[00:00:00](#) I want to be capturing this. So what is he just press a button. All the say the same thing for yourself. It's all over talks about it. That's good. That's good. Okay. Looks like we are getting good signal. Good signal. Yeah, that's good. All right. Uh, we don't have a speed round. No, just go no speed round. Jim, how do you pronounce your last name? Look, it's spelled goose cat. I think it should be pronounced. Khrushchev. Think well, I'm not not Polish. I'm American. I grew up in the country when you say it, when I was growing up at those in Ellis island mistake. But no, I say Gousha but I think it should be a Cha. Okay. Z CZ is like, that would be one letter in Cyrillic. I don't know how we get out and get along without it, but it's s h c h like kept like Gush-ka.

[00:00:48](#) "Goose – cha," that's my name. Okay. Goose Cha. Yeah, just say good show. That's what everybody says. That's what I say. So it's, I just leave off the CZ, G U S H j

Jim Guszcza, welcome to Behavioral Grooves.

Thank you. It's great to be here.

We are a, just for our listeners' sake, just to let them know that the audio is very different because we are actually recording in a Marriott courtyard overlooking the university of Minnesota. Not as glamorous as it sounds, but it's wonderful. And so we are excited to be here. We were lucky to have you in town so guys are interested in, yeah, so this is, this is fantastic. Yeah. So can we start with a little bit about what you do? Sure. Because it doesn't necessarily fit with behavioral groups, right? I mean your job is not behavioral in nature. It certainly didn't start that way. My title is US chief data scientist at Deloitte.

[00:01:43](#) So I'm a data science by I suppose by training but, but not really. I mean I have a PhD in philosophy, and I started as an actuary, but I can't, I can't, I don't, I know it's a cliché, but it's not that at all. I sort of morphed, but the reason I became an actuary is that in my ignorance, I assumed that actuarial science was what we now call data science that turned data science doesn't exist back then. So it just kind of like entering the field from outside from like this kind of philosophy background. I just wanted to do something scientific in the business world and I sort of intuitive that this is like a really data rich, you know, kind of field. And really a lot of people think that the actuaries of the original data scientists, I'm one of them. And in a way data science goes back 250 years when, when, when, you know, when data was first used, the price insurance contracts.

[00:02:26](#) Um, and so now, now that it's being generalized, there's this data about all aspects of business and people's lives, which is one interesting connection with behavior, right? A lot of the, you know, people talking about big data all the time in big is usually defined as being like high volume, high velocity, high variety data. But a lot of, a lot of times, B stands for behavioral because it's data about you, is it about your actions, you know, you paid this bill late, you like this thing on the social media content, you stop watching the streaming, you know, series midway through with this episode. But you binge watch this other series.

All this stuff tells us a lot about your behaviors that can be used to make predictions going forward, maybe in very different domains. And there's a lot of controversy about this. So that's, that's one connection with behavior.

00:03:16 Um, but yeah, but that's actually not how I first got interested in behavioral science. It was really, there's actually an interesting university of Minnesota connection with how I got interested in, yeah. Tell us about that because we started talking about that a little bit before. So I want to hear more. So this is all right. So I first, I'd, I'd heard the names, condom and then diversity way back when I was in Grad School in philosophy, but I never really investigated, I was doing philosophy of physics, so I never, you know, I just knew the names. I didn't really know much about what they were doing cause I was pretty ignorant, willfully ignorant, really. I first, um, I first learned about this stuff when I read a review of Michael Lewis's book, moneyball written by guests, wait for it. Richard Thaler and Cass Sunstein. The review was written by Thaler and Sunstein.

00:03:57 Correct. Because I was, I was kind of like procrastinating at work one day, but this is kind of productive procrastination, surfing the web in the afternoon, having my coffee and I just read money ball. I bought it, you know, cause I, I connected moneyball with what I was doing is a data scientist, right? I was building algorithms to help underwriters, it, commercial insurance companies, um, better select in price risks. As I heard about moneyball, which is about using data to help, you know, baseball scouts make better hiring decisions. I kind of like made this connection, this, there's an obvious analogy, right? But you know that, so that was nice as far as it went. But when I read Thaler and Sunstein his review of moneyball, I just had this like, you know, not minor, major epiphany. That kind of changed my, the way I thought about my own career.

00:04:35 It was like I had been thinking of that, you know, that I'd been thinking about our algorithms as being valuable because I was such a good data scientist because the data was so powerful. And sure that may be true, but what was really important and what I was sort of neglecting was that the reason our algorithms were so valuable is because the ways humans make decisions is so suboptimal in a lot of settings. And this is not saying that people are stupid or you know, there'll be a lot of times people criticized condom and saying that it's a very pessimistic view of human cognition. And I don't think that's fair. I think that it's fair to say that our, you know, our brains evolved in a certain set of circumstances. They, they evolved to enable us to survive in the wild. They didn't necessarily evolve to, you know, help us make optimal decisions when we put on a suit.

00:05:19 And sit around the board room and make decisions. Right? So exactly. **So you know, you know, in the same way that my, I need eyeglasses cause I'm myopic, right? So eyeglasses helped me see that era as like a human invention to help me extend my capabilities while the predictive algorithms I build are kind of mental prostheses, their eyeglasses from the mind that health insurance company, underwriters, baseball scouts, hiring managers, judges, you know, um, doctors make better decisions.** All right, so that, and that was the kind of insight I got by reading the Thaler & Sunstein review of moneyball. They're there, they're there asking why could it possibly be the case that these highly paid professionals, these baseball scouts whose sole job it was just to make a certain kind of decision in a high stakes field where all, you know, a lot of money is at stake.

00:06:00 These people are being paid high salaries and it's data rich. Yet they would make the suboptimal decisions. How could that exist? And I think the, the, essentially what they said was that it takes, um, discipline and practice and you know, willpower to switch from simple intuitions to a careful assessment of evidence. And that's what was dramatizing the movie moneyball. Right, right. It's like there's a struggle. Yeah. Like Philip Seymour Hoffman, his character was a real skeptic. And he's like saying, you know, I, you know, I, I know this is a good baseball player, you know, and [inaudible] I see. You know, I see it, I forget what that line was that he was talking about, but it was great. Yeah, exactly know, it's just, you know, it's kind of like an overconfidence bias, you know, it's like, and it's, you know, your, your, your, your level of confidence in somebody who's not a, it's not a measure of statistical confidence.

00:06:43 Like, like we talked about in data science or statistics, it's more like a feeling. Right. And you know, failure in sensing talked about very specific heuristics, like, like the availability heuristic, you know, like, you know, we, we assume, you know, when, when you ask about what is the frequency of English words and ing, you'd give that a higher frequency than words who's second best letters and that sort of thing. Right? And so like, buy an LG and insurance if the last risk I on the road had a certain kind of like I'm frying machine in the kitchen and there's a bad claim associated with it. That claim could have been partly bad luck, but I, I recall that episode very, very vividly and the next time I see a similar risk, I might not want to ride it. Right. So it's like, that's the reason why my algorithms were, you know, were, were so, um, economically, you know, significant.

