Panel 2: Rendering Visible, Understanding, and Reducing Historical Disparities
Moderators: Elizabeth Mynatt (Georgia Tech) and Alondra Nelson (SSRC & Institute for Advanced Study)
Speakers: David Grusky (Stanford University), Jennifer Richeson (Yale University), Tiffany Veinot (University of Michigan), Suresh Venkatasubramanian (University of Utah)

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00:03:33.450 --> 00:03:39.630
Beth Mynatt: Good afternoon. I hope everyone had a great 30 minute break and I'm just thrilled to see so many folks

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00:03:40.500 --> 00:03:47.100
Beth Mynatt: In our virtual audience. We're going to pick up on a number of our discussions from this morning's the first panel.

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00:03:47.790 --> 00:03:55.230
Beth Mynatt: As we saw folks beginning to grapple with relationships of the information ecosystem and ethics and it's

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00:03:55.770 --> 00:04:09.120
Beth Mynatt: The implications, especially for long standing questions of trust, long standing questions of disparities as often times the most vulnerable populations are the ones that are exposed

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00:04:09.540 --> 00:04:23.970
Beth Mynatt: I in these complex interactions between information infrastructure and society and trust and other aspects of it. In fact, that's one of the things that we're going to see in our panel today is we're going to connect to.

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00:04:24.780 --> 00:04:28.860
Beth Mynatt: The thread around computational social science, but you're going to hear from our other

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00:04:30.150 --> 00:04:41.430
Beth Mynatt: Our other panelists relationships to other parts of the IT infrastructure in particularly, we'll look at health informatics as well. So enough from me. Good to see folks here.

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00:04:42.000 --> 00:04:50.880
Beth Mynatt: As before, I'll ask my panelists to please introduce yourself, share your screen and you'll hear the chime as we need to move to the next.

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00:04:51.480 --> 00:04:58.590
Beth Mynatt: Presentation and reminder to everyone else to please use the zoom chat channel as well as our slack hallway chatter

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00:04:59.100 --> 00:05:12.900
Beth Mynatt: Channel as a way of posting questions. Commenting to each other and getting us ready for our 30 minute discussion period. So with that, David, I see you and David Gretzky if you would please lead off.

11
00:05:14.070 --> 00:05:20.460
David Grusky: Great, thank you very much. It's a, it's a pleasure to be here. I'll, I'll get right to it by sharing, sharing my my screen.

12
00:05:27.330 --> 00:05:27.630
And

13
00:05:29.940 --> 00:05:32.520
David Grusky: I'm going to be talking about data systems.

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00:05:34.470 --> 00:05:37.110
David Grusky: And there are two two types of

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00:05:39.180 --> 00:05:42.900
David Grusky: Data sub questions that are relevant when you talk about data systems.

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00:05:46.020 --> 00:05:48.630
David Grusky: The first type of question is all about.

17
00:05:52.170 --> 00:06:02.550
David Grusky: What types of data systems are needed for rendering visible disparities? And the second question is, what types of data systems are needed for reducing disparities? And I'm going to address each in turn.

18
00:06:04.110 --> 00:06:11.520
David Grusky: So first off, what types of data systems do we need for the 21st century when it comes to rendering visible disparities and

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00:06:11.700 --> 00:06:12.150
And if

20
00:06:13.380 --> 00:06:14.640
Beth Mynatt: We're not seeing your slides.

21
00:06:15.540 --> 00:06:17.190
David Grusky: You're not seeing my slides.

22
00:06:18.090 --> 00:06:19.890
Beth Mynatt: We're seeing a beautiful image of you.

23
00:06:20.820 --> 00:06:22.230
David Grusky: Excellent. Now,

24
00:06:24.270 --> 00:06:24.750
David Grusky: Okay.

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00:06:37.650 --> 00:06:39.750
Beth Mynatt: So we need you to use the share screen.

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00:06:41.040 --> 00:06:41.700
Beth Mynatt: There we go.

27
00:06:43.140 --> 00:06:45.630
Beth Mynatt: And now in presentation mode.

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00:06:47.880 --> 00:06:48.240
David Grusky: Good.

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00:06:48.870 --> 00:06:59.100
David Grusky: Perfect. My apologies. Um, so two types of variability that we would want our data systems to capture

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00:07:00.660 --> 00:07:05.190
David Grusky: With respect to rendering visible disparities and the first geographic variability

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00:07:07.860 --> 00:07:16.380
David Grusky: We know that there's immense geographic variability and we know, furthermore, that that it refracts institutionalized disparities in all sorts of ways.

