Week 4 transcript-- Introduction to Research Design (updated June 2021)

4.1 What Does It Mean to Know? Knowledge and the Standard of Proof

So in one sense, we're asking a really simple question here. What does it actually mean to know something so that you can act on it? A fancy way to say that in my business is to use the word "epistemology," which is probably too complicated for what it sounds like. But it's really just in a very practical sense a kind of theory of knowledge or a notion of, what does it mean to have knowledge, and how broadly can one apply it? A kind of nature and scope of knowledge philosophy-- but actually, for our purposes and what we want to do here, we can really be very simple about this. It's really how we as a community of actors, or maybe as a company or maybe a group of people in a room, how we are going to decide amongst ourselves and agree with each other that something is true. Now, for philosophers, this is a really complicated subject. Epistemology is a philosophy that people have been struggling with for thousands of years. For us, it's really a practical art. It includes some elements of the scientific method that we've talked about, but it can't really adhere to it slavishly. Look, here's a really concrete example. As a college teacher, I really would like to find a way to know if I'm helping my students learn what they need to know 20 or 30 years later. In other words, are they becoming better citizens? Are they better workers? Are they happier? Are they more satisfied in their lives because of something I taught them? And if I knew that, that would be great. But even if I could collect the data for a scientific assessment of that, that data is not going to be available for 15, 20, maybe 30 years, and by that time, it's too late for me to go back and change how I taught them 30 years earlier. That's just not useful for my purposes. We actually need to be practical about what we can and what we need to know. So the real question is what epistemology should demand of us as decision-makers, and that depends a great deal on actually what we want to do with the knowledge that we claim we're going to have. There can be very different standards of truth depending on what kind of decision you want to make. One standard of truth might make a lot of sense if you're, say, working for Tesla and you're trying to decide, what do you think the most popular paint color is going to be for the car next year? And we're going to have to plan our build runs in the factory. That's a piece of data, a piece of knowledge. And we could argue about whether we've got it right, but the cost of not getting it right are things we might be able to manage. It's probably a different standard of truth if, say, you're sitting in the White House in the United States and you're trying to decide, is this rebel group in a country in the middle of a civil war taking money or not from a terrorist organization? That might be a different standard of truth. And in fact, it might even change over time. And if you're sitting in a hospital and you're thinking about, again, an experimental medical treatment, you might want another standard of truth to apply to, say, stage three clinical trials for an anti-cancer drug or an anti-dementia treatment. You wouldn't want to have to apply the same standard of truth to all of those three cases, because the stakes are really different. By the way, when we dig into this-- and actually, it's intuition. We'll see it this week. We'll see it some other times as well. I think you'll come to recognize, as I have over time, that actually, the most important arguments in the real world are actually not over whether something is said is true. That's not what people really argue about, although they do. What really matters in most decision-making situations happens prior to that discussion. It's actually the argument over what standard of proof ought to be applied. And I found, sometimes to my benefit and sometimes to my detriment, if you can win that argument before you actually argue about the truth, if you can win the argument about what the standard of proof is, then you're much more likely to win the argument about what's true and what we ought to do about it. And so I think being practical about that means getting really self-conscious about the phases of those discussions and the decisions that need to get made along the way. And if we think of ourselves as data science advisors, then helping the people around us to do that in a way that makes what we have to bring to the table-- the data-- most effective and most beneficial inside the organization.

4.2 What Does It Mean to Know? Perspectives on Truth

Let's take a little step backwards, but an important step backwards, for just a touch of philosophy of science. And we're doing this because I want to contextualize how hard a problem this really is and has been for a very long time, way before anyone even imagined anything like data science. And so I want to talk about three slightly different perspectives. The first perspective is what I like to call the kind of ancient correspondence notion of truth. And it still exists actually in some forms. This isn't like, only ancient. The core theory is really simple. It's just that true beliefs and true statements, things that are true, correspond to the actual state of affairs in the world-- what's really happening. This is what Plato was looking for in his theory of truth, his epistemology. What we're looking for here is an accurate description of things as they are. It sounds self-evident in one sense, but also impossible in another. And anyone who has ever built or worked with any kind of reasonably complex model-- scientific, social scientific, model airplane, for that matter-- realizes that correspondence of truth isn't actually possible for any meaningfully complex system, because after all, the

whole
point of a model in any of those domains is to simplify, exaggerate the important stuff, and then add the complexity back. A model that was an accurate representation of reality wouldn't be a model anymore, and it almost certainly wouldn't be tractable in a scientific manner. And for purists, the model would still need to be described in words or symbols. And since neither of those perfectly represent reality, there's always going to be some form of non-correspondence. The point of this is to make it work for you, not against you. But that's only one way of thinking about what truth actually means in practice. There is a second notion which I like to call the social constructivist notion of truth. Social constructivist. This is just what it sounds like. What counts as truth is really a social construction-- what people in a specific place at a specific time agree amongst themselves is true. And in this view, what is true depends on culture, depends on history, and of course, it depends on who's powerful. I mean, not everyone has an equal say in the discussion over what is true and is not true. For example, inside a country, inside a family. And if you have more money, you can buy ads on TV or the internet and you can try to move the levers of truth. If you're respected for having been extraordinarily successful these days in a technology startup, you get the power to define what is or ought to be true in other areas of human action. I mean, think about Bill Gates with developing country public health programs and now with education. He was extraordinarily successful in technology and he's now getting to define what is true in these other areas. If you're the CEO of a large corporation, you know, it's not really enough to say that you get to make the most important decisions. In practice, it's really more than that. To a certain degree and to a degree that I think will surprise many scientists, the CEO actually gets to define what is true inside that company. Think about someone saying, you know, we are a design company. That's not just a statement about what's true, that's a statement about who we are. It's more than a strategic conversation about what markets to enter. It's really about identity. And you know, Karl Marx understood this. It's what kept him up at night. In fact, John Searle, philosopher here at Berkeley, had a really simple and powerful way to think about this. He called them brute facts and social facts. Now look around you for a minute. Knock on a wooden desk. [KNOCK] You know, that's a brute fact. What you just hit your head on is wood. But it's a social fact that it's a desk. Nothing in nature says, we sit at this desk and work. In some other society, people might think this is a prayer bench. Somewhere else, people might agree that it's god. So what is truth? Actually all of these things and none of them. It depends on where you are at the moment. And then finally, a third concept. It doesn't really rise to the same level of generality, but it's particularly important inside contemporary organizations in the way people try to determine what's true. I call it the John Stuart Mill method of truth, or JSM for short. John Stuart Mill. Come back later, you

probably know, was a British philosopher and economist from the mid 1800s. He argued that truth is something that human beings arrive at. And the way they arrive at it is through a particular form of argumentation-- the clash of opposing viewpoints. Think of truth is what you get closer to over time kind of asymptomatically through hard-edged debate. You know, you take this position. I take that position. We bang them up against each other. We do that over and over again. And over time, the debate kind of starts to extrude the false statements and selects for the one that are closer to the truth. Now John Stuart Mill believed also importantly, and this is very significant for most organizations, that truth has a kind of entropy built into it, that it tends to corrode over time, and that if you don't constantly reinforce it, it will corrode. That's a really interesting notion. And I suspect it really rings true particularly for people who spend much of their lives inside large organizations. You can't win the truth debate only once. But it's a hard notion for people who are scientifically and technically minded to accept. I mean, once we know something is true, unless the environment changes, why should that truth corrode. But think about how you've lived that reality in your own business. So what is a data scientist going to do with all that? How can you most effectively move the search for important, actionable truths forward inside a real, living, breathing company? Let's look at a simple set of instructions that just might be useful.

4.3 The Impact of a Philosophical Worldview

How Your Worldview Influences the Design and Methods You Choose

This element addresses the following learning objectives of this course:

- LO2: Design and apply research questions.
- LO4: Justify an analytic approach that informs decision making.

You don't need to explicitly identify your particular worldview and say something like, hey, I subscribe to the correspondent's view of the world,or I'm a constructivist. You don't need to do that. But within each project, we should think about whether we are out to test a theory and measure some objective truth, or are we going to take a more inductive approach and one that incorporates the subjects and their views of the research process. In reality, in a particular project, you might do a little bit of both.

The important takeaway is that we should be deliberate with our design. And we should think about the consequences of the design decisions we make. Do we think that all our interactions with subjects or our customers occur in a sterile environment? Or do we think that who the subject talks to in our organization will influence their experience and the data you collect from them?

Similarly, do you think that we could approach data science from a kind of white lab coat objectivity? Or should we think about how the experiences of the researcher could affect the interpretation of what they observe?

Now, even if you deal exclusively with machines, you might think, hey, none of this applies to me because I'm looking at production lines or trying to predict machine failure. I don't have to worry about this post positivist constructivist stuff. OK, but I challenge you in the following way.Once you come up with whatever insight you derive from your research, you'll have to persuade someone to make a decision.

Now, this is moving a little bit away from the philosophical worldview of research. But I would encourage you to acknowledge other people'slived experiences and incorporate them into the message you deliver because someone else will have to act on the insight you provide. The more mindful you are of people's backgrounds, the more effective you will be at changing behaviors.

4.4 Worldview and How to Measure Customer Attitudes

Spend five minutes on the following prompt:
Imagine the following scenario: Your company cares about measuring what customers think about your product. You are asked how feasible it would be to measure sentiment. First, develop an answer based on a correspondence view. Next, develop an answer based on the social constructivist view.

4.5 The Scientific Method Overview

The Scientific Method, in Brief

This element addresses the following learning objectives of this course:

- LO2: Design and apply research questions.
- LO4: Justify an analytic approach that informs decision making.