00:07:30 Right. That's, that's the reason why they added so much value to companies. It wasn't just because the data was good because I was a good data scientist. It's because I was like, we're, we're giving people a tool that can use to make their decisions to enforce a little bit more constraints. The folks who were, had had difficulty seeing, no, that's exactly right. And so yeah, I can't remember. It was the review or you know, miss got me reading and I quickly learned that that, you know, one of condiments forefathers was a psychologist that here in Minnesota, the University of Minnesota named **Paul Miele**, who back in the mid-fifties wrote this, got a classic book called, I think it was called *Clinical Versus Statistical Prediction*. And he had a s he had kind of like this moneyball epiphany way back in the fifties in his field, which is psychology.

00:08:08 And he found, I think it was, and again, I'm not an expert, so this is from memory, so you know, caveats, LBO listeners. But I, I think, I think the first thing he looked at was, you know, who could be, what would do better will be more a better way to diagnose people for schizophrenia, a clinician using his or her clinical judgment based on a lot of training. And a lot of graduate school and many years of work and interaction with lots of different people. All of that. Right. Exactly. Or you know, a 10 factor regression model or whatever it was. And you know, it turned out the regression might look up, performed a clinician. And then he started testing this in a lot of different fields. Like you know, which team's going to win the football game, right? There's the Vikings game today, you know, which, which, which wine has higher quality is going gonna be a higher quality wine, you know, you know, you know, you know, w you know, which, which patient is more likely to have this disease.

00:08:54 And he said that in every single one of these studies to be served, I think there were 20 or so studies. In each case the algorithm did at least as well as the clinician. And in most cases the algorithm outperforming the clinician. And so it's, and it's not that we want to replace the clinicians for the algorithms, it's just that in the same, you know, no, no more than you want to replace my eyes with eyeglasses. It's just kind of like the silly misconception about artificial intelligence, but we just need this kind of help. And so that, that's when I sort of realized that this thing I was doing was going to explode and this is going to like take over all areas of business. Wow. Yeah. And so it's just a very interesting, you know, that's a, that's a big leap. No, I'm just thinking about your ability to have that Aha moment, uh, because of this information I think is remarkable.

00:09:37 Well, Thaler and Sunstein, you know, it's like that review of my balls. Really. What, what was the different [inaudible] I later learned that Michael Lewis learned about the subject w when he read the failures and some of these review of his own book *Moneyball*, he wrote in there, he wrote in the [inaudible] cause I, that that review is kind of what set him thinking about this stuff and that's, that's how he backed down kind of in store and started that whole process. Wow. And when was this? When, well, I read the, I read the review in 2004 the recruiters called who's on first? I thought it was also published in the University of Chicago Law Review, but I read it in the new, in the new republic. Oh yeah. So that was, that was, that was a big epiphany for me. So you, uh, you have an academic background, uh, I mean, cause you, you, you went through a doctoral program, uh, do you think you, would you characterize yourself as someone who looks at the world through a scientific lens?

00:10:30 Yeah, I think I do. I met my PhD is in philosophy and um, the specific subject was philosophy of physics and philosophy of science. Um, so I always think about things through a scientific lens. Um, and, and I, you know, I, I come, I come, it feels from outside it's like I have double imposter syndrome, right? Because I'm a data scientist who does not have a PhD in statistics or computer science, right? It's a PhD in philosophy. And here I am like talking to you guys about behavioral science. Like, what the hell am I even doing here? You're doing great. There is enough meat in the sauce [inaudible] I think I'm a lousy cook. What can I say? Um, but yeah, so I tend to, I tend to think about things from like kind of first principles and sometimes that makes me kind of slow but, but um, other times you can can't pay off cause I might make connections that might not occur to me.

00:11:15 So in, in the world of business, I think that that we are often missing that scientific mindset. Right? I think we are in the, the just go do it mindset in business. Have you run into that or what, what kind of value do you think that scientific lens brings to the world of business? Cause I think it's really important.

00:11:34 Yeah, that's a really good question. I don't know how I take that. It can be, but yeah, like my field is called data science, right? Yeah. And right now, there's a lot of talk of, this is um, tagline called **democratization of data science**, which if you look at it in one way makes a lot of sense. But democratization of data science is basically saying let's use kind of automatic AI machine learning tools to enable essentially novices to analyze big data and find patterns that we can find interesting. You know, it's like you, you, you can like, you know, you can take high school kids who are kind of prodigious or not even prodigious, but you know, just like kind of intellectually curious kids given these really powerful machine learning tools and they can build algorithms that will classify cats, they can like label photographs and this is a cat, this is a dog, right?

00:12:15 It's really, really impressive. And the idea of democratization of data sciences that now it can take, you know, kind of people have gotten their MBAs and you know, kind of people with good domain knowledge and it start having them do data science even if they've just been to a look at kind of a Code Academy bootcamp. And I actually think that that's kind of taking us in the wrong direction a little bit. I think it's very good to bring domain experts close to the process of analyzing data, but you don't want to lose sight of the fact that the operative word in data science is science, not data. It's a scientific method. So these tools are great if they enable the analysts to spend less time doing rote data scrubbing and data munching and kind of like pedestrian stuff and more time actually thinking scientifically about where did the data come from, what am I trying to predict?

00:12:58 You know, like what is our business goal in kite? Can I translate this business goal into the design of some type of an analytical project and how can I use, how can I bring data to bear? If you do that in this, in a kind of naive automatic machine learning way, like if you gotta outsource critical thinking to a computer, you might get things like algorithms that are biased against women. There's, this gets us back to behavioral science, right? Like you know, from moneyball, you know, we know about when the Babcock's nearest bone. That's research, right? I mean it, you know, moneyball ironically was a story just about hiring mannose about baseball players. But we know that a lot of these heuristics that people use in the real world can be biased against females and minorities, right? And so if you, if you can bring data science to bear properly, you know, on lines of Paul Mele and Daniel Kahneman, Moneyball, Richard Thaylor, we can use elders to ameliorate human biases.

00:13:47 But if you just take big data, right a lot, you know, data about previous hiring decisions and correlate, you know, with, with previous hiring decisions, you're never going to get past what that initial bias was. The, the, the, the, the implicit biases from human cognition, our, you know, reflected our decisions. Those decisions are encoded in data. If you use automatic machine learning and democratize data science and a naive way, it's got to extract pennants in that data. Guess what guys you're going to be, you're going to build an algorithm that kind of encodes a lot of those human biases and can amplify them if you're very naive about it. So there's a famous story about how a data scientist at a big company discover this into their credit. They audited their own algorithm, they realized this. They never used it. But that's, that's, so that's, that's maybe a small illustration of how you need not just data but science in a sort of an ethical opponents who are too.

00:14:35 Yeah, yeah. Very much so.

I think the technical term that you're searching for is garbage in. Garbage out. Right here?

That's right. Well that's Ginkgo and there's also maybe **BIBO = bias and bias out** [inaudible] I just made that up, but I think, I think that's a keeper. I think it is a keeper. Absolutely. So, uh, getting back to your work, so you become fascinated with the behavioral science side. How are you integrating it into, into your work at Deloitte? So you know, early on it was okay of a talking point to be, to be honest with you, for many, between that reading, that failure sensing review in 2004 till about, I'm a slow learner until maybe 2012 or so. God, it's a long time. I was mostly thinking about one of the three pillars of behavioral science, bounded rationality. Okay. Bias. Rationality.