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00:07:17.340 --> 00:07:24.780
David Grusky: So, for example, most famously Raj Chetty has shown that, that there's much geographic variability in upward mobility.

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00:07:25.230 --> 00:07:35.130
David Grusky: Across across the neighborhoods with the US and in fact that that that variability swamps the amount of variability that you see across, across rich countries and the amount of upward mobility.

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00:07:36.540 --> 00:07:40.530
David Grusky: The second key dimension that you'd want your data system to capture is temporal variability

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00:07:41.190 --> 00:07:50.040
David Grusky: If there's anything we've learned about the 21st century, it's that we're going to have the likely never ending sequence of crises that again refract disparities and important ways.

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00:07:50.550 --> 00:08:02.430
David Grusky: All we're going to see in all likelihood, many more environmental disasters, many more health disasters, many more political disasters, many more economic disasters and we want our data systems to be able to

37
00:08:02.880 --> 00:08:07.410
David Grusky: Understand what's happening to these disparities as these as these disasters, unfortunately, unfold.

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00:08:08.730 --> 00:08:18.210
David Grusky: So here's my thesis. It's that the set the country's qualitative infrastructure needs needs a fair amount of help and meeting these two challenges.

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00:08:18.780 --> 00:08:31.200
David Grusky: But let me talk about the quantitative infrastructure. It's hardly perfect and takes lots of work as well to bring it up to up to up to speed. But, but, nonetheless, one might say it has done a decent job on the rendering physical challenge.

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00:08:32.400 --> 00:08:32.820
David Grusky: We have

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00:08:35.250 --> 00:08:45.270
David Grusky: Big Data various types like tax data that allows to capture geographic variability and, in particular, capture disparities reasonably well when linked to other other sources like like census data.

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00:08:46.290 --> 00:08:56.460

David Grusky: On the temporal variability side we have flash surveys, we have real time, big data that the do a decent job hardly perfect but decent, but I want to focus on on a zone in which I think

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00:08:57.510 --> 00:09:10.020
David Grusky: We haven't yet to the same extent risen to the challenge. And that's on the qualitative side and the first point that I want to make here is that it's obviously been a critical part of the country's data infrastructure.

44
00:09:12.540 --> 00:09:16.590
David Grusky: When it comes to to exposing and rendering visible disparities to just think about

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00:09:17.880 --> 00:09:29.160
David Grusky: Evicted by Matt Desmond or Unequal City by Carla Shedd or $2 a Day by Kathryn Edin. These these these pieces change the conversation by rendering disparities visible.

46
00:09:30.630 --> 00:09:43.560
David Grusky: But I worry about whether the qualitative form is is well positioned to to exploit all that's extraordinary capacity in the 21st century and there are two problems that I want to, I want to point out here. One is the geographic variability problem.

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00:09:44.790 --> 00:09:51.060
David Grusky: We typically have one off studies of iconic sites--very, very important, but that makes comparison accumulation difficult

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00:09:52.410 --> 00:10:03.480
David Grusky: And secondly, when it comes to real time monitoring of crises we typically rely on journalists-- we see to journalists when it comes to crisis monitoring. I'm an avid consumer of qualitative research that journalists carry out

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00:10:04.200 --> 00:10:13.950
David Grusky: But I think we have some value at that that uh is left on the table because journalists are forced to rely on self selected samples.

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00:10:14.490 --> 00:10:21.930
David Grusky: they're forced to rely on their hunches about the story that needs to be told, and hence the discovery mission, which is the fundament of the qualitative form

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00:10:22.410 --> 00:10:28.710
David Grusky: Is to some extent, not fully realized. So I want to talk a bit about the American Voices Project because it, which is an attempt to

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00:10:29.010 --> 00:10:38.100
David Grusky: To overcome some of these problems. It's currently in the field. And there are five commandments behind the American Voices project that tries to address some of these problems.

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00:10:39.510 --> 00:10:47.610
David Grusky: The first commandment is that of discovery. Don't just visit iconic sites as important as they are, but instead draw

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00:10:48.480 --> 00:10:58.140
David Grusky: A sample of all types of neighborhoods in the US, in this case 200 neighborhoods and then draw representative samples of households within those neighborhoods. The second commandment is that of comparison.