Now I'm going to discuss how we would look for a new law. In general, we look for a new law by the following process. First, we guess it. Then We-- now, don't laugh. That's really true. Then we compute the consequences of the guess to see if this is right, if this law that we get is right,we see what it would imply.
And then we compare those computation results to nature. Or we say, compare to

experiment or experience. Compare it directly with observation to see if it works. If it disagrees with experiment, it's wrong.

And that simple statement is the key to science. It doesn't make a difference how beautiful your guess is. It doesn't make any difference how smart you are, who made the guess, or what his name is. If it disagrees with experiment, it's wrong. That's all there is to it.

4.6 The Scientific Method in Practice

Let's take a little deeper dive into the traditional formulation of scientific method as it's generally thought about by people who do this stuff in practice. There are really five key steps and we know them, but I want to delve into them a little bit so we can get a little bit of texture about how they actually work. So the first step always is to formulate the question. And for most people, this is actually the most important part. And when you dig into it, there's a lot of disagreement on what are actually the best kinds of questions that people ought to be trying to answer. Are they the ones that we pretty much know can be answered in the course of a set of experiments, like, for example, which is more common among 30 to 40-year-olds, skin cancer or colon cancer? Or maybe the best questions are a bit more open-ended, like, why has colon cancer become more common in the United States in the last decade? I think what everyone has learned by rough experience as we go through our scientific endeavors is that poorly formulated questions are just really nasty things. They waste enormous amounts of time-- effort. They cause confusion. They cause frustration. Everybody hates them. And yet we've all seen questions that we just know from the beginning can't be answered through scientific reasoning of the kind that we're going to do with data. So I have really simple advice about that. Don't ask those kinds of questions. And don't let people around you ask them. Now, how to actually do that, we'll come back to that a little bit later. So let's assume we've got a decent question formulated. What do we do next? Well, the traditional scientific method says, find out what's already known that bears on this question. That sounds obvious. Why wouldn't you do that? But it's actually also extremely tricky. Think about 20 years ago. The risk for someone like me 20 years ago was that there might be a piece of knowledge out there tested and confirmed perhaps that you really or I really would have wanted to know before I started my experiments or my research, but I just wouldn't know about it because I wouldn't have found it. It was sitting in some obscure library somewhere on a dusty stack that I never would have found. In fact, when I was in grad school, this was everybody's greatest fear. How do I know that there isn't some other graduate student out there that has just finished precisely the dissertation that I'm just starting? This is in the pre-internet era, and actually, it was a real fear. Now, we like to imagine that today, searching for the existing literature or finding out what's already known about a question has become really easy. And there's no doubt that the internet has made a huge difference and made it much easier for us. But let's not forget that there's still sometimes a competitive aspect to this question. There are people out there who don't want you to know what's already known about this question, whatever it is. My grandmother in Brooklyn used to say, does Macy's tell Gimbels? And for any of you who grew up in Brooklyn, you'll know what that means. They're two competitive department stores. They're not going to share data on what their customers are doing. In many respects, that risk is still out there, but there's another risk. And it's even more insidious in some ways, and this is where the internet's made it harder. It's when and where do you stop searching for relevant preexisting knowledge and proceed with your own experiment. The web has made it really easy to just keep searching. Some people call it "analysis paralysis." Keep following the long tendrils of inquiry out into all the areas that might just somehow be relevant to your question. Advice-- on this one, there's no formula for how to do this perfectly, but there are some rules of thumb for knowing when it's time to stop the search. We'll come back to that later, too. Third point-- third thing we do is generate a hypothesis. Everybody knows this one, too. We're going to generate a hypothesis. Think of it as a hunch. It's a hunch about what the answer to the question might be. Well, there are good hypotheses and bad hypotheses. The best hypotheses are those that you draw for a reason. You have a reason to expect the answer to be x rather than y, maybe because of some other knowledge that you have, maybe because you have confidence in a theory which suggests that, even though it hasn't been proven. But the reason people sometimes call this a hunch is because sometimes hypotheses are actually just more like random guesses or gut feelings. Actually, you can work with both, as we always do. But it's very, very important to know and for others to know which are we really working with because the basis for a hypothesis in practice has a big impact on how quickly or how slowly we're going to be willing to discard it if a bad or discrepant piece of data comes in that suggests it's wrong. So for example, think about purely empirical A/B testing, where we don't really have an ex-- we don't know if the blue button's going to work better or the red button is going to work better on this web page. So that's kind of a hunch, and we should pay very, very close attention to the large randomized clinical trial of the blue button versus the red button. But if our bet is based in some kind of deep knowledge about how human beings choose between red and blue, then we probably want to look a little bit more closely about the surprising results that come from an A/B test which appears to falsify our hypothesis. We might be a little bit more resistant to discarding the hypothesis if we have deep reason to expect that it's right-- could be that the experiment was faulty in some way. So this can be a very tricky situation in practice. That's point four. Here's what we need to do next. We need to do the experiments. And actually, everybody wants to jump to that as soon as possible. Sure, I do, too. I want to get into the lab. I want to get that hypothesis, I want to make predictions about something that could happen, and I want to design an experiment that evaluates whether those predictions are correct. And I want to get to it as quickly as I possibly can, but it's hard. It's much harder than it seems because of all the statistical confounds that creep into everyday life, which we're going to learn about in other classes, because of all the variables that are so hard to control when it comes to human affairs, and-- oh, yeah-- because of gremlins. There are always gremlins in experiments. And again, we'll spend lots of time later on in this course-- other courses. But I want to highlight one important piece of this here. Progress towards shared understandings in real-world decision situations just depends enormously on prior acceptance by the people you're trying to convince that the experiment that you are proposing is a reasonable one to test the hypothesis. You've got to get that agreement upfront. Otherwise, it's just going to be too easy for people who don't like your findings to come back later and criticize the design of the experiment. There are obvious ways to get around this in large clinical trials, double blind studies, and other such things. But actually, in organizational decision making-- much, much harder. There are ways to get around this, there are ways to beat it, there are ways to work with it, but you can't skip the critical step. It is very rare that the findings are going to be so compelling that they're simply going to overcome the intellectual and emotional opposition of people who don't want to believe what you have to tell them. They're just not going to win. So you've got to get that agreement upfront. Finally, you need to analyze the results of the experiment, draw the appropriate and justified conclusions, communicate the results, and then, of course, iterate. It never ends. What matters here? The obvious stuff-- precise analysis, the right level of confidence in the conclusions, and crystal clear communication about both of those things to everybody around you.

4.7 The Scientific Method: Competing Hypotheses

The Analysis of Competing Hypotheses (ACH) project was developed at the U.S. Central Intelligence Agency and is now available in an open source setting for widespread use. As you read the outline below, you will see the ways in which it tries to compensate for some decision biases and fallacies of reasoning. One of the reasons ACH is particularly interesting is that it aims to grapple directly with the issues that arise as many analysts try to interpret imperfect evidence, with the ever-present risk that they will "talk past each other" and disagree without having a clear and precise understanding of exactly why they disagree.

The following list is quoted from Heuer, Richard J., Jr. 1999. “Psychology of Intelligence Analysis.” *Center for the Study of Intelligence*. Chapter 8: Analysis of Competing Hypotheses. Page 97. If you would like to read the entire chapter, the course syllabus includes instructions on how to access the material through the University Library.

Step-by-Step Outline of Analysis of Competing Hypotheses

1. Identify the possible hypotheses to be considered. Use a group of analysts with different perspectives to brainstorm the possibilities.
2. Make a list of significant evidence and arguments for and against each hypothesis.
3. Prepare a matrix with hypotheses across the top and evidence down the side. Analyze the “diagnosticity” of the evidence and arguments— that is, identify which items are most helpful in judging the relative likelihood of the hypotheses.
4. Refine the matrix. Reconsider the hypotheses and delete evidence and arguments that have no diagnostic value.
5. Draw tentative conclusions about the relative likelihood of each hypothesis. Proceed by trying to disprove the hypotheses rather than prove them. 6. Analyze how sensitive your conclusion is to a few critical items of evidence. Consider the consequences for your analysis if that evidence were wrong, misleading, or subject to a different interpretation.
7. Report conclusions. Discuss the relative likelihood of all the hypotheses, not just the most likely one.
8. Identify milestones for future observation that may indicate events are taking a different course than expected.

This element addresses the following learning objective of this course:

- LO4: Justify an analytic approach that informs decision making.