00:15:23 Yep. And I was basically using it as like a talking point was like a way of explaining why what we're doing works and oh, can I say guys, it's not just big data, it's that we're using the right data to overcome human biases. Right. And I think that's an important distinction. So, but it's a bit philosophical. Sometimes it would make a difference. Like there was one time when, um, I was building an algorithm to help child support enforcement officers do a more efficient job of reaching out to noncustodial parents who are at higher risk of going to arrears and falling under their payments so that they could improve their jobs rather than just being reactive. They could actually proactively reach out to people and prevent the bad thing from happening. Great. And actually I can come back to this when we get to nudge later on, but when I was, I was actually at a very interesting, um, child support conference for this.

00:16:06 All this, all the heads of the county level, heads of, of child support enforcement in this, in the state. **And I gave him this kind of eyeglasses for the mind metaphor and I could just see how they connected with that. Like they're like, it just made it very clear that we're not doing this to replace you and we're not doing this because there's something wrong with you. We're doing this because you're human.** And like, you know, there's something wrong with me because I wear eyeglasses and there's nothing wrong with a, with a professional using an algorithm to improve his or her professional judgment. And they're like, oh my God, this is great. I can actually use this to make my job more satisfying. I mean, and I, you know, you can generalize the saying that you can use AI to humanize work more generally, something we can get back to later.

00:16:42

Um, so that's kind of the way I thought about this stuff for the first half of my career. More recently it occurred to me that these other aspects of behavioral science, like we talked about, **bounded rationality**, Thaler talks about the three bounds, right? **There's also bounded self-control and bounded self-interest**. It took me a bit longer, but I kind of connected that with data science. Um, and how, so give us some, give us an example of, of connecting bounded rationality to data science. Sure. Easily. And actually I can give you an example outside of my own work. I can tell you how I came up with idea. It was after the Obama was reelected, I read two articles in New York Times. I got my ideas by reading these news articles, right? Um, I read two articles in the New York Times in close succession. One was about how the Obama campaign used big data, behavioral data really to reach out to persuadable voters.

00:17:34

So they didn't reach out to voters who are definitely gonna vote or just very highly likely to vote Democrat because like, why would you reach out to somebody who's almost certainly gonna vote Democrat? You're wasting your time, let sleeping dogs wasting your money, wasting your time. Yeah. Well you want to do is reach out to people who you can make a difference with. Like people who could be persuaded to vote Democrat or intend to vote Democrat but might not get around to it, you know, unless, unless they're, you know, kept giving the right message. So that, that's, that's an interesting kind of data science nuance right there. And again, another, another example of using science. Um, you know, thinking scientifically about the problem, not just using democratization of data science and pressing a button and just trying to natively make a prediction. You want to think about what are you trying to predict now?

00:18:13

Not so much "Who's going to vote" but "who can be persuaded." That's a very interesting distinction. And were messages tested then as well? Will that, this is where the behavioral science gives in. The other article was about how a t I think *The New York Times* called the Dream Team of behavioral scientist informally advised the Obama campaign. I think **Craig Fox** was the leader of this coterie of data scientist. He's a behavioral scientist at UCLA. Um, somebody think very highly of, and that got me thinking. So what I remember one of the examples from the article I remember reading about was through use of commitment cards. Okay. So you know, you know, you know, are you gonna vote for Obama? And you say yes. And I walk away feeling very satisfied. Like I've done my job. Well really that would be a missed opportunity. I would be, I'd be more effective. I asked you to sign up a pre-committed.

00:18:54

All right. All right. Yes. All right, well why don't we sign this card to, you know, and we'll get that again, using those behavioral science principles that we understand what actually drives behavior. Cause that's the big thing. It's that goal. Intention versus implementation, you know, you know, actions and various pieces, intention, 00:19:12 action, gap that, that's kind of metaphorical for why I think about this stuff too. I think that organizations, they don't care about algorithmic outputs. They care about better outcomes. Right? So in insurance it's, it's fine if I, you know, build a model that says that this risk is, you know, safer bet than that risk. But if you don't use that, if you don't make that decision, it's often not. Or if, if, or if Paul de Podesta builds an algorithm for Moneyball and Phillip Seymour Hoffman doesn't use it. Again, you're not going out with the huddle. And by analogy, you know, it's, you know, for these. So those are for thinking slow decisions for economic decision. You have to kind of take the algorithm and make the economically efficient decision and there can be organizational biases to doing that and be it to overcome that. But in these other applications like voting behavior, the last mile problem, you know, bridging the gap between like the algorithmic output or the better outcome is human behavioral, right? [inaudible]

00:19:59 in this case it's the intention action gap. Or if I'm working for a health care organization or, or a health insurance company, what if the algorithm, you know, flags me as being someone who might be at risk of developing a lifestyle based disease like diabetes or obesity. Again, you can't just give me information, you know, like you should eat this way, you do this, that won't change my behavior. So that more knowledge isn't going to help you overcome it. Exactly. So in a business setting, you know, sure. Knowledge, you know, giving people more information there when there are economic consensus at stake, that's a big piece of the puzzle. But when it comes to like human behavior, like purchasing behavior, voting behavior, health behavior, employee benefits, behavior, public sector behavior, like, you know, like the, the restaurant owner, making sure his restaurant or her restaurant is all these things, you know, it's not enough just to build the algorithm or building the algorithm I'd say is maybe helpful or maybe sometimes necessary, but not sufficient to really go that last mile.

00:20:58 Yes. You know, using behavioral nudge tactics to operationalize those algorithms can really add a lot of value to our algorithms. Yeah. So it's a little bit like, the analogy I sometimes make is, you know, the salad tastes better before you put the salad dressing on it, right. That, you know, the data, the algorithms or the salad, but the dressing is like a small, maybe even a low cost at an additive that just transforms the whole experience. Yeah. So that, that, that's the epiphany I had like circa 2013, 2014 that every, you know, **that every organization that has a data science capability should also have a behavioral insights capability.**

00:21:28 So how are you using that? So how are you using that new found insight to do the work that you're doing?

00:21:35 Well, I'll give you, I'll give you one example. Um, and this is kind of early. This is right around the time I was writing my first article about this. Um, and it was an offshoot of our insurance work. So a colleague of ours, his name is **Mike Green**, when my, one of my favorite colleagues, brilliant guy, um, got me on the phone and was talking about a project that we just embarked upon for one of the u s states. There was New Mexico and it was an insurance problem and public sector, this unemployment insurance. And um, the goal was to kind of lessen improper unemployment insurance payments. The idea is that if, if you lose your job, you're supposed to kind of log onto a portal every week and certify that a, I'm looking for work. Here's what I'm doing to find a new job and be here.

00:22:18 Here's how much money I collected last week by you know, maybe tracking Uber or you know, you know, landscape or whatever it is. Now the more you report, the less you're going to collect from the state. So there's this kind of natural, you know, temptation perhaps to under-report your, your, your income. So the state asks us to build an algorithm, um, to use whatever data we could maybe, you know, you know, demographic data, maybe web click data, um, to predict who's most likely to be collecting benefits and properly. And so we were on a call brainstorming different machine learning approaches to come up with a predictive, classify the Zack as accurate as possible, right? Natural thing to do it. Here's an example where the behavioral economics comes in. It started with this kind of technical observation, which is that any can we going to build a classifier like this?

