of many groups. And people either just saw normal price tags or they saw our 10-year energy cost price tags or they saw a few different versions we tested that didn't work so well, such as 10-year energy savings, or one year energy cost, or the number of kilowatt hours used on average for each product. We tested a lot of different labels. And the nice thing about running these hypothetical surveys is that it's easy to test a lot of different things and get a lot of data. However, they were just hypothetical choices.

And one of the issues with research in general and especially with sustainability, is you can't always trust what people say they will do. It's important to get real measures of behaviour, measure what people actually do, because people might say, “Oh, yeah, I would totally be green”. Of course, people will say that. But, you know, are they actually going to pay a bit more for that more efficient product? So that's why we also partnered with London Drugs a bit later and we ran a field study here in Vancouver. It was run in five different stores over a period of six weeks. And we actually randomly changed the labels on the light bulbs between different stores, switched them back and forth week after week.

Every week, three stores would have one label, two would have the other and we switched them back and forth. And we measured actual sales in the stores at the register from each kind of light bulb. And what we saw was the overall volume of sales didn't change, but between the less efficient and more efficient bulbs that we were labelling, we saw when the normal, everyday price tags were used, people got the energy efficient bulb 12% of the time. Whereas when the 10-year energy cost was shown, people chose the efficient bulbs 48% of the time. So, from 12 to 48 it's a huge, huge increase.

APPELT: And if I remember correctly, one of the most difficult parts of the study was restraining yourself from buying light bulbs while the study was active so you didn't spoil the conditions.

HARDISTY: Yeah, it's true, drugstore just a couple of blocks around the corner, I had to be careful not to buy any lightbulbs. I'm known to go on efficient light bulb, shopping sprees.

APPELT: I think one of the nice things about that project that I wanted to bring up is you have these two great partnerships and you were able to combine the hypothetical lab studies with a real-world field study. I think another nice thing that pulls on what we talked about in a couple of our modules is the idea that it was the cost framing that was effective. And so can you talk about where in the theory of behavioural decision sciences that idea came from.

HARDISTY: Sure. Well, I mean, the real, first origin of it is from prospect theory that people don't just think about, you know, dollars in general or outcomes in general. They always think with respect to a reference point. So, am I saving money or spending money? And in this case, most energy efficiency things are often framed around saving like, “Oh, you could save $50 if you do this”. And, you know, we care a little bit about saving money, but not as much as we care about cost. We really want to lower our costs. And that's especially true when we're making decisions about the future.

A lot of my work on decisions about the future focusses on something called the sign effect and has found that, you know, saving $50, 10 years from now, I really don't care, right. But avoiding spending fifty dollars, 10 years from now, I do care a little bit. The long-term energy cost is much more effective than long term energy savings. And that's what that's what we found in this project.

APPELT: That's really great. Another thing I really like about this project is I think it's beneficial for everyone involved. So, it's like a triple win. It's good for the environment, in that encourages people to have more energy efficient products. It's good for the consumer because they're spending less in the long term. And it's also good for the retailer because they're able to sell the product that is better and has a higher price for them. What do you hope comes from this project? What are future results you'd like to see?

HARDISTY: Well, it would be nice, for one thing, just to see it rolled out on a larger scale, right? We've tested it and we're working on publishing it right now. And I would love it if businesses would pick it up or if not businesses then government maybe would make it. I would like to see it as mandatory on all electrical products in BC or even in the world.

I humbly believe it's the best energy labelling out there. It's something that is easy for people to understand. Number of dollars compared to something like that, the European energy label, which gives products for the most part how it's like “This one has an A+. This one has an A++ or that one has an A+++”. That's what most of them are now. Then these European-style energy labels don't do much of anything in terms of influencing choices. So, that's number one of what I would like to see.

Another direction on a theoretical level is maybe interested to see how it influences not just one-time costs, but behavior over time where it's something like, you know, might it influence using cold water laundry versus hot water laundry on an ongoing basis rather than just a one-time purchase? That's an area where we're looking into now.