4.8 The Scientific Method: Popper and Kuhn

Over the course of this unit, you may feel that we've turned this into a pretty complex landscape. And it is a complex landscape. But now, it's time to model it a little bit or at least simplify it into a workable model. So for that, let's turn to a simple rendition of the core views of two 20th century philosophers who actually really tried to make this issue operational in their own way. So the first is Karl Popper, who many people have probably heard of. Popper was very familiar with and friendly to the way we would think about the core scientific enterprise. Popper believed that what makes science different from everything else is that scientific inquiries are about creating falsifiable hypotheses that are clearly derived from a theory. And so like what is the iconic act of a scientist? The iconic act of a scientist is to falsify a hypothesis, not to prove a hypothesis, but to falsify it. So nobody can prove that the sun will rise tomorrow. You can formulate a theory about why the sun rises. And you can derive from that theory a hypothesis that the sun will rise tomorrow and every other day. And actually, that's a falsifiable hypothesis. Because you can go out there every morning and if the sun does not rise even one single day, then the hypothesis has been falsified. And you may need to reject the theory and replace it with something else. So what makes a scientist different from everyone else is that a scientist is trying to prove their hypothesis wrong. Now, look, that's an ideal. And there's more wiggle room than people like to admit, but the aspiration that Popper had, I think, is really clear. Scientists seek falsifiable hypotheses, and then what do you do? You go out and you falsify them. And in doing that, you're constantly moving forward with reformulated theories that might get closer and closer to the truth. Here's the bad news. Data scientists are not going to often have the luxury to be Popperians, which are the word for people who believe in Karl Popper. Instead, actually, more often, you're going to have to live in a world that is unfortunately perhaps more like that that was described by Thomas Kuhn. So let's talk about Kuhn and Kuhnians. Thomas Kuhn wrote really a fantastic book that has stood the test of time called The Structure of Scientific Revolutions in 1962. In fact, he's the guy who came up with the phrase which has now entered the contemporary lexicon, paradigm shift. And everyone's heard it. It comes from Kuhn. Kuhn is not really a philosopher. He's sort of a sociologist. Instead of studying the sociology of science. A sociologist of what scientists actually do. He actually wanted the world of science to work like Popper said it should, but as he went out and looked at how scientists actually work and have worked over time, he found that even though popper was perhaps the best way to do it, that's not the way people actually moved science forward. Instead, what Kuhn saw were what he called reigning paradigms. Theoretical belief systems that people would hold onto really tenaciously for as long as they possibly could. And actually, usually, longer than that. He referred to this as normal science. And it was reinforced in the way it continued to reinforce itself was not so much through findings or experiments or data, but actually in his view, through power relationships. For example, he looked at the fact that academics who control what papers get published in journals get to say what the reigning paradigm is. In the business world, big companies that do certain things get to define what other companies call best practice, because that's what the big companies are doing. And that's the reigning paradigm, whether or not it's actually best or just what somebody is doing. Now, this is actually really important, because people who question paradigms generally get marginalized. They find it hard to get jobs in the academic world. They can't get published. Some of them can't even make friends, even though they actually may be right. They tend to get extruded from the mainstream conversation. Maybe not forever. And then they look like heroes. Because eventually, enough anomalies, enough hypotheses, will break down and the sense that something is wrong really begins to accumulate and then the rebels get a chance. And they break through. And then, rather suddenly, in Kuhn's view, a paradigm shift happens. But the point is, it takes a lot longer and a lot more grief and blood and sweat and tears than any scientist ever looking back at the actual evidence would say it should have taken. And unfortunately, some people usually get hanged, whether that's literally or figuratively, for some sacrilege in the interim. Look. Think back about theories of the universe. And this is what Kuhn draws his formal insight from. Copernicus said that the Earth was not at the center of the universe. Turns out he was right. Ptolemy viewed the Earth as the center of the universe. He was completely wrong. But actually, sadly, Ptolemy had a much more successful career. So here's the thing. Most data scientists, because they're scientists by training and by inclination, are going to want to live in a world that works like Karl Popper. But most of the important problems that data scientists are actually going to be called upon in their day to day work to answer the questions that they're going to be posed, the problems that they're going to have to be solved, they're going to be more like Kuhnian problems. Take an example. Imagine, for a moment, that you're working for the Republican National Committee. And you are asked to put together a data set to prove that immigration is bad for the US economy or for US workers. That's not a Popperian world. And in fact, if you go out there and do what a scientist really believes he or she should do and treat that like a Popperian problem, you're going to find yourself unemployed in a very few weeks. But if you treat it like a Kuhnian paradigm problem, well, you may have a hard time justifying what you're doing and looking at yourself in the mirror sometimes. Nobody's asking you not to tell the truth, but they are asking you to modify the story so that it actually has a chance of moving a paradigm from one place to another. That's going to make you much more effective or at least giving you a much greater chance of being effective and using data to make a difference in the real world.

4.9 The Scientific Method and Society

The Societal Context

This element addresses the following learning objectives of this course:

- LO2: Design and apply research questions.
- LO4: Justify an analytic approach that informs decision making. ● LO6: Navigate organizational, personal, legal, and ethical constraints to facilitate better decision making and improve communication.

Let's talk a little bit about the social context in which science operates. You could kind of think of this like Thomas Kuhn applied, or you could also think of this as the School of Information perspective on science and society.

We should be mindful on how our work will be received by others. People perceive our work via their existing beliefs and their professional and lived experiences. The more we are mindful of the paradigms that structure the thoughts of others, the more persuasive we could be.

Now, there's also an element of social responsibility in what we do. I encourage us to think about how information and technology affects people. Think about the impact of our innovations and how we may expand access to information. And think about privacy and security as wecreate new things.

4.10 Paradigms

Spend five minutes on the following prompt:

What paradigms are dominant in your field? What impact do they have on your work?

4.11 Certainty, Part 1

So we have spent a lot of time so far putting roadblocks and barriers in the way of being certain. And hey, that's what academics are really good at. That's what we're trained to do. In fact, academics is probably the only profession I know where people can get paid, at least on a consistent basis, for saying, I don't know. Without saying anything more about what to do next. In fact, we get paid for that as long as we say it in an interesting way. But most people don't actually have that leisure. Someone once told me that in the real world, where we actually want to operate, you can't replace something with nothing. You got to replace a bad idea with a better idea. And I think that's actually a very wise person who said that. Decision makers, people who have to make choices, do not want to walk into a room and be told here's the list of things you can't possibly know. And they definitely don't want the elements of confidence that they do have to be consistently undermined. There's no better way to make your boss angry than to say, you think you know x, but you're wrong. In fact, sometimes that's what they really need. And sometimes it's intellectually honest. And sometimes they need to be brought to that recognition slowly. But I'll tell you, no one survives long in any organization by being Mr.

or Ms. Naysayer. It just doesn't work that way. In fact, they might even drop out sooner. And the more they are correct, the sooner they might get extruded from the discussion. Now, that sounds obvious for those of us who worked in organizations, but it actually flies in the face of a lot of literature and advice that people have been given over centuries on how to be a good leader. Go to a bookstore in an airport and pull out one of those business books. And it talks about leadership. And you'll always see a chapter that says, you as a leader should seek out the dissenter on the team and listen really hard to that person. To the person who is the iconoclast. To the person who is constantly disagreeing with everybody. In fact, there's a wonderful book called The Age of Heretics, which actually champions the role of the heretic inside the organization. And this has been true for centuries. Think back to the Middle Ages. You have the King. And all the people around the King who are scared to death of telling him the truth. But the King has a Joker. And what is the Joker allowed to do? The Joker is allowed to use humor to speak truth to power. You see it in politics all the time. Lyndon Johnson, for example. George Ball. A guy who sat next to him and Johnson would constantly turn to him and say, George, tell me why this argument that everybody else is making is wrong. But he didn't actually listen to George Ball that much. And kings don't always listen to their jokers. In fact, most bosses, most leaders, go about this in a ritualistic way. They pretend to listen to dissent and ironically, it almost makes them more confident in what they believe. They go through the motions and that's about it. So that could be a pretty depressing story. The point really is, people who have to make decisions generally want levels of certainty that just aren't possible in the real world. From their perspective, they'd actually often rather be certain than be accurate. More certainty is almost always better, even when it's actually not. And maybe this is even hardwired into the brain of decision makers. The brain is, after all, a complex pattern matching machine. It's always looking for patterns. And many of those patterns may not be there. That's why human beings unfortunately are not born with an innate understanding of statistics. It would be good if we were. We wouldn't have to take statistics courses. We wouldn't have to take statistics courses. They'd be better. But many of the decision biases that we'll talk about and we have talked about, they are locked in to the way in which brains work. So we've got to deal with this. The practical question really will be what do you do with the desire for greater levels of certainty? Particularly when you know that they actually can't be provided. Let's talk to someone from the intelligence community who has to deal with exactly that issue almost every single day of their lives.

4.12 Certainty, Part 2

Interview with **Craig Denny**

4.12.1 How Experts View Certainty

This element addresses the following learning objectives of this course:

- LO1: Describe the role of data science in organizations.
- LO4: Justify an analytic approach that informs decision making. ● LO5: Identify the audience and the most effective method to communicate a persuasive argument.

Now these are really big questions with really big consequences for how people think about strategic relationships.Presumably, you've got strong ideologies which are going to predispose some of the people who are going to be reading these reports to really want to come down on one side or the other. And you've got this presumably big kindof mix of all sorts of different kinds of evidence or qualities of intelligence, and so on and so forth. Just in practice,how does one think about bringing data evidence to bear on questions like that in a way that actually have the potential to change someone's mind?

Well, at the end of the day, you just abide by the mantra of an intelligence analyst, which is to be objective and check your own politics and ideology at the door, to the extent that's humanly possible, while admitting and acknowledging that no one can fully escape their own cognitive or much less ideological biases. But you know, I strive to do the bestI could in that regard, and I think most analysts do, if not all.

You know, and so you just call it like it is. And so for example, you know, I remember doing, you know, pieces that were more reflective pieces that President Bush would be reading at his ranch, which is where he tended to read more reflective-type pieces or more cerebral-type analytic pieces that weren't more tactically oriented. And you know, I
can remember trying to get in some data and some information on comparative global income inequality.

And I mean, you know, some of the stuff maybe I should or shouldn't be talking about, but I think it's fine. Feedback Came down through the chain that some of the advisors around the president-- I don't know if it was the president himself or the vice president, whomever-- you know, might have tripped up on that particular section. Like, they just didn't want to hear it. They didn't want to look at that.

You know, so those types of things, all you can do is just put forth the evidence as you see it, surrounding a given hypothesis or a state of affairs on some question, and hope that it's given an objective read. Now in the same respect,other things in that report were deemed favorable, and they might have seemed controversial, given the political disposition of that administration. And I'm not just citing that administration, because they all have that.