00:23:12 There can be a lot of false positives, right? If the overall exit is really still cognitive bias, it's called base rate neglect. This is not intuitive to people. If the overall base rate is low, even if you have a very powerful classify that might be 95% accurate and the overall base rate is 5% the probability, you know, like you think you have your doctor write your, your, your, your disease, your diagnostic algorithms, 95% accurate. The disease has like a 95% base rate for the kind of person that you're, that you're treating right now. The person tests positive for the disease? Yes. The doctor. What is the probability that this patient has the disease? The doctor might say 95% yeah, no, the answer is more like 17% yeah. It's a BZ and posterior probability by an LG here with unemployment insurance. Right. If we, if we build this algorithm a, you know, the, the, the highest scoring, the most risky people flag by the algorithm most more often than not are going to be collecting that if it's properly, not improperly.

00:24:02 So this is the last mile problem. If we use this algorithm to shut up benefits, we're going to be doing the wrong thing most of the time. And we are, our algorithm, which is a good algorithm, could be what **Kathy Neil might call a weapon of math destruction**, right? So what I suggested is it's all, it's not just the building. The algorithm isn't what do you do with it? Right? So these are not always thinking slow decisions. They can be thinking fast decisions. So rather than use the algorithm to select them as shutoff benefits, let's use the algorithm as a nudge engine. And you know, hypothetically say you've been collecting benefits for four or five weeks and you've been logging on every, I don't know, Tuesday morning, nine o'clock saying I made 100 bucks last week and $150 last week. Maybe in week five or six you log out on Saturday instead of Tuesday in the sun. You're not lying, you're not reporting $100, you're putting $150 or you're you, you say you're reporting maybe $650 instead of $150 that might take you into a higher risk category. If, if then you see a message for the first time, I'm saying, did you know that nine out of 10, if your neighbors report their earnings properly, it might just get you to introspect a little bit. So we actually use rubber Cialdini's, you know, kind of social norm, norm, norm nudge messages.

00:25:10 This sense, since we are in a hotel room, we could, you know, think about the Child Deni study on uh, raising cows.

00:25:17 Exactly right. And it's the same principle. I mean, it's like most of the people in this room, in this hotel like reuse the towel and you know, of course it's the, yeah, it's also with the UK behavioral insights scene used to get taxpayers to, to pay the taxes on time. So I would argue that this is what we today call, uh, an example of ethical AI, right? It would be unethical. A, so you know, and implication of this is that when you're thinking about algorithms in talking about ethical AI, and we talked about biased algorithms earlier, so that gets a lot of attention as well as should. But I think what's neglected is it's not just the algorithms that can be biased. Also what you do with it, it has a moral component to it too. So how do you act on these arguments? And so it's like very often nudge can be a very, um, you can generalize from this, but I think, I think nudge gives you a new set of tools that make it more likely that you could be able to find kind of pro-social pro person use, uh, use of these kinds of algorithm.

00:26:07 So I want to, I want to extrapolate out, I'm sure, because I think it's really interesting because you brought it up, you actually brought up the Obama team using some of that early data science in the 2012 election. Right. And, and getting those, those potential Democratic voters that are on the, on the fence to actually do that

00:26:29 either on the fence or maybe they just, you know, they just get stressed out on Tuesday morning. They just forget to do it. Or they say out, you know, exactly.

00:26:36 Move out to 2016 yeah. And Bring Cambridge Analytica into the, into the fold. Never heard of it. Yeah. Well if you have it, let me tell you. And, and again, there's this component of Cambridge Analytica that is going in, right? Having, having insight into some personality components that supposedly, um, based upon your Facebook likes and dislikes and gets a, a big five personality profile of you down to understanding what is your most biggest fear and various different things. And then using that in an election cycle to message [inaudible], you know, different participants. Is there a difference in your mind between those two because you here and let me hear your, your, your conversation here.

00:27:27 I think it's a brilliant question. Um, by the way, I wrote an article about this actually with my husband Shantanu who's here at the university today, six years ago. And in that article it was about pro social uses of big data. And this is, you know, behavioral big data, right? And we actually cited at the time this little known study coming out of the Cambridge University second metrics lab about how they analyze a sample of 58,000 Americans. And they had ground truth data about are the Democrat or Republican, are they gay or straight or Christian and Muslim? What are the big five personality traits? And they said, we can predict many of these things with 80 or 90%, you know, area under the curve accuracy using Facebook likes. And it's like, it's sort of like a cautionary tale about, about how the state can go.

00:28:08 I think to me, the implication will just, you know, kind of cutting to the chase. I think the implication of this is that a lot of the, um, ethical discussions surrounding nudge, you know, sensing things written about the ethics of influence, failure talks about when is it, you know, what, what is nudging for good means? Supposed to nudging for evil sludge versus not. Slouchers is nudge. Exactly. That's, let's say the N. Dot. Moynihan. Right. And his new book on administrative burden, he's gonna speak at our **Nudge-A-Palooza** in, I believe in a, in a December at Georgetown University. You heard it here first. You guys should come and record that. Oh, we would? Yeah, let's do that.

00:28:39 Yes, definitely.

00:28:41 Okay. Anyway, Georgetown, December 9th. Um, yeah, I think that a lot of the discussion around, around the ethics of influence and the ethics of nudging and what does nudging for good mean, a lot of that should port onto these new discussions about AI ethics, right? Because a lot of AI is based on behavioral data and you know, think about what I w you know what we were saying earlier about how you can use algorithms to extend people's capability. Yes. Eyeglasses for the mind. Right. You know, so I can, I can use algorithms to give people information they can use to make better decisions and be, and be smarter, more effective professionals. That's better thinking, slow through algorithms like that are living through chemistry, right. Better living through data science,

00:29:17 but it just awesome, faded better decisions through data that you have. Every corporate tagline right there. [inaudible] pharmaceuticals. It's like a symphony if

00:29:26 taglines. I love it. Um, so you know, the end you can, and the, you know, the, I think the implication of this last mile idea is that we can also use, um, algorithms together with behavioral insights to help people make better thinking fast decisions, right? So maybe we can use algorithms in digital environments, l people nudge people to walk more. So we're doing, we're doing a pilot study right now with the Penn Medicine nudge unit where we're trying to use behavioral data collected through wearables to kind of, you know, get a sense of people's behavioral phenotypes and maybe we can figure out which kind of nudge is most effective for which kind of person to prompt it to walk more kind of on an LG with precision medicine. Maybe there's a precision nudging concept we can do now that's speculative. Who knows if that exact idea will work. But it's an example of how we can use data together with nudges to help people achieve their goals.