APPELT: Great. Thanks for that deep dive into that project. It remains a favourite one of mine. I always love hearing about it. Another fact I know about you is that you are a self-proclaimed data nerd and so data can be a bit of a scary topic for some folks. I was wondering if we could hear a bit from you about what draws you to data, what you like about data.

HARDISTY: I do love data. And to me, it's exciting because that's where you learn about the world. Like you run a study and, you know, you do all this effort. And why are we going to all this trouble? To learn the answer. When you look at the data, you get that answer, I guess. Yeah, it's just I love knowledge and learning. And especially in research, you're learning something brand new that nobody else has known before forever, right. It's not something that you can find on the internet. So, to me, it's inherently exciting.

APPELT: That's great. I assume it's not all roses and that there are some challenges about working with data. Could you speak a bit about what's challenging, working with data?

HARDISTY: Sure. One of the challenges about working with social science data, particularly behavioural science data, is that it can be messy. I'll give you two examples of challenges. One is sometimes you're not sure, especially on self report data, if people are filling in a form, if data is real or not, like an easy example would be if you're looking at demographics, and somebody said that their age was 600 years old, well, you're sure that's bad data. You're going to throw that out.

But what if somebody said they're 105 years old? Right? It's probably a mistake in data entry, but, you know, it's possible. And so sometimes there's border cases where you're not sure if data is real or an outlier. That can be a challenge knowing how to deal with. And another challenge with data analysis is you always want to see patterns and tell stories.

And sometimes you see what looks like an interesting pattern, but it's not statistically significant. It's tough to remind yourself, “Hey, this is probably just random”, but you want there to be a story there. You have to always exercise caution, see if it replicates, and that that's a challenge.

APPELT: Our own biases coming into play. Confirmation bias, once we find something, we want to keep looking for evidence for it and not look to disprove it. You've talked a little bit about what you like about data and the joy you get in finding that new knowledge. Are there other things you find rewarding about working with data?

HARDISTY: I mean, to me, it's rewarding when you find a good way to communicate it. You make a really compelling summary because there is all this messiness. And then sometimes something jumps out at you like, "Oh, wow, this is a really interesting result". And you make that graph or that table and then sharing it with other people, that's very rewarding, right is sharing that insight that you learn.

APPELT: And you enjoy data so much that not only do you conduct your own data analysis, you actually teach data analysis. What do you enjoy about teaching data analysis?

HARDISTY: I enjoy that it's a real skill that I feel like benefits a lot from teaching. And it's something that it's hard, it's a bit difficult, I think, to do it on your own. But it gets a lot easier if you have somebody helping you along. I feel like there are some things like you could memorize vocabulary on your own and learn things online, whereas data analysis, mentorship and teaching make a huge difference.

And it's a real, I mean, it can be a real light bulb moment where you can see it in the students and the people that learned it. It's like, "Oh, I get it. Oh". And then it's useful. Right. It's very useful these days. We just have more and more and more data around us. And so, I feel like it's just in life kind of a required skill now, knowing how to work with data.

APPELT: I totally echo that. And I think that's one of the parts of our program that I'm so excited about is that students will get their own data. Because I find in my own life and often when I've taught data or worked with people who are new to data, it's only when you start playing with your own data that you really have those light bulb moments. You'll have them a bit when you're practicing with fake datasets. But when it's your own data, all of a sudden it makes sense in a new way. I'm really excited for students to experience that. That said, data analysis can be really challenging. What tips do you have for students who are new to data analysis, who might be exploring data in a more rigorous way for the first time as part of the program?

HARDIST: I would say a couple of things. One is just that it is a skill. And it is almost like a bit of a foreign language, there's a lot of weird terms at first, you'll be seeing you know, T-test and ANOVA, means and medians, and logs and transformations. And it can at first be a bit overwhelming and confusing. But it gets better, just like learning any new skill or new language.