In fact, there was another example where-- much more tactical, but surrounding an arms sale decision where I was called on to provide assessments of the comparative regional military balance and give my take on what a prospective arms sale-- and I won't go into the details. It's a long time ago, but a prospective arms sale might do to that balance. And I called it like I saw it, that it was going to be disruptive and have a lot of counter escalation effect on the part of two or three other actors or states in the region.

And it was not what the decision maker in this case wanted to hear. Now this wasn't at the level of the president. It was the more intermediate level in the Pentagon. But ultimately, someone responsible for regional defense policy in a given case. And you know, they just didn't want to hear it.

Now the way that got resolved was ultimately, I got called into a room with the senior analyst for that region for the intel community, at least from the defense standpoint. And I laid out my case, and the senior analyst or the senior rep backed me up. He had my back, because ultimately, he's an analyst like me, and he basically was going to go with the expert-- in this case, me-- you know, where my gut feel was coming down. And I say gut feel meaning the combined, you know, repository of evidence.

And I mean, there was pushback. But then once we all left the room, the backstory on it was that the policymakers ultimately-- it took a few more iterations in the intel cycle and the policy process, but ultimately they backed off,because there was some concern that they would be accused of politicization.
[LAUGH]

That was kind of interesting. Of twisting the intel to fit their desired policy goal.

Presumably, you guys, highly trained intelligence analysts, spent a lot of time studying cognitive biases in order to try to root them out of your own analysis. Did you spend a lot of time, or what was the comparable tools you guys used to think about the cognitive biases that might be existing on the sides of your customers and how to best work with them? Assuming that they're not spending the effort that you are to them out of themselves?

Well, I think the main thing was just to find a common foundation and speak a common language that you knew they would understand. And you know, that gets to the issue of one of the questions you ask, which is, what do policymakers want to most know about the world around them? And the common foundation or fabric around which you can have a really solid discussion that can quickly get complex, but it's a good foundation, is to answer some of the questions that you know are foremost in their mind, whether it's a more tactical near-end question or something a little bit longer term.

And it starts with, you know, who are the key actors? I mean, after you get beyond, you know, what's going on with X, Y, or Z? You know, they want to know who the key players are. They want to know what their leverage consists of,what instruments of power they're bringing to bear to shape the outcome, whether it's economic or social or political or technical, whatever, or military.

They want to know what the key player's intent is in a given situation, and whether or not there seems to be a unified intent on the part of the actor in question. If it's a country, is it the key decision making unit, or are there bureaucratic and organizational factions, if you will, that are coming into play that are leading to a less than unitary sense of purpose? And in that case, tell us how that's shaking out, you know? What the intent is of the different players are and what their different leverage points are.

And then they want to know what the key player's capabilities are. So you know, what their capabilities are, whether,you know, economic, military, technological, whatever. They also often want to know what their points of vulnerability are, what their pain points are.

And this starts bleeding quickly over into kind of opportunity analysis, you know, which the intelligence community can get pretty uncomfortable with. But if you look at a smaller government like Singapore or Australia, you know, theyfuse this stuff together so that it's more seamless, which is interesting. They don't have the walls necessarily that have built up over time, in some cases for good reason, that exist in something as cumbersome and large as the USgovernment.

Those are the key things, you know? It's basically, get on the same foundation with them in terms of trying to assess key players, sources of leverage, capabilities, intent, and also points of leverage or points of vulnerability and opportunity for the US.

The last thing is a little bit more difficult to get into unless you're literally brought into the room and, you know, you're actually given free flow to speak off the record, and nothing that goes into the books on some of the questions surrounding US leverage or US opportunities. And sometimes, by the way, the way that is framed that you can address from an intel standpoint is opportunity analysis with respect to, hey, policymakers or decision makers. Give Me three or four prospective US courses of action, and then I'll give you my take, or we as a group in the analytic community will give you our take in terms of how the various actors are going to respond and how this might shakeout in those three or four different scenarios, if you will.

So when you list the kinds of things that that decision maker would like to know from you at that moment, starting with intent but actually going on from there, the information, obviously, requirements of that kind of analysis just go on and on and on and on, ad infinitum.

Absolutely.

Yeah. And there are very few--

Especially around intent.

Yeah, right? And beyond. So talk for a moment if you can not so much about your frustration in what do you wished you knew when you walked into that room that you weren't able to know, but maybe the decision maker's frustration.Like, what is the thing he or she is most frustrated about that you can't answer for him or her?

Usually, why can't you give me a call? Why can't you tell me what's going to happen? You know, which, ultimately, back to the issue of common language, gets to they often want to know what variables are in play. Or actually, they really just want you to make a call. They don't want you to give them all the soup and nuts, unless they're one of these consumers who's more sophisticated and really wants to see what's going on behind the curtain.

But ultimately, it comes down to multivariable complexity if you're an analyst, and trying to convey that multivariable complexity to a consumer that there are multiple factors in play. From a cognitive standpoint, it's hard for me to quantify, you know, intimately human and social factors in terms of their relative weight in a given situation, and muchless how they'll interact and combine to produce one outcome versus five different outcomes. Particularly, you know,as you know if you're looking out over a longer term time horizon. But even for the nearer end, that's tough.

As more intelligence assessments are released, or at least declassified versions are released into the public domain,we learn out in the public more and more about things like, we assess with moderate confidence, we assess with high confidence, et cetera, et cetera.

But the underlying question, to the extent that you can talk about the challenge of communicating up the chain of command, up the levels of government, granular assessments of just how confident people are in the trenches of what they think they know. How hard is that? What tricks have you learned? What works well?

Because you can imagine that happening in a corporate environment all the time, right? Something of moderate confidence then becomes a social fact at higher levels. And the person down there who knew what the real data said is saying, no, no, no. Don't you understand? Like, I didn't really know that for sure.

Right. Right. Well, lots of different ways to address that. I would start by-- I want to talk about the estimates thing a little bit. But before I get into that, I want to say that for folks who don't know the process, they need to make sure they differentiate between, like, a formal community estimates process on a high-impact question such as, where'sIran going with its nuclear program, versus something that is being looked at, but not with full community eyes or in a formal estimated process.

So if you're working just on a country account or a topical account, oftentimes, you know, if it's a smaller account, it might just be you making analytic assessments on a given question. Sometimes it's going to be a group.

But that's short of being a formal estimated process. In those cases, I would have to say that it's still decidedly kind of-- I don't want to say seat of the pants, but it's certainly not as far along as the estimates process with a formal mechanism built into it to lay out probability and confidence. I'll come back to that, though, in a minute with respect to the estimates process.
I mean, sometimes it comes down to making analytic judgments based upon kind of a gut feel that sounds like what we called in the business a SWAG, a Sophisticated Wild Ass Guess. It's actually not. It's actually based on steeped immersion in the content.

So there's a lot of subliminal, implicit content analysis going on with the neurons firing on a daily basis where you might pick up something interesting, whether it's a validation of a given course of action that you might think was plausible or an anomaly that leads you down to thinking about an alternative scenario path. Sometimes that gut feel can be good. Sometimes it can be bad. Sometimes it can be mixed. And I can give you lots of horror stories, but I won't go into it.

But the second point is there are a lot of ongoing debates around probability and confidence in the IC. Typically, I'm going to call it straight and tell you that analysts don't have time to get mired in these things, because they typically involve methodologists who are non organic to a given analytic cell, unless they've been fused in there. And methodologists are a particular animal wherever they are.

[LAUGH]

If they're in the government, quickly these things can devolve from something that's practical and useful to an analyst into abstract, highly theoretical arguments. But usually, they revolve around or center on the precision of language and how precise language is in a given document or a given assessment. And you know, there's a lot of imprecise language.

And language around probability, you know, such as we judge that or this is probable or this is most likely, or lots of caveats being thrown in there and lots of adverbs surrounding your language. So there are lots of important debates being held around that. But by and large, at least from the past, I could say that this isn't something that's well done or anything that's systematic.

Now with respect to the estimates process, I do think that's somewhat of an exception to that rule, because there you're actually gathering a community of analysts from disparate agencies and organizations, asking them to bring their own repositories of evidence and their own interpretations of that evidence into the mix and to come out with an assessment of where things are going. And sometimes that can lead to a full community judgment that it's going one way or the other, or sometimes there are alternative paths that can be specified.

But now, you know, as of-- I don't know, maybe 10 years ago or something, there were reforms put in place that basically started having analysts start making probability and confidence calls around the hypothesized outcomes.But I can't go into a lot of detail there, but I would say they're not systematic or quantitative other than taking stock of the people in the room, you know?

So much like in the corporate sector, there's room for improvement around that stuff, but it has to be configured in away that can be actually implemented in practice. If there were actually really convenient ways to demonstrate sort of the dispersion of opinion, or one of the things that we've looked at is the open source version of assessment of competing hypothesis software, which was developed obviously at your agency, and then is now available open source to everybody. It's a sort of interesting tool. It's not exactly user-friendly, but you can see the direction in which it's going.

Yeah.

To help people, you know, kind of manage in a way that they can actually deal with cognitively what the dispersion of opinions are, where that dispersion lies and where it doesn't, just what the standard deviation is, et cetera. Really simple stuff, in a way.

Right. And importantly, you know, linking the dispersion of opinion to the key factors that are behind it, which typically reside around-- and this gets back to big data-- typically reside around critical uncertainties. Data gaps. There's a crucial data gap surrounding this, so analysts are reluctant to say that that course is going to happen or that other group, you know, their opinion of what path is going to unfold is going to actually occur.

4.12 Certainty, Part 2
Interview with **Jonathan Star, Consultant**

4.12.2 The Demand for Certainty

This element addresses the following learning objectives of this course:

- LO1: Describe the role of data science in organizations.
- LO4: Justify an analytic approach that informs decision making. ● LO5: Identify the audience and the most effective method to communicate a persuasive argument.