[00:30:14](#) Well, so sorry to interrupt you, but Tim and I actually just grooved on this just yesterday cause we were talking about the, the, the next iteration I think in any behavioral change design component is this element of, of making sure that that intervention that, that you are at that part where it is a, at that moment when you need it. And, and we talked about, you know, taking a pill, I could get a nudge to take a pill at eight o'clock every night. That's great. But what if I'm out at dinner at eight o'clock at night and I get the text message and you don't take the pill with you. I don't have a pill with me. So how can we use these things? And so what I'm hearing you say is this precision nudging is, is that component's on good. I'm glad to hear that there are people doing that. Um, and I'm sorry to interrupt. Well I

[00:30:59](#) think it's exactly right. I mean like the nudge up lose a couple of years ago, like I think it was Wendy woods, she just uttered this phrase, nudge 2.0 and or let people talking about digital nudges, you know Shlomo Benartzi has this book called the smartest screen. I just think that nudging and digital environments that are data rich, I call it the three D's data. Digital Design and design is in the sense of human centered design. And you guys probably know this, right? The book nudge was inspired by **Don Norman** spoke the design of everyday things. So nudges. Like I always, I don't, I don't like the libertarian paternalism taglines so much. It doesn't really, I don't really Grok on that, but I, I call it Don Norman ask, um, human centered design for choice environments. So like, so just to kind of summarize, I mean, it's like we can use better decisions through data, right?

[00:31:41](#) Both in a thinking slow sense and the thinking fast sense. Either way, you can use data together with, you know, you know, good explainable AI or a good choice architecture to help people make either better deliberate decisions or better automatic decisions. But there's a, there's a potential dark side, like any technology can be used at help us or hurt us, right? So we can use this stuff to extend our capabilities. Like MIT Media Lab, they call it, they like to say extended intelligence that have artificial intelligence. And I completely agree. I love that. I love that term. I know I'm, I'm a big fan of that as well. I am too. You know, we, I interviewed Tom Malone from MIT Sloan, um, last fall with my colleague Jeff Schwartz and you know, he talks about human computer collective intelligence. That's why I like to think about this. You know, it's like, you know, we have smart teams of humans, computers working together.

[00:32:26](#) We can use computers to extend our capabilities. But I think that example you gave earlier about, you know, using social media likes to make predictions that are then used to kind of um, determine interventions or messages that might kind of prey on my fears or my prejudices. Is that extending my capabilities or is that manipulating me for someone else's end? Yeah. Right. So that's the dark side and a less, there's another, I think all these things relate. There's another tagline that comes up a lot in AI these days called x AI or explainable AI. Okay. The idea is that, you know, if a, if a DA, if a judge is using an algorithm to make a parole decision or if a doctor's making it using an algorithm to make a medical diagnosis, the doctor or the judge needs more than just the number 42. You need an explanation of why you need a notion of how confident the algorithm is and why is it saying what it's saying so that I can make an informed decision about what should I listen to this algorithm.

00:33:18 Should I ignore it? Should I compliment it with some other insights that I might have? Because I have human common sense and contextual awareness. And so you want it, you want to is, I always say we, you know, in the same way that nudges about human centered design for choice environments, AI Needs, human centered design. You know, we're, we're, we're trying to create tools and people can use to make better decisions. And so, you know, I'm making this analogy in the same way that we can nudge for evil using the data to manipulate people. You can also unwittingly create AI that short circuits are thinking slow decisions too. And I think, right, so human centered design, this is part of it. And I think implicit, like when a lot of people are saying human centered design, they're saying implicitly we're saying in an ethical way. And it's like it that, no, this is the one philosophical thing I'll say.

00:34:03 Right? The one thing I learned in Grad school, that's fine. I took gum concept ethics from Kris Koraskard, who's now at Harvard and um, she was a general student, but you know, it's the Kantian categorical comparative, right? **You know, it's like you don't want, you want to treat people as ends in themselves, not as means to your end.** So if I'm, you know, if I am, you know, a tech startup and I'm creating a wearable app that's digital, that's data rich and infused behavioral design to help my customers achieve their goals of walking more and being healthier, I would call that ethical AI because I am helping people achieve their own goals as stated by them. But if I'm another company that's trying to, you know, use, you know, advertising to manipulate people in ways that they would not choose. If they had unlimited self-control and unlimited rationality, then I'm, I'm using AI and data to prey upon human frailties rather than using AI to extend people's capabilities. And I think this is consistent with the way failure and sensing. You talked about the ethics of nudge. They're saying they're saying it's good at nudging for good. And again, if I'm wrong, then please correct me. But that's only for good means. We're helping people make the decisions they would make if they had unlimited control and unlimited rations.

00:35:19 That's the foundation. Yeah, that's the foundation. I think there's, this is where it gets, this is I think in my mind where it gets tricky. Yeah. Because there's that, there's the definite evil component, but here, right, you were, you could say, oh, there they're grabbing this information and they're, they're using it in such a way that you're manipulating, you know, the end user. And then there's the definite good as you've mentioned and you know, wearables and, you know, helping them achieve their, their self-set goals. What happens though when you're using this component in a, it might be murkier in Tim and I had a conversation a long time ago now with, with a, with a group, I can't remember even the company, but they were using AI to look at temperatures inside of San Francisco micro-climates in micro climates. Um, pairing that with some data they have about the individual, uh, and then sending messages about buying beer.

00:36:16 Um, because they, they, they, the correlation between the temperature and when someone has apt and five different temperature ranges. And so, you know, outside of just being creepy, right? You know this components of, Oh that my GPS, you're located in this area town and now, wow, it's, it's 82 degrees there you get a message of, you know, you can go to the store down the street and buy Coors light, you know, and get a 10% discount on it. And you could argue that if I'm going to go buy beer anyway, then maybe this is okay. But it still feels incredibly creepy to me to think about. We're going to nudge you right at that. At the point in time that the temperature hits the right place for me and boom, that's, now I'm going to get the, I'm going to get the nudge. Yeah. So Tim might be 82 degrees, I might be 78 degrees, you know, so I don't know that those are those I know gray areas and everything. This gets to be such a moralism to alter ultimately underlying all of this, right? I mean because good and bad are still relative terms.

00:37:21 Well and I'll watch and say there are a lot of cases where they just involve kind of inherent tradeoffs and they, they involve things for like different reasonable people may come, might come to different conclusions and that's what you guys are saying it right. They are saying needs to be their gray areas. So I don't know if I have a fixed opinion about this exact case, I would need to think about it a little bit more. But in general, you know, again like I think this is like a, you know, kind of channeling the, the content idea is that you like kind of like w when you're thinking through like if I'm a start company, this is my business model, right? I'm not gonna, I'm not talking about this specific one, but just more generally do I want to live in a worlds, you know, that's just completely infused with this kind of technology and this kind of marketing where you know, where all this data is being used to make these precision, you know, predictions and kind of influencing me in ways that I'm not really opting into. And then I'm not really privy to, is that really the kind of world I want to live in? So this is the idea is kind of generalizing your action to like, well what if everybody did it? Is that, does that result in the kind of world we want to live in? And if the answer is no, then that might be a [inaudible]. Again, we're talking right here at six. That might be a useful, you know, kind of like the ethical heuristics

00:38:27 to think about this. If this gets extrapolated out to the vast majority of things. Is this something that I would like for me? Exactly. Then in that perspective. So it was at minority report that had the, the movie where you know, the, the advertisements changed as you walked by. Right. And all of those various different things. I mean it's, I mean that was a supposedly a dystopian kind of future perspective. Do we want that? I mean is, is that what we really want? That's, and this will be future. That's a business model. [inaudible] I want to go back to your three D's data, digital and design. Can you talk about those because I'm not sure if I easily can separate out what w what those are standing for.