You know, the first time you get on a bike, it's pretty rocky and then you practice it a few times and pretty soon you're riding around like a pro. I'd say it's the same kind of thing with learning data analysis and statistics is it just takes time and practice and you'll get there. And don't worry if it's difficult at first. That's natural. I mean, I've taken sometimes the same class from different people, multiple times, and I get more out of it each time, like an intro stats class taught by a few different people, it's actually valuable to take it more than once.

APPELT: Absolutely. And I remember my own stories on that account where the first week in grad school, we had a stats class with a very esteemed faculty member who was brilliant at stats, but not as brilliant at understanding where we were as students, and he launched into the class with that complex terminology. And we all just sat there for 20 minutes until I finally raised my hand and said, "What are you talking about?"

Data analysis is a good place where you have to ask those questions, if you don't follow what's going along, it's a great time to raise your hand and ask for clarification, because, like Dave said, it is like a second language.

And the terms if you're not familiar with them, the only way to learn them is to ask and practice. So, if students remember one thing from your data modules, what should that be?

HARDISTY: Look at your data and distill it down to one good graph or table, your job is not to look at all the complexity and then pass on all the different confusing things to your audience. It's for you to look at the complexity, find the real story there, and narrow it down to one key insight or a set of insights.

APPELT: Yeah, I would echo that as well from my own experience having worked with various clients, is we as academics, I think have a tendency to say like, “Oh, there's all these great analysis in here”, and then just give them pages of data analysis. But that's not always helpful. Often one of the biggest services you can provide when you're working on a project is to, like you said, distill it down to a couple of messages and not just here's what the results are, but what you can do with it. Translating it into actionable insights is a really important skill, I find.

HARDISTY: And surprisingly difficult. And you're saying that it's academics that want to look at all these complexities, but I found also, even for my students, whether they're undergrads or grad students, it's difficult when you're first getting started in data analysis, it's like, “Oh, well, some people did this and some people did that. And here's all the different frequency distributions and this and that”. And it's like, “Wait, what's the real takeaway here?” It takes some practice to get good at that.

APPELT: Yeah. And maybe a good analogy for people who are less familiar with data, is thinking about when you have a huge, long paper and you do an abstract or a summary, the data analysis you present in any kind of report is more often like the summary version, the abstract version, rather than your full complex, something which might be in an appendix.

Another thing that I think would be useful to chat about is some of the recent developments in data which have been around the idea of ethics and data and a re-evaluation of how statistics are used and either intentionally or unintentionally, sometimes abused in the sciences. That's a new topic we haven't talked about much in the program. Could you explain in layperson's terms what this revolution in data has been over the last few years?

HARDISTY: Yeah, so maybe the broad term would be the replicability crisis, where there have been a number of published studies that later when somebody else tries to run the same study, they don't get the same result. Usually, they might get a null result often rather than a huge effect that was reported originally. And there are several things that lead to this. One of the most famous has been called p-hacking, which essentially so the p-values, as we'll learn in class, is basically the chance that you found something by chance.

So, if it's a p equals less than 0.05, it means there's less than a five percent probability that you observed this result by chance, more or less. And however, if you've been, you know, a clear example would be if you have a big dataset and you look at 20 different things, and then just then by chance, you probably will find one that's significant. And then when people write the paper and report it, they only report that one that worked. And they don't report all the 19 other things they looked at that didn't work. And then they'll pretend like they predicted it all along, right. Post-diction.

This can lead to reporting of results that seem like they're statistically valid, but actually they're not. That's one form of p-hacking. There are other things that can lead to it as well.

APPELT: What you're saying is that basically there has been a tendency to make results seem that there's more confidence in results than there is warranted based on the data.

HARDISTY: Yeah. One solution to p-hacking and the replicability crisis has just been increased transparency, things such as preregistration, so before you run the study, you say, “Okay here is the analysis we're going to do. Here's how we're going to transform the data”. Because, by the way, that's another way to do p-hacking is how do you deal with outliers, right. Or “How do you transform the data? Do you log transform it or not?”.