<u>Welcome.</u> In this unit, we've spent a lot of time talking about practical epistemology or what it means to really know something in an action context. And to dig into some of the practical lessons of how that actually works-- this case, ina client-consultant relationship-- we're going to turn to Jonathan Star, who is currently a consultant at Monitor Deloitte.Jonathan, thank you so much for coming.

You're welcome. Good to be here.

Could you tell us a little bit about your background and how you got to this kind of work?

Yeah, I'd be happy to. So I'm trained as an economist. I spent a number of years at universities in the UK and atLondon Business School. And after a while, I found myself much more interested in public policy research. As a result of that, I worked then for a government agency called Scottish Enterprise that was an economic and environmental development agency based in Glasgow. Effectively, it was set up to help the competitiveness of Scotland, thinking about what might be the situation 10, 20, 30 years into the future and what you can do policy-wise about that.

Because we were thinking about this situation so long into the future, we were particularly intrigued by thinking about, who has an interesting futures perspective on what might be happening? And we found that in regular public policy, it really wasn't a very good situation. So we looked out for a number of different research organizations who are doing interesting thinking about the future, about the situation when conditions are very uncertain. And we found this organization in the Bay Area called GBN.

And so for a number of years, I was a client of GBN's. We asked them to do a number of pieces of research for us.They did wonderful work. And after a while, I found myself more and more interested in their general work and actually made the move from client to consultant, and maybe the more significant move of from the UK to the BayArea of California.

And so then I found myself in GBN, which was part of this strategy consulting organization called Monitor. And so for the last 10 years, I've been applying various different futures techniques, mostly scenario planning, into client situations and helping organizations really deal with conditions of uncertainty, trying to get them to figure out, what's the best set of decisions that they can make, even though they don't know the future?

Jonathan, thinking like an economist for a little bit, going back in the earlier days of your life, it seems like economists actually have a very ambivalent relationship with the concept of uncertainty. On the one hand, they're very comfortable with variables and equations, but on the other hand, there are kinds of uncertainty that feed into, for example, development theories that make people really uncomfortable. Can you tell us a little bit about an experience with that ambivalence and how it manifests in a real situation?

Well, I think my experience, Steve, is that I found myself, when I was learning economics and being taught economics,that I could be comfortable with the logic of it. And yet somehow, it didn't seem to track with the real world. And so I Found myself since my training in economics moving so far away from those models and that logic.

And actually, it's been so fascinating to see in the last 10 years or so the rise of behavioral economics, the rise of almost a greater acceptance that decision-making isn't just a matter of maximizing utility. And it is much more around societal norms. It is much more around biases. And there's a whole series of things that I think now make economics a more rounded, and possibly a more humble, approach to thinking about policy.

Possibly more humble.

Possibly than it was 20 years ago.

Interesting. So in your experience working with decision-makers who are obviously having to face difficult,complicated situations and making high stakes decisions, presumably, at least some of them are drawn to higher levels of certainty. They come to you because they want answers to questions, and they would like you to give them higher levels of confidence in their actions. How do you deal with that kind of desire when maybe you think it's not actually appropriate for the situation?

Well, I think you mentioned senior executives there. In some ways, it's endemic to everyone. Everyone wants to make decisions that they feel good about, and if that decision is made in a context of certainty, the chances are you're not going to regret it. And we know that when you make decisions, it's actually-- it takes a great deal of effort to struggle over decisions.

So for example, if I was told with 100% certainty that it's going to rain tomorrow, then I'm going to take an umbrella.That's a decision, and it's no problem. I'm going to do that. But if I was told there's a 30% chance it's going to rain, Istart thinking about, OK, do I need to take an umbrella? It's a little bulky. It's going to fill up my bag. What if I don't use it? What if I lose it?

Now, just in that trite example, it starts to-- in the absence of certainty, you start to see that decisions become that much more painful. Now, when you're now thinking about executives, they have obviously much more significant decisions to make. And yet everyone-- as humans, we always want to have that certainty because we don't want to regret decisions.

So the desire to avoid regret is really, really strong, but when the consultant tells you you have a 70% chance of avoiding regret or a 70% chance of not being able to avoid regret, that's a hard message to deliver sometimes.

It's definitely a hard message to deliver. I think the other thing that's important here is that senior executives have grown up making decisions. They got to where they are because usually, they've been driven. They've been forceful.And they've made decisions that have actually worked out for them.

A number of other people might have made similar decisions in the past, and it hasn't worked out for them. If it hasn't,the chances are they're not senior executives. And so there's a sense in which once you become senior in an organization, I think you believe a little more in your own certainty, and I think that gets reflected in the fact that you would like advice in a corresponding way from your advisers or from your consultants.

Interesting. So would you say it's particularly difficult to get someone to put a question mark over something they think they already know or to answer a question about which they are already uncertain?

So here's how I see this. I think part of the problem here is that you may well get executives being willing to think twice, being willing to cast doubt on maybe their own assumptions, being willing to challenge the way in which they're thinking. But in the public realm, that actually isn't rewarded.

So if you're leading an organization, you're leading a group of employees. They want a conviction from their leader.They want a degree of certainty that that leader knows where he or she is taking that organization. In terms of if you're in a public company, the markets reward focus. They reward forcefulness. They reward certainty.

And so in some ways, Steve, I see that even if you've got an executive that is willing to almost acknowledge that there is doubt, in the public realm, it's really hard to do. And so one of the things that I try and do with my clients is I try and separate the public from the private, and I look for situations where I say, sure, you've got to go out and you've got to tell the world, or you've got to essentially have conviction about the way in which you think this decision is going to play out. And yet when you close the door and you just work with your executive team, you need to have this incredibly curious, inquiring, doubtful mind always about whether that's the right decision or not.
And so I find that when I work with clients, if I can get a senior executive to balance between the public conviction and the private doubt, as long as they don't turn schizophrenic, then that's a good thing because over time, their public pronouncements actually become a little more qualified. And I think they're a little more careful as to what then they want to go out and say, I'm certain about the following.

Jonathan, the question what is knowing in the business world may sound really abstract to people, but I really want to thank you for bringing this subtle experience and understanding to it. I think it's really helped us an awful lot.

You're welcome.

Thank you.

4.13 The Goal: Fewer and Better Disagreements, Part 1

I confess that more than once, I've woken up from a dream in the middle of the night with a big smile on my face. And it's a dream where the world is made up of rational reasoners who update their beliefs according to Bayes' theorem, and the clear and compelling data that I provide to them makes them change their minds. And boy, if only the world actually were to work that way. Now, I don't know. Maybe somebody whose world does work that way. So if any of you has had or will ever have a boss like that, please, please send her my way because I want to work for her, too. But that's, I think, more of a dream than a reality. In this world, what it means to know something is always going to be a negotiation and what we're going to do about it in terms of what we know and how that relates to our action even more so. I have to say anyone who lives and works in the world of politics as I have knows this to be the sad but just real truth of the game. If you live in Washington DC, sometimes it's simply the person who screams the loudest who gets to define what's true. And people become really cynical about that over time, and maybe they should. But look, skepticism is good, cynicism not so much. Cynicism just makes people bitter and ineffective. Skepticism can make you more effective as long as you can put it to use. And look, everybody has to figure out how to essentially make peace with that reality in the situation that they're in. This is a struggle. It's been a struggle for me. It's been a struggle for most scientists that I've talked to. And the best way I've found to do that or at least to think about that is a really simple motto that I learned from Baruch Fischhoff at Carnegie Mellon University. Baruch is probably one of the world's great decision theorists, but he's very, very practical about how this stuff actually gets integrated into real life. And his view of the purpose of scientific inquiry in the real world is just this simple, to try to move over time from wherever we happen to be today to a place where we have fewer and better disagreements, not to consensus, not to a world where everybody knows the truth but to a place where we can disagree more effectively by having fewer and better disagreements. So let's dig in a little bit to what that phrase actually means and how you'll know when you're getting there.

4.14 The Goal: Fewer and Better Disagreements, Part 2

Interview with **Baruch Fischoff, Professor, Carnegie Mellon University**

This element addresses the following learning objective of this course:

- LO5: Identify the audience and the most effective method to communicate a persuasive argument.

Welcome to Baruch Fischoff, who is a professor at Carnegie Mellon University, one of the world's leading theorists on decision making. And,Baruch, thank you so much for joining us today.

Oh, Steve, thanks for having me. Nice to see you again.

And likewise. So can you tell us a little bit about your trajectory in the decision science area and give us a sense of what you actually think is practical and pragmatic for data scientists entering during the real world of decision making in organizations?

The way I got here that did an undergraduate degree in math at Wayne State in Detroit, and then I was out of school for a while. And when I went back in school, I decided I didn't really have the passion and maybe not the aptitude for math but-- and was fortunate to end up in a branch of mathematical psychology that was being started by my graduate school advisor [INAUDIBLE] and [INAUDIBLE] which look at decision making problems in a way that was informed both by formal models and by empirical methods.

And I pretty much stayed the course that since then-- I think the formal methods are important-- I think that the formal methods are important because they force us to look at the decisions that other people are making in a rigorous way. That is we-- it forces us to take an inside view in how they're looking at the world, which helps us to overcome what is one of the most pervasive of psychological biases, which is to exaggerate how well we're communicating with other people, how well we understand them, and how well they understand us. So thinking about-- walking through somebody else's decision-- and this could be your boss, a subordinate, a legislator, a customer-- and saying, what are their objectives,what are the options that they see, what information do they have, how might they be confused helps us to provide people that relatively small set of information that anybody is capable of absorbing at any time.