00:39:08 Yeah, it's the, the, the idea was that, um, I'll give you, I'll give you another example of data in digital. Like data is like my early example, my earliest examples of data scientists was I told you guys before set recording, I built a credit scoring algorithm for a big insurance company. And I discovered, and again, this is like early days of behavioral data, but it's kind of, I've been thinking about this for 20 years now. I started when I was 12, by the way.

00:39:31 I was going to say eight, don't look a day over 26, right? Yeah, exactly. Let's turn the lights on now.

00:39:39 Yeah, no, but what I saw firsthand was that your personal credit score is a stronger predictor of who's likely to crash the car, have a homeowners claim than a lot of traditional x were waiting elements big time. Um, I have a mental freeze right now. You guys might need to edit a little bit, so that's okay. We can do digital design. Sorry. Say, um, you know, the, the, the, so just be about data, a lot of data's behavioral data. We can use this data to make surprising, strong predictions a lot in a lot of domains, right? You just gave the example of you seem to influence elections. My earliest example is building a credit scoring model for, for a big insurance company. And I saw that behavioral data, namely a credit score, is much more predictable of who's going to crash their car than a lot of traditional rating elements.

00:40:26 So I've been thinking about data for a long time. Fast forward to today, the analog of credit scoring data is telematics data and people's cars are connected to the Internet. Yeah. Well part of the Internet of things when you're driving now and so in insurance companies can know a lot of fine grain details about your driving behavior that can be used to make ever more fine grain actuarial predictions and segmentations, which may be fine, right? That's the kind of traditional business model of insurance and that that's the way insurance works. And maybe, maybe that's okay, but that's d that's, that's the first thing that three days, right? There's also digital. Digital's what's making all this possible, right? With this digital revolution, right? It's one of the biggest, it's changing everything about our, you know, our business world and our personal lives. Everything we do is digitally mediated now.

00:41:09 So that's why this insurance can be [inaudible]. So yeah, credit scores. Maybe the earliest example of this digital revolution where ordinary quotidian day-to-day behaviors lead behind digital breadcrumbs, and you can use those digital breadcrumbs to make surprisingly strong predictions is if the insurance industry 40 years to figure out that these digital breadcrumbs about your bill paying behavior are also very predictive of who's gonna crash their car. That's a canary in the coal mine example of what's now ubiquitous, right? We're digitally connected, you know, we leave behind these digital breadcrumbs that they can be used to. All these ways we just talked about the use of ethically dubious ways. The Third D is design. And I'm going back to, I want to interject because I'm still, because digital breadcrumbs still sounds like data. It is. Yeah. I'm saying about specific kinds of data. So it's instead of data, you know, being, being cast off by, you know, like an RFID tag, you know, from a, you know, um, you know, a machine part, you know, so you can use data about, you can use data about machine parts to predict when a part is going to fail.

[00:42:03] That's like one kind of big data. All I'm saying is that a lot of this big data that organizations use is really data about people. It's, it comes from people

[00:42:11] behaviorally based. Yes. Behind it has a digital component because we're so, so wired in today's my, my understanding of this is that yeah, you could have a record of car crashes, right? Which could be pad dumbed through paper and you have a, your, your, you know, car track history. But now you have telemetrics that says, Hey, you break card. And that's all digital information. And by exactly talking about this, right? And so you're getting, you're getting that digital information beyond just the, the actual behavior that we're actually doing.

[00:42:42] So that means that the, unless the implication of the social media likes stuff before to like the, these things that we just do in day to day life, um, they, they, they're, they're much stronger predictors, predictors of our future behavior than Democrat. Traditional demographic traits. Like what demographic box are you in or what you say on surveys? Yeah, so I think, I think one of the, one of the people who started talking about digital breadcrumbs early on was a guy named sandy Pentland at MIT media lab. So I'm kind of using his tagline, digital breadcrumbs. But when I first heard him say it, it's completely reflected my own experience doing the stuff in the insurance industry. And other places too. I mean, when I, when I built my credit scoring model for an insurance company, it occurred to me, wow, that if this insurance company had, you know, supermarket club card data, we could use that club card data about people's shopping behaviors to predict are they likely to crash their car because it's behavioral.

[00:43:28] If you're a six year old male motorcycle driver, that's demographic. Well you get high price for insurance. Right? But if we know from your shopping behavior that your 60 year old male motorcycle driver who reads Martha Stewart Living magazine and only eats Vegan organic produce, you probably a safe bet. Right? Cause you're very deliberate and you know, we could use that to adversely select against our competitors. So that's, that's the, that's the, that's the, you know, that's the, that's that's data and I'm digital, right? It's like it's, it's data, but it's coming through these digital media and because it's this kind of like, it's data about people's behaviors. It's just they're automatic behaviors that digital media are capturing. We can make all these predictions that we couldn't make a few years ago. So for me, the missing link that maybe is the missing link that enables ethical, ethical AI is this idea of design, human centered design, and one s, you know, one aspect of human centered design is explainable AI.

[00:44:20] You know, it's like we need to take into account human psychology. We can't just tell people, here's the number you need to explain why you need to come taken to about human needs when you give them the algorithmic output. But in a thinking fast setting, um, you know, think, think about going back to this um, insurance company example, they're capturing all this data about my driving. If we take behavioral design to account, we could use Robert Cialdini's psychology and influence again to give something back to, to the, to the people generated the data rather than just using the data to kind of like determine their, their riskiness. We can actually give them information back about the riskiness. We can both inform them but also nudge them to be safer drivers through digital media.

00:44:59 Your driving is at, you know, a 60% of everybody else driving on the road. Here are some tips on how to get it up to 80% that's is different things you could, you could have those types of interventions.

00:45:13 That's exactly right. So then that would be inherently pro, socially the customer, the insurance company to have more customer touch points. So it's more customer centric. It'd be good for the driver because you're actually helping the driver achieve his or her goals, which is to kind of get around safely and it's good for society. You can lower the c. So these three things, data, digital design I think can motivate new business models and new types of products are inherently ethical, which is the new wine in a new bottle rather than new wine in an old bottle. Got It. That's exactly right. Yeah. Yeah. So I just think that the, this 3d tagline, it's, to me it's like a helpful tagline for kind of thinking through these things. You know, you know, you know, there's a new book called surveillance capitalism by **Shoshana Zuboff**. I admit I've not read the book, it's like a, it's like 800 pages long. I think I want to read the [inaudible] types really yet. I've bounded self-control. Okay.

00:46:04 Okay.

00:46:04 I'm doing with a capital h like everybody else and I really do want to read it. Um, but you know, I've been thinking along the lines of I believe of what she's been writing about and I, I think that if you sort of like pour the new wine into old bottles yeah. You get maybe models of you get business models and maybe a metals capitalists that might not be sustainable in the long run. But if you kind of think about human needs, which is essentially what nudge is all about, thinking about human needs and you know, human capabilities and how can we help me help people overcome their natural frailties? You're more likely to get ethical AI out of it.