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00:10:59.760 --> 00:11:10.980
David Grusky: So go beyond the usual one off study and you do so by delivering the same protocol across all 200 sites that's making, making comparison accumulation possible

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00:11:12.120 --> 00:11:14.190
David Grusky: The third commandment is all about inference

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00:11:14.520 --> 00:11:27.330
David Grusky: Don't assume that the law of large numbers is just something that works for for for quantitative data, it's also relevant for qualitative data and hence you need large sample sizes as expensive as that is that's critical. And so the AVP as a PSID-sized sample.

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00:11:29.100 --> 00:11:41.400
David Grusky: The Fourth Commandment is about cumulation. Don't allow the data to be used just once, and then and then destroyed instead allow for open access, while at the same time, of course, protecting confidentiality.

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00:11:42.480 --> 00:11:54.540
David Grusky: And then the fifth the Fifth Commandment is all about real time monitoring. Don't cede that to journalists as important as they are, Ah, but also allow allow for for for qualitative research that is based on a representative samples in real time.

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00:11:56.070 --> 00:12:03.960

David Grusky: So we're collaborating with Federal Reserve Bank of Boston to deliver real time reports on what's happening in the current crisis, all with a focus on disparities.

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00:12:04.860 --> 00:12:12.330
David Grusky: So on the rendering visible challenge, my conclusion is the quantitative infrastructure, obviously flawed, needs some work.

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00:12:13.200 --> 00:12:25.680
David Grusky: Um, but what I really wanted to focus on was the problems that are in play with respect to our qualitative infrastructure. It's lucky that the American Voices project happened to be in the field when the current crisis unfolded.

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00:12:26.310 --> 00:12:37.680
David Grusky: But we need a standing immersive interviewing panel that allows us to monitor future crises, as they play out. And as they refract and change the way in which disparities

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00:12:40.050 --> 00:12:41.190
David Grusky: Are in play in the US.

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00:12:42.330 --> 00:12:44.970
David Grusky: Okay, let me turn now to the second

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00:12:47.880 --> 00:12:50.520
David Grusky: type of question that's embedded in today's panel and that's

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00:12:51.060 --> 00:13:06.300
David Grusky: What type of data infrastructure do we need when it comes to reducing disparities, not just rendering them visible but reducing them? And the obvious point with which I want to begin is that this is obviously a center a century of pretty daunting distributional problems--

68
00:13:08.580 --> 00:13:18.720
David Grusky: rising income inequality and transmitted poverty and homelessness persistent racial and gender inequality rising immigration status discrimination declining absolute mobility and on and on.

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00:13:20.100 --> 00:13:34.050
David Grusky: So I would say this is our Do or Die century. As important as basic science is and needs to continue, we also have to make sure that our data systems are up to the task of taking on these big problems that almost always are about disparities.

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00:13:35.880 --> 00:13:50.010
David Grusky: So how do you build a problem solving social science with respect to our data systems? Here I think we really need massive upgrades to both our quantitative and qualitative infrastructures and I'll just lay out a bit about what what what I mean here. On the quantitative side,

71
00:13:52.710 --> 00:13:56.130
David Grusky: If you want authentic evidence based policy

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00:13:57.480 --> 00:14:10.140
David Grusky: That can speak to how to reduce disparities, then you need a big panel data system. Other countries have this and they built their public policy around the evidence because they had big panel data.

73
00:14:11.010 --> 00:14:29.820
David Grusky: We don't have big panel data and yet we have the capacity to build big panels and, indeed, there's an opportunity in play-- The American Op-- There's an effort in play: The American Opportunity study that that seizes that that that capacity by by linking cross sectional data.

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00:14:32.040 --> 00:14:35.820
David Grusky: And building a panel there by and this is a joint effort between the Census Bureau,

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00:14:36.840 --> 00:14:47.340
David Grusky: Opportunity insights, and research with a variety of other institutions. The basic idea is that you can link decennial censuses with the households and individuals and decennial censuses and thereby convert

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00:14:48.540 --> 00:14:54.630
David Grusky: cross-sectional data into battle data and and then and then allow those data to be analyzed in secure facilities.

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00:14:55.770 --> 00:15:05.520
David Grusky: Once you have that it's a big project and it will take some time, but once you have that, you can use that big panel data to evaluate thousands of programs and interventions.

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00:15:07.560 --> 00:15:12.090
David Grusky: And lots of social scientists, quantitative social scientists who want to do nothing but figure out

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00:15:12.540 --> 00:15:18.630
David Grusky: How best to reduce disparities. That's our commitment but they haven't been able to realize that commitment because they don't have access

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00:15:18.990 --> 00:15:28.650
David Grusky: To big panel data. Only only a small number of social scientists have that kind of access, and we need to open it up, live up to the Open Science promise and allowed the

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00:15:29.010 --> 00:15:36.210
David Grusky: These interests to be realized. Unleash the interests of thousands of social scientists who want to understand how best to reduce disparities.