So it's my sense that when new technologies come on board in decision making systems, whether it was like expert systems 20 or 30 years ago or potentially really sophisticated data techniques today, the first reaction of a lot of folks who are expert in the techniques is this stuff is so powerful that it's going to overwhelm traditional sources of disagreement and decision making pathology. And I wonder if that's been your experience and if you could reflect a little bit on maybe the trajectory of how that stuff moves over time.

People-- how do we get through life when do things confront us? Whether they're medical problems or technology problems, we build on whatever mental models we have of related problems. And if the new situation is like the old situation, we can learn a little bit and fend for ourselves.

When new technologies come along, even ones that have aspirations to be transformative, then we're often at a loss. And on the one hand,people may just reject them because they're too hard to get into. Or, you may find that people end up using them in totally unexpected ways,either because people independently figure out what to do with them or because somebody figures out and then tells his or her friends who then tell their friends. And people actually master the technology not from a textbook, or from instructions, or from looking at the pull down menus, but they master it by modeling or copying what other people do, which is how we learn lots of things in life.

So that makes the adaptation of technology often surprising to the inventors because they don't know-- let's see how I can put this a little different-- so as a result, the adoption of technologies often is unpredictable to inventors. In part, because they, by virtue of being inventors, are very different than the people that they are hoping will use their technology. So their intuitions are particularly bad about what's going to be used and how it's going to be used.

Probably there are a lot more unpleasant surprises where potentially great technologies don't get used. They don't get adopted because people can't figure them out. And occasionally, there are unexpected surprises where people find uses or find ways to tutor one another in the technologies that makes them take off much better than their inventors had any realistic expectation for.

Yeah. It's hard to--

What the social sciences do is they give us an attempt to get ahead of that and ask potential users, of our information or our technologies, to get a disciplined look at how they might use them, what are the problems that they might be using them for.

That's going to lead me to a sort of unfair question, but I'm going to ask it anyway. Which is if you had a couple pieces of advice to give to someone with really sophisticated data science skills who was walking into a decision meeting with a bunch of people who actually didn't have those skills and were just a little bit skeptical of overreach on his or her part, what would be the advice about how to best communicate conclusions, or methods, or just interact with that group that's just a little bit skeptical?

I think the best advice would be to pre-test your message. That is, find people are like the group, run it by them, have them be candid about what they understand and don't understand. And there will always be surprises. So it's a kind of communication malpractice to test your message first on the people who really care about.

That would be it. Test it. You'll always be surprised.

We've been developing surveys and communications for many years. We pre-test everything. And people always surprise us.

Even after the pre-test, right?

That's why you pre-test it and then you adapt and adjust it. And then you do another pre-test. And at some point, you've either run out of time or you run out of surprises. But if the stakes are worth doing any preparation, invest some of that preparation in pre-tests. It is totally remarkable how often large organizations, important people choose to fly blind in relying on their own intuitions or that of their close associates who may share the same cultural, perceptual, educational biases or be afraid to challenge one another.

Well, I know it's my instinct, you know, when you find that compelling answer to a question that people are struggling with, you just want to runout and explain it to everybody. And pre-testing the communication strategy sort of above feels like a bump in the road at that moment. But it's critical, huh?
Yeah. And often what happens is that we don't show due diligence in pre-testing our messages, they fall flat and then we end up blaming our audience.

Yes, exactly.

So I'm an optimist on our being-- we have a very large literature showing people's judgmental biases. We have this large literature on the judgmental biases because that's how our science advances by finding things that people don't do well, because they tell us something about how people process information.

And generally speaking, people make pretty good decisions. They get through life. They don't offend people in every conversation. They don't get run over crossing the street. They don't get fleeced all that often in their investments. You have to search to find things that people have difficulty doing well.

And so we do have this large-- and they tell you something either about the environment, or about the people, or their interaction, or their training. They tell you something about their psychology. But that doesn't mean that people are inherently bad decision makers. So I'm an optimist. I think we can usually explain most things to a motivated audience if we understand the audience. And part of that understanding is knowing the psychological literature which gives you general processes. And part of it is talking to people and testing our messages.

God, I love optimism. It's so rare that one hears that. But let me ask one last question, just end with this thought. For those of us who have scientific background, it's continuously frustrating to walk into meetings around the table where you just feel like the discourse is happening on some other level. And as I said in an earlier part of this week, you kind of wish you lived in a Paparian world, but you certainly don't get to live in that world.

And I remember you once saying in some setting, I think, that sort of the pragmatic goal was actually not necessarily to move towards consensus all the time, but to move towards a world or a situation of fewer and better disagreements. And I just found that a really compelling way to think about it. I wonder if you could just say a little bit about how you came to that view.

Yeah. So again, I tend to be-- I think perhaps something I would fault our field for us is that we as a field have found that pessimism sells.

Yes, it does.
Talking about other people's limitations. You know, some of which resonate. We know how to tell that story. Journalists like to repeat it. So we're perhaps overplaying our hand to some extent.

I think in communications, I think you find that-- so you can have disagreements because people misunderstand one another. And you can have disagreements because people understand one another and recognize that they have conflicting goals.

So let's address the first part, the first case. Let's address the cases where people are in a disagreement because they misunderstand one another by better communication and finding what the common ground is. And in situations where there are legitimate disagreements, then let's negotiate rather than assuming that, well, they just don't understand. If they only understood, they would do things my way. No, if they only understood, maybe they would see that my way is in conflict with their way.

Well, I'm hoping that we can bring some of that insight and discipline to the corporate world and maybe even one day to the world of politics,but we'll see.

OK. Well, thanks for talking to me. Sounds like you have an exciting course.

Yeah. Baruch, thank you so much. This has actually been the perfect way to wrap up this week. I really appreciate it.

4.15 An Overview of the Research Design Process, Part 1

The oldest fight in the world of a research design is in fact just induction versus deduction. Let's make it really simple. Do we want to start with a theory or start with data? There is no simple answer to this question and no single answer, of course, but pretty much in every instance, somebody has to decide what pathway they're going to take for a particular project. What's troubling is that a lot of these debates actually end up in a theology. Some people say, well, deduction is better because it's more scientific. And others will say induction is better because it comes with less preconceptions. I think the point is it doesn't really need to be a matter of theology. It can be a matter of practical, common sense. Think about it. When data is cheap and easy to collect and theorizing is just really hard, maybe we ought to lean towards induction for a while and then come back around. And when the opposite is true, maybe we should do the opposite. The trick, I think, in practice, is not getting stuck in an extreme position and staying there longer than we should. So there's a lot of experience with this. Almost a pendulum that swings from one extreme to the other over time between inductive and deductive preferences. Let's just talk for a moment about the way people thought about human psychology in the last 100 years. You go back to the very early 1900s. It was all about the theory. Freud, Young, people like that developing really complex and by the way, largely untestable theories of human behavior. And actually, they treated their patients on the basis of these theories. And they built up a body of experience around it. But they never actually tested the theories in any meaningful sense. 40 years later, the next generation of psychologists got sort of tired of these untestable propositions about why people do what they do with vague concepts like super ego and collective unconscience. But these people had better access to larger patient populations. And so they advocated for much greater attention to just simply unbiased data collection. Let's not get too fancy. Let's not come up with crazy theories. Let's just actually watch what people do in normal behavior every day and some carefully engineered situations and then aggregate that data. This was called, in psychology, the behavioral revolution. It was never purely induction. But in some researchers' hands, it came pretty close. Just look at the data. And now the pendulum is sort of swinging back again. People are starting to become concerned about maybe the declining marginal utility of another big database about human behavior. And now, they're worrying again about noisy data and garbage in, garbage out. And are the experiments in labs that use undergraduates really representative of regular human beings. And is the data really that clean? And so there's a bit of a return to deductive theorizing with the hope that that will explain and inform experimental design and data collection and vice versa. Here's what the friendliest psychologists always say. What they say is that we just really hope that the inductively minded and the deductively minded people can meet in the middle and help each other out. But that's the exception rather than the rule. It doesn't really happen that much. There are real differences in status in the academic profession when it comes to this. Just ask a friend of yours who is a physicist. Is it better to be a theoretician or is it better to be an experimentalist today? Look, this is going to continue to be a dynamic debate for as long as any of us are alive. And people are going to sort themselves out on where they want to be at this at any particular moment. The availability of data wants to push us in the direction of induction. But if it's pushing you further than it makes sense to go at this moment, then it's time to push back.

4.16 An Overview of the Research Design Process, Part 2

So in this slide, you'll see a depiction of what I call the linear model of research design as imagined in the fake scientific method-- not that it's really fake, but it's not the way people really do things. Unfortunately, this is the way many social scientists are taught to do scientific method. They're told that this is the way real science happens, the kind you do in labs. In fact, most of those social scientists have never actually been in a lab. Somehow, they seem to know what happens there, except they actually don't, right? They're taught very, very simple rules, like never select on the dependent variable, which is a way of saying, look for the effects of causes, not the causes of effects. I've heard that 100 times from social scientists telling you what real scientists do. But wait a minute. I have friends that look for the causes of cancer. Is that not real science? Of course it's real science. So this isn't the way real science happens-- sometimes, but not most of the time. Actually, in real life, people iterate. They go back and forth between different phases of the scientific method. Yeah, they break down the process. They try to optimize each step. And you can't skip steps. You're going to have to do all of these things. You're going to have to develop a corpus of data. You're going to have to gather the data. You're going to have to analyze it. You're going to have to develop a research topic. But nobody says it really, absolutely must be done in the imaginary order that the fake scientific method says, because that's not the way people actually work. Here's the way people really work. They move back and forth between the research topic and the data gathering and back to refine the research question and back to the data gathering and then a little more analysis. And maybe they try a write-up, and in doing the write-up, they find out that they didn't have enough data, so they go back to the data gathering, and that leads them to refine the question. There's a really simple metaphor here. Sometimes, it is really good to just walk away from the data for a while and just think. Imagine. Wonder what else is going on-- not jump too quickly to hypotheses, and certainly not the falsifiable hypotheses. Everybody's gone through this experience where they collected, collected, analyzed, and realized, I got to go back and reformulate the question. That's what people do. It may not be the real scientific method, but it's the right way to do it. And in practice, here's the key operational decision that I think a lot depends on when you're inside the organization, because sometimes the question you're trying to answer or the research topic that's given to you is not one that you get to choose. It's one that a boss, a customer, or somebody else is placing out for you and that you have to work on. Sometimes the most important thing is to figure out, where in this process am I going to go back and engage with my boss or engage with my customer to tell them that they've asked me the wrong question and that I need to reformulate it? This is really a profound problem in big, hierarchical organizations, but it's probably the most important thing to think about when you're thinking about iterated research design.