00:46:37 Yeah.

00:46:40 Oh, I, I know, I know. I'm just not, I'm, I'm [inaudible],

00:46:47 we're at, is this an edit part? Is this what this is too abstract guys? No, this is not too abstract at all. In my mind. I think this is, this has been fascinating to me because I think there's no, because there's, there's some real interesting components here and the, the data digital design glens itself into this whole component of thinking about where are we going in the future, right? So we can take this into the future and I think there'll be many businesses that would probably take this and, and put that new wine into that old bottle. And, and that's gonna it might get a new like, hey, here's this splash. Um, but as you said, it's not sustainable. And I think there's others who are going to be thinking about this in a whole new way. And when you think about it in that whole new way, we have to take this new world into consideration.

00:47:40 It's kind of this component of, you know, what the, the solutions of the past, and this is Corny, right? The solutions of the past aren't going to solve the issues of the future. Um, and you know, I, I think about automation, I think about, you know, the component of how many people have lost their jobs. Um, because of automation and, and that, that's uncorked. It's not going to stop. We're not going to be able to say, go back in time and say, let's fill these plants back up with human workers instead of these robots. And you know, it's all, you know, anyway. And you look and you extrapolate that out in the future and you look at trucking and you look at retail and you look at accounting, you look at some of these things that you know, you already look at. Uh, you know, people go, oh well it's only the manufacturing jobs. No, you, uh, what's the tax, you know, turbo tax or whatever, where pay you just enters, you know, the computer does it all for you. Yes. There we're going to lose so many jobs that way and people you know, aren't going to be retrained into doing, you know, all those things. We have to think of a new way to answer that question. That's a

00:48:46 great point. I, I completely agree with you. I think it's very analogous. It's almost, it's almost a different aspects of the same conversation. If we just kind of think in terms of the way we've always been doing things, we're gonna lose. We're gonna, we're going to do things that kind of like hurt the overall population, but, but also we're going to miss a lot of opportunities, like a very simple example, which I've thought about and like my colleague at Deloitte, John Hagle is also use this as an example recently is thing about call center operators. It's like a very straightforward type of AI as chatbots, right? And you could imagine, oh great, if you're a business under, like we can get rid of all of our call center operators just replace with chatbots. Now is that really customer centric? Is that really employee centric? No, and it kind of gets it, you know, going back to the AI theme, it gets back to kind of what I believe is a misperception about about AI.

00:49:33 Again, like just think about the simple example of, you know, Paul Mele here at University of Minnesota discovering a simple regression model cannot perform at clinician. We're not saying we want to replace the condition with a regression. Not think generalizing from that. There are two different types of intelligence going on. There's one narrow type of intelligence, which is the algorithm. You know, intelligence is just the ability to achieve a goal here. The goal is to make a diagnosis, right? The algorithm can achieve very simple goals. Like maybe you can automate simple diagnoses, but the, that goal is better achieved by the human working with the algorithm. This kind of idea of an extended intelligence or a human computer, collective intelligence. Um, can you give me one second to think about this by analogy? Um, so you know, so the, the general principle is that, you know, algorithms are good at some things. Humans are good at others, but they're complimentary forms of intelligence. They have complimentary capabilities. So yeah, chatbots can absolutely handle simple calls. And like if I call to, you know, an airline and saying, hey, you know, is my flight on time? Yes, your flight is on time automated. That's great that that's, that pleases me. It's faster than human could do. Right? But what you should do is use that to free up the humans to use common sense and humor and empathy and spending more time

00:50:41 and not, not saying humans, you have 15 seconds to get this person onto the, you know, off the call. No, now you have that ability to be a human with another human and let's spend the amount of time necessary and you're not being ranked and rated on, you know, I got through 34 calls in this past hour. Right. You know?

00:51:01 Exactly. Yeah. So gets me on kind of Taylorist command and control workplaces. So it's a more human centered form of management, but it's also more customer centric forum because you creating new value for customers. Yeah. And it's, I think it maps onto going back to Paul meal's domain of medical science, right? Same thing with doctors. You don't want to use albums to replace doctors. And there've been like recent prominent examples of AI Research. Richard's researchers saying we shouldn't train, um, uh, oncologist anymore because deep learning algorithms can do a better job of flagging cancers, tumors, and x-rays. But I think Eric Topol has a new book. Again sounded my list. I read it, I promise, but I, but he's basically saying AI can give doctors the gift of more time with patients. So it's kind of going what to to what you're saying about how if we use creativity and really think about what human needs are, think about the nature of these algorithms and

00:51:45 how they can complement us rather than short-circuit us and think about the nature of the work and think about how do we as humans a want to interact with others. Both from a an employee perspective can be a customer perspective, right? And you can create a, you know, not saying a utopian world, but you can, you can definitely get out of that. Taylor kind of, you know, how many widgets am I producing today as my only measure of success? Why is it so hard to convince business leaders to make those steps to, to go in that direction?

00:52:19 I think we'll often say, well, you know, again, it's a lot of, this is a pure effect. So a lot of this is going back to Cialdini. I mean if everybody is talking in terms of using AI to replace workers, you just not thinking along these lines. And the person who says something it, you know, kes some seen a few years ago wrote a book on group thing. Um, if every, if everybody is kind of saying one thing and you have a different thought, you've sort of self-censor that because you are like, well, they must know something. I don't know. Or I'll just sound like a Weirdo if I say this kind of thing. It says it's kind of hard to overcome those kinds of things. You know, it's like, you know, that's why there are kind of, you know, fads and businesses I think too. Um, but also there's this new group at Stanford called the Stanford human centered AI initiative and I think one of the points they make, yeah, I've been saying about human centered AI in recent years too, is you can kind of tell, right?

00:53:02 Like, we need to kind of bring human needs and kind of human, we need this kind of start with human behavior and build AI around that rather than say, build AI and hope that humans conform. Right. That's the basic idea. But like one of the points these Stanford human centered AI people make, it's called Stanford Hai, is we need to bring more diversity into the AI field. So this is more of a specific thing that you're talking about, but we don't want you to just have computer scientists. We have diverse people that do define please. Good question. Yeah. I think people with more diverse backgrounds, people from the, you know, different kinds of, um, walks of life maybe, but also people trained in different fields too. So, you know, like I, I, I'm hoping that what's coming out of this conversation is that behavioral scientists have a role to play in developing AI technologies.

00:53:41 Well, this is exactly Carnegie Mellon with their social and decision sciences group. That department is mathematicians, astrophysicists, economists, psychologists, all of them in the same group solving problems together. For me as a fan. No, I think that's exactly what we need. And I think that a lot of these kind of like maybe less than desirable business models come from kind of monocultures of thinking. And I think if we've got people you know with, you know, kind of, you know, different scientific perspectives, different disciplinary perspectives, but also just different, you know, kind of, you know, backgrounds, we're more likely to get sustainable technologies. Yeah. Diversity is such a, an important part of all of our growth. Right. I mean, and, and historically I just think about how a tribes got stronger when they brought people from other tribes in. That's right. You know, so we have a rich history in, in doing well with, with having diverse skills and, and a bunch of things.