And it can be done, of course, it could happen in unethical ways, but it can also happen from somebody that's really just trying to find the truth. But we know because of human biases, you'll convince yourself that the right way to analyze the data is the way it supports your hypotheses, right. And so even unintentionally, it can lead to results seeming more reliable than they really are. We do have good methods now to correct for these processes. And I think we have much more rigorous behavioural science these days to overcome that.

APPELT: You're saying that, you know, we're finding solutions for the crisis. For people who are just embarking on their data analysis careers, what are some best practices to ensure that you're doing a high-quality ethical job of working with your data?

HARDISTY: Number one would be just transparency as much as possible. If you can, it's great if you can share the raw data. I know that's not always possible due to privacy concerns, but sometimes you can, for example, remove all personally identifying information from the datasets. You don't have any names or addresses. You only put in a participant number as an identifier. And often once that's in place, you can actually share the data and make it publicly available and sharing the raw data. And now anybody else can always go back and look at your data, what choices you made and reanalyze it. That's one thing you can do.

Another thing that is usually possible is sharing your full materials. If you run a study, you do a survey, you actually report the whole survey, not just the questions that worked, right. Sharing materials, data, that that's number one, I would say.

Then the second thing is, once you get a bit more confident, you could start doing preregistration. I would say don't worry about preregistration right at the beginning because you're going to be doing a lot of learning as you go. But later, once you become more sophisticated and confident, then you should start preregistering your studies.

APPELT: And just as a clarification, preregistration is basically like a commitment in advance to what you're going to do with the data and how you would describe it.

HARDISTY: Yeah. It's a plan for the data collection and analysis. You say how much data, what your methods are, what your hypotheses are, how much data you're going to collect. Because that's another room for wiggling as you collect some data and you see, “Oh, it's almost significant, we will collect a little more data. Not quite there. Okay, I'll collect a little more. Oh, it's significant, I'll stop collecting data”.

This is called a flexible stopping rule. This is another thing that can lead to p-hacking. Less reliable findings. The preregistration covers that as well as which stats you're going to run. What transformations you're going to do, right? You're just basically calling your shots. And then you can still do other things. If you have an idea later, you're still welcome to add a new analysis. But it's clear that it was exploratory. Right. This was after the fact. So just being clear about what you predicted and what's exploratory.

APPELT: Thanks. I think that's a very helpful walk through some of the key ideas that have been kind of innovations in the data analysis field over the last few years. Do you have any other data or non data related messages for our BI practitioners in training?

HARDISTY: Mm hmm. I'm excited to see you all soon. And I guess I would say that data is more fun with a friend, too. If you have a question about something, can show other people your results and ask for their ideas. Usually, people are pretty interested.

I always find it really rewarding if I find a pattern of data that I don't quite understand and then bring it to somebody else. Usually it's interesting for them too, kind of a puzzle like “Why do we see this, or what's going on here?”. I would encourage you to get a data buddy, maybe even marry a data buddy.

APPELT: Giving away our trade secrets. Any last thoughts? Questions I should have asked and didn't?

HARDISTY: How are the Seattle Sounders doing? You could have asked that. That's my soccer team, they're in first place right now in the West. They just beat Vancouver 2-0 in their last game. So sorry, Vancouver.

APPELT: Well, we couldn't end on a better note than a victorious notes for the Seattle Sounders.

HARDISTY: That's what's most important here. That's the main takeaway from this interview.

APPELT: Thanks, Dave, for joining us today. We talk a lot about BI in our house, but I enjoy talking about BI with you every time. And I think hopefully for our listeners, it was interesting to hear a little bit more about data and maybe get a little more excited about our data modules. Thanks for joining us today, Dave.

HARDISTY: Thanks for having me on, Kirstin.

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