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00:15:37.830 --> 00:15:38.280
David Grusky: So,

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00:15:40.980 --> 00:15:54.690
David Grusky: Is that enough? I think it's important, but I think there's another side to the equation. I want to convince you that we also have to ramp up our qualitative infrastructure, if we want to have a problem solving social science and social science, they can take on disparities and and

84
00:15:56.040 --> 00:16:02.940
David Grusky: The point here is that the the quantitative infrastructure is really good when it comes to a variable based approach.

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00:16:03.720 --> 00:16:09.930
David Grusky: What's the drill here? You all know it, but I'll just rehearse it quickly we characterize individuals and social systems as a string of variables.

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00:16:10.650 --> 00:16:15.810
David Grusky: We determine which variables have causal effects on outcomes like say EITC reduces disparities.

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00:16:16.230 --> 00:16:23.790
David Grusky: And then once we decide we determine which variables have those causal effects or treatments are all about- are all about manipulating those variables

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00:16:24.240 --> 00:16:35.580

David Grusky: To generate the desired outcomes. A powerful approach, but would you want to rest your entire bet on on how to how to reduce disparities on that approach alone? Let me try to convince you that you should.

89
00:16:36.900 --> 00:16:41.160
David Grusky: Think about what we do with medical interventions. Do we proceed this way exclusively?

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00:16:43.770 --> 00:16:46.320
David Grusky: We know when someone presents in say

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00:16:47.220 --> 00:17:01.770
David Grusky: At a hospital, we don't take the patient's blood pressure, heart rate, body temperature, and then treat each of those separately, you know administer some norepinephrine for blood pressure, a beta blocker for heart rate, and so forth. We don't do it that way, unless it's a true dire emergency

92
00:17:03.000 --> 00:17:13.200
David Grusky: Instead, we proceed holistically. We identify the underlying condition, it might be coronary artery disease. We identify the mechanism behind the condition, maybe inadequate exercise and we intercede at the mechanism.

93
00:17:13.620 --> 00:17:19.380
David Grusky: And the presumption is that when we do that, the correct levels of each of the individual level variables will be restored.

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00:17:23.280 --> 00:17:27.450
David Grusky: Okay, we're almost done. I just want to say we've done the same thing with social science.

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00:17:28.080 --> 00:17:39.780
David Grusky: Flexicurity is a holistic, you might not like it, I happen not to, but that's not the point. Flexicurity is a holistic diagnosis of the problem of swift product cycles.

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00:17:40.770 --> 00:17:55.290
David Grusky: It's that type of approach the AVP makes it possible to to to see systems holistically and can be coupled with with quantitative big panel data to deliver a powerful science for solving problems. And I'll leave it at that. Thank you.

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00:17:57.810 --> 00:18:09.420

Beth Mynatt: Thank you, David. That was terrific and a great way for us to start and I'm glad to see the discussions are going and to the chat channels and I'll ask Jennifer she can pick us up from here.

98
00:18:10.590 --> 00:18:15.240
Jennifer Richeson: Happy to. I can't unmute my video. However, so I need someone on your end to do it.

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00:18:18.690 --> 00:18:21.630
Beth Mynatt: Let's see. Alexis, you got us

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00:18:23.160 --> 00:18:23.640
Beth Mynatt: There we go.

101
00:18:26.700 --> 00:18:27.120
Beth Mynatt: Perfect.

102
00:18:27.690 --> 00:18:28.110
Beth Mynatt: Excellent.

103
00:18:28.170 --> 00:18:34.350
Jennifer Richeson: Good morning to those on the West Coast, good afternoon to those of us in the East Coast and everyone in between.

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00:18:37.980 --> 00:18:49.680
Jennifer Richeson: I am. I'm a social psychologist by training and I guess still have that job. They haven't kicked me out yet. And I want to present some work, arguing that

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00:18:50.310 --> 00:19:05.310
Jennifer Richeson: In order to render inequality more visible, we need to do more than have more data or different types of data. In fact, I think it's more, it's an addition to a data problem and a technology problem. It's also a psychological problem.

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00:19:05.730 --> 00:19:14.850
Jennifer Richeson: And just to as a kind of way to think about it. I want to talk a little bit about some work we've been doing theoretical work on what I call what we call the mythology of racial progress.