4.17. Research Design Neglect
Social Network Case Study

This element addresses the following learning objectives of this course:

- LO1: Describe the role of data science in organizations
- LO2: Design and apply research questions.
- LO3: Assess and select data and the data collection methods that best fit a specific outcome or need.
- LO4: Justify an analytic approach that informs decision-making.
- LO6: Navigate organizational, personal, legal, and ethical constraints to facilitate better decision making and improve communication.

Today, we're going to be talking with Galen Panger, who's a PhD student here at the School of Information. Has very, very interesting background, both in the academic policy and corporate worlds. I'm going to ask him to tell us a little bit about that. And then we're going to launch into his perspective on the famed Facebook study of 2014.

So Galen, say hi to the audience, the crowd.

Hello.

Thanks for joining us today. Do want to say a little bit about who you are and your background and where you came from?

Yeah, sure. So I'm in my fifth year as a PhD student here at the School of Information. And my dissertation actually looks at some of the stuff that we're going to be talking about today. So some of the uses of social media data to understand human experience.

So the Facebook experiment was really just very right in my wheelhouse and just really interesting. So I definitely come at it very critically, but I also really-- I'm very optimistic and excited about the uses of social media to understand the human experience. So hopefully I don't come off as too negative about the uses of this data.

But before the school information, I was in D.C. working for Google in a public affairs, PR, government relations role. That was for about three years. And then prior to that, I was at Stanford majoring in public policy.

Right. Can we tell everybody that you had spent the summer as an intern at Facebook. So that you have a sense of the way in which a study like this would be both conceived and used inside the organization, right?

Yes, and I know the lead author, too, which I think gives me some sensitivity to his perspective.

Great.

A little bit of knowledge of some of his prior research.

Yeah. So we're going to want to address a little bit the faults in the research design. But most importantly, I think what we want to focus on is the conceptualization of the study and how it could have been improved as an impactful study within the organization to help Facebook, actually. So why don't you start by telling us a little bit about the question they were trying to answer and the significance of that question or where it came from.

Yeah, so that's actually open to debate-- what was the question that they were trying to understand. And so this is one of-- I think one of the most important pieces. Or one of the most important things about this study is that it was framed for the academic community as a study of emotional contagion. And so you can imagine that it was peer-reviewed by emotional contagion researchers and just generally evaluated as-- the evidence was evaluated against the theory of emotional contagion.

But then when they went out into the public sphere and started explaining the study to the public, both the lead author and Facebook PR said that it was really about trying to disprove the notion that Facebook was bad for you. That these positive happy posts on Facebook that we see make us feel negative or unhappy or depressed. And so they were trying to combat that notion. And so in the study itself, well-being does get some treatment.

They do sort of say we're also interested in how emotional contagion plays out with happy posts because if it's the case that happy posts are contagious and people become more happy, then it disproves this idea that happy posts lead to depression and social comparison and any sort of negative well-being effects. And so they say that they, but do nothing other than sort of just mention that well-being is an interest of theirs within the study. the. Majority of the study, the bulk of the study, is all about emotional contagion.

OK, so let me just highlight a piece of that. Maybe one of the reasons why the study became so controversial was actually because the results of this study were-- let me put it this way. Facebook would benefit much more clearly from one result versus another result. And so there was a fear in the external community, but presumably within the organization as well, that the results would be biased even if the experimenters weren't trying to bias the results.

Yeah. So it's interesting because I think that the organization itself was really interested in the question of whether Facebook makes them happy. Because there's been a lot of research suggesting that very thing. And there have been a bunch of different theories offered. There have been different sorts of data offered. And I think that people on Facebook see that research and it's upsetting.

And so one of the Facebook's top vice presidents of products-- what's his name? Chris Cox. He was on Facebook praising Adam Kramer, the lead author of the study, for helping to disprove this notion that Facebook makes you unhappy. And Adam Kramer was framing the study that way in the public as well.

So I think that it helped address an internal fear about Facebook. But still, the research was framed and evaluated as an emotional contagion study. And I think that that moves some of the limitations of their data, limitations of social media data from a category of like important limitations to crucial limitations. Because if you're not capturing-- which I can get into more detail-- but if Facebook status updates don't capture all of the emotional consequences of Facebook, then you're not going to really be able to see the full consequences of Facebook GIFs.

So let me ask you then to delve into that a little bit for a few minutes. Talk about their research design. And talk about, in particular, what's good about it but also what you feel was inadequate and made them so vulnerable when the research was actually published.

Yeah. Well, I think just going to your earlier point, actually, I think that the controversy was really about the ethics. And so that's where the whole explosion happened. It was like, how dare Facebook manipulate people's emotions, and that sort of thing. That's a really important discussion and I'm really glad we had the discussion but I think there's another really important discussion we didn't have, which was around the methodology of the study and how it was framed for academics versus the public.

And so the research design was essentially, the whole idea is that you can remove certain posts that might be positive or negative from the news feed. And those removals cause emotional changes in users who are observing those news feeds. And then you can measure those emotional changes in those users by then observing their own status updates.

So it's a little backwards, which is why I prefer to talk about it as if you increase positive emotion or increase negative emotion, do people then become more positive or more negative in their own status updates as a result? It's easier to think of it that way. It's more intuitive to the concept of emotional contagion.

So they had like four different groups, experimental groups. And they had some 700,000 participants, or unwitting participants. I shouldn't sound biased. That makes me sound biased.

Well, it's factually correct.

And so in one condition, they removed something between 10% and 90% of the negative posts in those people's news feeds. In the next condition, it was 10% to 90% of the positive posts were removed from news feed. And in the other two conditions, they were controlled conditions to basically remove other similar proportions of status updates at random from news feeds.

Got it.

So there's different amounts of positive posts and different amounts of negative posts. And so taking 10 or 90% of those results in taking different amounts of content out of news feeds. So that's why they have two different control conditions to randomly remove similar proportions.

Quick question. Were the coding of the posts, both in terms of the experimental manipulation and in terms of the data that came back about how individuals responded, were those coded manually or were they coded by machine.

They were coded by a machine using a sentiment analysis algorithm called LIWC, a Linguistic Inquiry and Word Count.

Got it.

[INAUDIBLE].

Yeah, OK. So you're doing this at a pretty large scale. So what happened? What did they find? And how was that finding communicated?

Yeah, so then what they did was look at the status updates that people subsequently posted who were in each of these four conditions. And so they found that that's when they removed positive posts that people became less positive in their own status updates and more negative. And when they removed negative, they became subsequently less negative in their own posts and more positive compared to those two respective control conditions. So that the effect sizes were extremely small which is, I think one of-- was actually not an insignificant thing.

But it is small. But they had such a large sample size that they still got significant effects with very, very small effects. So it was less-- even though they removed something like 10% to 90% of the positive/negative posts, they only observed changes in people's subsequent status updates in terms of the emotionality those updates on the level of like hundredths of a percent. So it wasn't 1%. It wasn't 10%. It was like 0.1% or lower, essentially, in the effect sizes.

So very small effect, but statistically significant because the sample was so large. So it's an interesting finding. Presumably because the research was done inside Facebook, it was meant to have some consequences for the way Facebook did something.

Right, yeah. I could tell you about that.

Yeah, talk a little bit about what--

Let's mention that.

--they would have done or what they did do with those results. And then we'll just get into the public blow up about it.

Yeah. So I think that to the academic community and to the public at large, studying the spread of emotional contagion through social networks is super cool because we're all now connected with these social networks. And so emotions are spreading at a rapid pace, or more rapid pace than they used to in the past. That's really interesting and could have interesting consequences for society. So that's a cool sort of academic motivation.

For Facebook it's like, OK, if we amp up the emotions of news feed or withdraw emotions from news feed, do people end up posting more or less? Do they start avoiding Facebook? Does it made people start feeling bad or good? What are the sorts of-- they're always trying to optimize news feed to make it more engaging and make people use it for longer amounts of time, make the product more valuable. And so studying how emotions might affect the value of news feed is really very interesting for Facebook, generally, as well.

OK, so where did it go wrong? I mean, it seems like-- let's take a step back. It's a legitimate study in terms of the knowledge that you want to gain. The results would be relevant to the organization. Where'd it go wrong?

So I think that the authors were pretty inattentive to the limitations of their data and the data generating process as a window into the human experience. So I would frame it as sort of the case of missing posts or the case of missing emotions.