00:54:35 But, and yet there is such a tendency to resist it as well. No, I completely agree. Did you want to go to music? I'd love to. I can tell by your, your body here you're going to music whether I like it or not. There you go. There is enough meat in the sauce. I'm just going to say that again. Um, yeah. So let's, let's, let's talk a little bit about music. You would prefer to listen to music that was recorded or happened before the 1970s, before the 1980s, before the 1990s. Kind of a man out of time. What can I say that you and Tim can have a whole conversation cause you're both in the same boat, but where I tend to, I tend to cling to or am drawn to music. Uh, that was written in the 60s, 50s, 60s, 70s. Um, you go back further with, with Gospel music.

00:55:26 Tell us about some of your, your interests in, in classical music. I like a lot of that stuff too. By the way. I'm a big Bob Dylan Fan. I like Van Morrison. I none of this one sentence. I mean, I, you know, I'm a gay guy and I'm not, not, not old enough to remember those guys, but I just a fan of that kind of music, let him call and I just like all this kind of stuff doesn't make any sense. You know, again, I'm like the 60 year old male motorcycle driver who, who is a Vegan and it doesn't really make a lot of sense. I mean, I, I didn't, I grew up with music in the 80s and I was kind of like appalled by it. You know, I, I look back on it now, it's kind of kitchen kind of fun. But at the time I was just like revolted by it. I, I'd wished I'd been born to, you know, to live through the 60s.

00:56:03 Wow. We are something very simpatico about that. [inaudible] um, we are grooving, but I also love the classical jazz music, you know. Um, I was lucky enough to go to a liberal arts school and one of my best friends in college, **David MacDonald's** is a composer at Manhattan School of Music. He introduced me to early 20th century *avant garde* music, like Baird. They burn from the second Viennese school. So I, I love, I love, you know, lots of classical music, especially chamber music. Um, yeah, my idea of a purpose, a perfect musical day. It's got to sound kind of weird. But I lived in London for a year and I love going to Wigmore Hall, which is one of the best places in the world to hear chamber music. And whenever I'm in town I try to go to their Sunday morning conference concerts and just like hearing a divorce jack string quartet or of Schumann string quartet or something on it on a Sunday morning.

00:56:52 It would more halls, my ideal musical moment. And maybe that evening hearing VJ IAR played a jazz club. That would be for me a perfect musical bag. So why, why do you think you like, uh, the, the smaller or the quartets, the chamber music settings, you know, smaller bands rather than, than, you know, the big classical, uh, full-scale orchestras. I have no idea and I'm just going to speculate. Um, I read a book by **Susan Cain** a few years ago called quiet and it's about introversion. So it's kind of a popular book about introversion and the kind of dim memory, but I think she sort of like reframed introversion towards, um, this idea of the HSP, the highly sensitive person. You said research, I'm forgetting the name of the, of the psychologist she cited. Um, but you know, highly sensitive people are in particular very sensitive to sound and you know, introverts very often have a hard time navigating social situations.

00:57:41 So there's a lot of background noise, you know, it's very hard to process out other conversations and focusing on one person. I feel that a lot. Maybe there's something about that with me to where I can, I can more easily embrace kind of smaller scale musical events rather than huge bombastic symphonies or huge rock concerts. I'm not really sure. Yeah. But I don't know. I don't know. I just tend to gravitate more towards like small jazz ensembles, Chamber Orchestra, small venues, that kind of stuff. More intimate types of music. Folk music is supposed to, you know, very bombastic electronic music, you know, so folk music? Yes. Um, EDM? No, not really. No. Yeah, not my thing. No, it's like, so it's more, I guess I, I guess I, you know, it's a personality thing that kind of trumps my demographics. You know, maybe I should like, you know, house music, but I never did that.

00:58:30 That's okay. You also mentioned Schoenberg, which I tend to associate with kind of darker, um, uh, musical themes. Um, maybe. Yeah. Yeah. I, I don't know. I don't think of it in terms of being dark. I just seen him in terms of being very interesting and us gear. Yeah. Yeah, absolutely. I mean it's, it's right. You know, the other thing is that like, you know, like Walt Whitman, right? I contain multitudes. Like I wouldn't, I wouldn't wanna listen to Sharenburg on a bright summer morning in Minnesota. Right. I actually went, I when I was in, when I was in Pittsburgh a few weeks ago, uh, Deloitte sponsored a class that Linda backpack is leading for the new behavioral science major. It, it of came Mellon. I was staying with friends in Pittsburgh and I was streaming the **Wonderboys** soundtrack and it was just kinda like, I just loved almost every single song gonna want to soundtrack.

00:59:21 And it just captured Pittsburgh for me because the movie wonder boys was filled in Pittsburgh. And so I was just having this kind of like, you know, kind of Crucey involvement. I'm thinking about, you know, that movie and just kind of like grouping on and Pittsburgh says, and listened to us streaming that as I was walking down the streets in Pittsburgh. So it's Kinda like I will listen to **Schoenberg** but maybe at a certain place in time, maybe like context context matters, like a, a moody fall night, you know, you know, walking around some town in the northeast, maybe I'll listen to Sharon Bird, but you know, bright summer day or spring day and Pittsburgh goes into the Wonderboy sun. That's all context. That's good. Could you leave us with three tips for someone who is interested in getting deeper into, um, the application of behavioral science in whatever field they're working in, whether it's data science or whatever.

01:00:05 What w what would you say to, to a listener that, that you could say, okay, here's three things that you should, you could do, you could read, you could, you know, pursue. Well, listen to this podcast for one. This is terrific. I listened to a lot of your prior episodes. I think they're terrific. [inaudible] I think that's the point. It's like this stuff has been popular. I said, I think the reason why condom and wrote thinking fast and slow is to change the way people talk about things. Yeah. So the people are less like of the poorer, you know, new wine into old bottles. Right. Um, so yeah, reading books like thinking fast and slow misbehaving is extremely entertaining. Nudge, you know, all these books. I think you're really, really helpful. Um, listen to podcasts. I think kind of like using common sense, you know, like, so like think, thinking about your own work and you know, trying to like learn about these principles and thinking, you know, how, how can it change the way I do things.

01:00:50 So like if I'm a data scientist, maybe I can use this to, you know, create more pro-social, human centric AI. If I'm an HR person, maybe I can use behavioral economics principles to rethink our management tactics. You know, hiring, how we hire, you know, various different pieces of hiring or think about administrative burden. Like, how much of a [inaudible] HR is tied up with paperwork, you know? Right. And it's like, if you actually think in terms of behavioral science, just, you know, don't get bogged down in the details. Just thinking at the high level, oh wait, this is what we've learned about human nature. How does that change the way I should do my work? Right. Um, so I, yeah, I don't know if that's helpful, but that's just, well, that's great. And my journey. Yeah, no, I think that's fantastic. Thank you. This has been highly, highly informative. Fun. She comes to me Annapolis more often. You should definitely come to Minneapolis more often. We could, we could, we could do this again, but thank you so much. We appreciate you being on the show. You Bet. My pleasure. We're done there. All right. Thank you.

01:01:54 Well, well, no, so this is the part that I think for us that, you know, you've listened to our shifts, so we will do it.