107
00:19:20.490 --> 00:19:23.100
Jennifer Richeson: And it goes something like this, right, we

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00:19:24.210 --> 00:19:39.180
Jennifer Richeson: Are off our, our American narrative of racial progress are basically rooted in this sort of general storyline that you know racial equality or tolerance discrimination if we plot that on the Y axis.

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00:19:39.630 --> 00:19:47.070
Jennifer Richeson: It's a higher numbers are are are less of it. Okay, so more equality, more tolerance, less discrimination.

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00:19:48.270 --> 00:19:53.430
Jennifer Richeson: What we say we tend to say, is you think that things are certainly better than they were in the past.

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00:19:53.670 --> 00:20:02.220
Jennifer Richeson: And they're certainly getting better. They're better now and getting there in the future, it's often a narrative, like, well, the past was really bad maybe starts in slavery.

112
00:20:02.610 --> 00:20:20.850
Jennifer Richeson: But then we had the civil rights movement and you know there are these often points of inflection, like the election of Barack Obama and we tend to think of it as something that's achieved at least all of the guardrails are in place so progress is happening naturally and automatically

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00:20:22.260 --> 00:20:28.050
Jennifer Richeson: And so what we've been arguing is that this mythology around our progress toward racial equality

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00:20:28.410 --> 00:20:42.540
Jennifer Richeson: Is something that itself shapes our perceptions and misperceptions of the actual current state of racial equality in the nation and those perceptions and misperceptions also shape what we believe is both necessary

115
00:20:43.080 --> 00:20:56.310
Jennifer Richeson: and required to actually achieve equality. And that's true for any number of programs and certainly I want to argue true in this new movement of thinking about technology and its possibilities for increasing equality.

116
00:20:57.420 --> 00:21:15.570
Jennifer Richeson: But first, let me just say a little bit about the this narrative of racial progress and how it might be revealed in our perceptions of racial equality. This is just data from a study I did with

Michael Krauss and others where we just ask people, Americans nationally representative sample,

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00:21:16.620 --> 00:21:28.440
Jennifer Richeson: Questions about their perceptions of the racial wealth gap at different years. So they would ask something- we'd ask something like for every hundred dollars of wealth accumulated by the average white family,

118
00:21:28.920 --> 00:21:40.920
Jennifer Richeson: How much wealth as the average black family accumulated? And so we'd say okay in 2016? What about 1985? What about 2000? Okay so across 11 different time points.

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00:21:41.940 --> 00:21:58.650
Jennifer Richeson: And what we saw was something like this. Okay. So on the Y axis is the per- the perceptions of the quality. Right. So again, higher numbers mean perceptions that the the racial wealth gap is basically closed. Okay.

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00:21:59.760 --> 00:22:16.560
Jennifer Richeson: And what you see is this general linear increasing perception that the ratio wealth gap is all but closed from 1960s to 2016. Of course you would compare this to data on the actual

121
00:22:17.610 --> 00:22:20.790
Jennifer Richeson: wealth gap from federal estimates, and you see this.

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00:22:22.290 --> 00:22:26.040
Jennifer Richeson: And so we can see from these data is that, you know, people are generally wrong.

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00:22:26.880 --> 00:22:44.490
Jennifer Richeson: And they're more wrong now right about the current racial wealth gap than they were in the past and revealing this sense that things must have gotten better. So things, we must be in a better position now than we thought we were that we used to be.

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00:22:46.260 --> 00:22:58.050
Jennifer Richeson: So of course, this is not true. So this misperception these false beliefs of course make it impossible really to do anything about these racial wealth gaps.

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00:22:58.710 --> 00:23:06.360

Jennifer Richeson: And this, we think, is in part because of our mythology of racial progress. So just to, you know, to turn a little bit. I'm going to skip through

126
00:23:07.560 --> 00:23:17.310
Jennifer Richeson: A lot of that what we call sustaining Miss or the our ideas, our psychology that really allow us to believe in this, despite lots of evidence to the contrary.

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00:23:18.420 --> 00:23:24.780
Jennifer Richeson: But one important one is our beliefs about the nature of practice. So let me just say a little bit about this.

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00:23:25.470 --> 00:23:38.730
Jennifer Richeson: So in this mythology, right. So, so one of the myths is that, you know, structural racism is also is a thing of the past. Right, and has now largely been replaced with interpersonal racism.

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00:23:40.410 --> 00:23:54.120
Jennifer Richeson: And what happens when we think that structural racism is not no longer a problem is that we fail to believe the evidence of disparate impact from policy, even without intent.