So when they went to measure people's status updates to see how they did or how they reacted to these different experimental manipulations, status updates as themselves may not fully encapsulate the emotional effects of their manipulations because status updates generally don't capture all of our human experience. And that's because we don't always spend all of our time on social media. And this is the whole other set of social biases that might result in people not sharing exactly what they're feeling in social media. I think that's pretty intuitive, but I can go into more detail on that. I'd be happy to.

And so I think the use of LIWC, the sentiment analysis algorithm, was also a really important limitation because they didn't present any evidence that LIWC is valid for the emotions of interest. And this actually goes to another problem, which is that they treated positive and negative affect or positive/negative emotions as sort of monolithic things. And in fact, the emotion of interest to them for well-being purposes is depression, which is different than other negative emotions like anger or anxiety.

And so simply lumping all negative affect together and reporting on that doesn't really tell us about the phenomenon of interest.

Yeah. Yeah, in some ways you can almost imagine how that would have been a convenient variable inside the corporation, but wasn't really a scientifically valid variable and thus ultimately wasn't able to stand up under scrutiny.

Yeah. So they didn't present any evidence of validity. In fact, they cited three studies. Two of which also didn't have any information about the validity of LIWC for social media. And one of which was actually by two of the co-authors of the Facebook experiment that said that LIWC couldn't actually recognize changes in negative emotion that they had experimentally manipulated.

Oops.

Oops. They cited this as support for the validity of LIWC. But if they had read the study that they wrote saying that it doesn't actually-- that it doesn't always produce valid results for negative affect, which is the variable here. And so if you look more broadly at the use of the sentiment analysis algorithm in the academic literature on social media or other computer-mediated communication, it has a very mixed track record. And I can just leave it at that.

And if you look outside social media, there is some evidence that LIWC has a bias against some of these low-arousal negative emotions like sadness. So that's able to recognize that. Which, again, could bias the results. Especially when you have such small effect sizes, any of these little biases could add up to an overall bias in their results.

So in the last minute and a half or so, I want to hear your thoughts. I mean, you've studied this very, very closely. And in fact, before we end, I want you to do a little bit of a pitch for the paper and give people the URL in case they want to read the paper about it. Your paper, not their paper. Although you could do their paper as well.

Your thoughts about from a research, design, and communication of results perspective, what's the most important thing these guys could have done more effectively to avoid the public firestorm? But more importantly, to have the results actually be useful to Facebook?

Gosh, I don't know. I couldn't tell you about their communication strategy. I think it caught everybody off guard.

Well, they probably never expected that it would break out into the public media the way it did, right?

Right. And I think that there are certain path-dependent reasons for that. But also, it's this idea that people are just sort of being manipulated. And that something special and very intimate to the human experience, like our emotional experience, was the subject of these experiments to serve Facebook's purposes without anyone's consent.

And so in my Medium posts-- which I'm trying to turn into an academic publication. We'll see if that happens. But on Medium, you can read a more blog-style interpretation of the study and its limitations. It's called "Why the Facebook Experiment is Lousy Social Science." You can Google it and share on Facebook.

[LAUGHTER]

I'll recommend it. It's a very well-written paper and a great read.

Yeah. So I mean, I suggested they use something called experience sampling instead of sentiment analysis and status updates as an indicator of how people feel. Experience sampling is a really cool method developed to just randomly sample via private reports how people are feeling at any one particular time in their lives. And so Facebook could just have a little pop up that says, while you're browsing news feed, how are you feeling right now? It would be a private report so it would be less subject to social biases.

It would be randomly sampled and not when people think to share their emotions, which leads to a bias called arousal bias, which we didn't have time to get into I mean it would be directly reported rather than interpreted by a sentiment analysis algorithm. And so experience sampling could be-- and also, in order to get people to report their emotions to this little pop-up, you might want to get their consent and tell them what you're doing in the first place.

You might.

I suggested experience sampling because I'm a fan of that method.

So slightly harder problem, but potentially multiplicative when it comes to figuring out the right answer to the question and making it of real value to the corporation. And actually, frankly, protecting yourself from a public firestorm over what could have easily been seen as a somewhat or potentially controversial issue. I mean, it's one thing to manipulate or experiment with people's e-commerce behavior. It's another thing to experiment with their emotions.

Yeah. You know, I've been thinking about a catchy way to sum this up for audiences of big data research. And I think a lot about the Daniel Kahneman and Amos Tversky biases. They're famous for the biases that they've shown to occur in decision making. And a while back, back in the 70s, they proposed a bias called sample size neglect. Where people neglect the fact that they have a sample size of 5 to 10 people, and then they try to extrapolate it about the whole population.

And I think that actually the era of big data is turning that on its head. And now we're facing something like social science neglect or domain knowledge neglect or research design neglect, where we're just not being attentive enough to the limitations of the data-generating processes that we're using. That's just really important. Because we know a lot about why people post on Facebook, why they don't post on Facebook.

We know that people self-censor about a third of the things that they start to type on Facebook and then they delete it. So there's just a lot of concern with this data source. And it would have been, in my opinion, a much better study if they had been very direct and very attentive to those limitations.

Great. So Galen, thank you so much for your insights on this today. Again, I will recommend the paper. And thanks for the "People over Pixels" poster. That's a beauty.

Oh, yeah.

Maybe it's the like the-- what's the British thing with the--

Keep calm and.

Maybe it's the "Keep Calm and Carry On" of our generation.

Yeah, totally. And you'll read about People over Pixels in my Medium post.

Excellent.

[INAUDIBLE]

Thank you so much.

Oh, yeah. Thanks, Steve.

Bye.

4.18. Creswell and Creswell Textbook

4.18.1 Review of Philosophical Worldviews (Chapter 1)

This will help you digest the required Creswell and Creswell reading. Please use these ideas as a starting point.

This element addresses the following learning objectives of this course:

- LO1: Describe the role of data science in organizations
- LO2: Design and apply research questions.

Here I want to link the concepts in the philosophical worldviews section of Chapter 1 in Creswell and the concepts that Kuhn talks about in the structure of scientific revolutions. Kuhn pushes us to think about the politics or sociology in which science operates. In other words, science operates within a broader social context. One of the examples that helps me understand this the best is climate science.

There's a broad consensus among climate scientists that the climate is changing and that human activity is a significant contributor to that change. However, who's in charge at the highest level of government gets to set the terms of the debate. The science hasn't changed, but those in power get to set the agenda. Paradigms, belief systems, worldviews, and power relationships influence how science progresses.

The Creswell text encourages us to think about how our individual worldview view impacts the type of questions we ask and our approach to research. So let's kind of think through an example, one of your examples. Think of your domain or a domain you're interested in. OK, now think about the big players or the big companies in that domain. Those big companies you just thought about probably have a disproportionate role in the design of best practices. What the big fish say has more weight compared to what a random company says.

In the health space, for example, when Blue Cross Blue Shield or the American Dental Association says something or promotes new best practices, people listen. In the tech space, when Google, Microsoft, or Amazon does something, the industry listens more than when some random startup does the same thing. The punch line is science operates within a broader social context.

4.18.2 Chapter 4: Writing Strategies and Ethical Considerations

This will help you digest the required Creswell and Creswell reading. Please use these ideas as a starting point.

This element addresses the following learning objectives of this course:

- LO6: Navigate organizational, personal, legal, and ethical constraints to facilitate better decision making and improve communication.
- LO7: Imagine, plan, and design a data science project.

Here, I'll talk briefly about writing and about ethics. Let's first talk about writing strategies. First, I want to acknowledge that writing is difficult. It takes a lot of drafts, and I personally find it pretty challenging.

I think one of the most useful guiding principles is to know your audience. And you've probably heard this, or you probably will hear this throughout the semester. What does that mean? That means who are you writing for, what's their incentive structure, and what are their motivations? What type of language would resonate with them the most?

Really, your approach to writing depends on the task. You're going to use a different approach if you're writing an email or a Slack message or something similar compared to if you're writing a final report for a client. And again, I acknowledge that the advice I'd give one or give you depends on the task. But here are a few pointers if you're writing something of somewhat importance-- i.e., not an email.

So first, you want to build time to step away from your writing. Why do you need to step away? Sometimes you get tunnel vision, and we can't identify our own errors because we've been staring at the same thing for so long. And that might mean stepping away for a day or maybe just stepping away for 30 minutes. So that's the first piece of advice I'd give.

The second piece of advice I'd give is to get someone else to look at your work. We know when we reread our work-- we know what we mean to say, and we kind of struggle to separate what's on the page from what's in our head. And so get someone else to read it that doesn't have all that kind of additional context and who doesn't know exactly what's going on in your head.

Second big idea is ethics. So Creswell pushes us to think about the many ethical issues we may confront in our work. We might confront ethical issues prior to conducting the study, at the beginning of the study, when we collect data, when we analyze data, when we share, report, and store data. This is the kind of framework that Creswell uses.

And I think there's a nice chart in the text that highlights the different types of ethical issues we may experience. And as you read this part of the chapter, I encourage you to think and engage with the following question. How often do we disclose the intent of our research or our analysis to participants or subjects or customers?

This is a challenge that we'll continue to address, because as researchers or data science practitioners, we may want to be transparent and ethical. And at the same time, we may want to avoid revealing so much to our subject that we unintentionally impact the results of our study. For example, imagine I have to choose how I want to inform subjects about the survey in front of them. I can say something like, "Here, we invite you to participate in a study to better understand how customers use our product." Or I can also say, "We want you to participate in a study to determine how appeals to emotions impact our customers' engagement with our product."

The second might be more transparent and honest. But it also might change the behavior of our customers because they were primed to think about emotion. And their behavior may be different because of this and may not be as generalizable to users on your platform that are not primed to think about emotion. So overall, I'd encourage you to think about how you disclose the intent of your research, and just be mindful of that.