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00:23:54.570 --> 00:24:06.810
Jennifer Richeson: In, you know, we believe we fail to believe that exists right and we allow for we tolerate policies, despite their obvious disparate impact. This is just one voter ID laws, for instance, okay.

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00:24:07.560 --> 00:24:14.700
Jennifer Richeson: And there's you know quite a bit of evidence. Now this is just data from CNN KFF poll. But actually there's Pew data on this.

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00:24:15.060 --> 00:24:30.150
Jennifer Richeson: That on average Americans believe, indeed, when asked what is the bigger problem today in the US: structural forms of racism or interpersonal forms, you know, two thirds of Americans of the sample will say interpersonal

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00:24:32.160 --> 00:24:42.540
Jennifer Richeson: And again, our the extent to which we believe this predicts the extent to which we believe that specific systems, whether it's the criminal justice system,

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00:24:43.620 --> 00:24:50.010

Jennifer Richeson: Health Systems, education systems, whether we believe they also have specific racial disparities.

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00:24:51.720 --> 00:25:01.170
Jennifer Richeson: So another version of this or belief about racism that underlies or I think sustains our mythology is that

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00:25:01.710 --> 00:25:10.350
Jennifer Richeson: Explicit or more overt forms of racism are in the past and have now changed and been replaced by more implicit

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00:25:10.950 --> 00:25:20.430
Jennifer Richeson: In subtle forms of bias. And it's not that of course implicit bias and subtle biases don't exist and aren't really important to understand and my field has obviously

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00:25:20.670 --> 00:25:31.800
Jennifer Richeson: Done a lot to promote the role of implicit bias, but it does not suggest that we don't have explicit problems due to explicit and overt forms of bias anymore.

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00:25:32.490 --> 00:25:44.940
Jennifer Richeson: So this overt racism thing is a thing of the past, this myth sustains our belief in racial progress. And of course, when you look at studies even more recent studies examining

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00:25:45.570 --> 00:26:05.940
Jennifer Richeson: Evidence of overt racial prejudice. So for instance, searches for the N word studies find that this type of bias actually predicts any number of health outcomes, disparate health outcomes, perhaps even more than the implicit biases of the people who happen to live in those spaces.

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00:26:07.470 --> 00:26:14.610
Jennifer Richeson: So now that we- we see more and more attention to implicit bias, It's also important to remember that

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00:26:14.910 --> 00:26:25.200
Jennifer Richeson: it- belief in this as the most prevalent and important form of bias right now leads to outcomes like this when you have an incident in this case,

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00:26:25.830 --> 00:26:32.280

Jennifer Richeson: The police being called on two young black men sitting in a Starbucks waiting for their friend to show up before ordering anything

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00:26:32.760 --> 00:26:38.160
Jennifer Richeson: It gets automatically often but certainly readily attributed to implicit bias.

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00:26:38.640 --> 00:26:47.580
Jennifer Richeson: Even when there's little evidence that it was necessarily due to implicit bias. So in our lab, we've been trying to examine this question of, okay, well,

146
00:26:47.850 --> 00:26:58.320
Jennifer Richeson: These attributions are happening, what are some of the consequences of them? Because, of course, if we're not holding people accountable or institutions accountable for implicit forms of bias,

147
00:26:59.190 --> 00:27:10.320
Jennifer Richeson: Then we certainly aren't going to make any, you know, progress in dismantling it. So here I'm just going to briefly talk about one study, but it's in the paper, where we're examining

148
00:27:11.400 --> 00:27:31.740
Jennifer Richeson: Where we provide information about cases of discrimination, for instance, this one, it's, it's about police- differential behavior of police officers with racial minority versus white citizens and, you know, regular if- there are all these accounts that we use in our studies are based on actual

149
00:27:33.930 --> 00:27:47.580
Jennifer Richeson: Incidents or even studies and it basically shows. So we basically provide this description and then we attribute the disparate behavior. So in this case, treating citizens kind of more harshly with more violence

150
00:27:48.870 --> 00:28:01.860
Jennifer Richeson: To explicit bias on the officers part, implicit bias on their part. And we asked participants then, you know, how accountable, for instance, should the police officers be?

151
00:28:04.680 --> 00:28:17.310
Jennifer Richeson: And so we find in this case is a general reduction of accountability. Right. So the police officer held less accountable if their discrimination is said to be born of implicit bias.

152
00:28:17.730 --> 00:28:35.970
Jennifer Richeson: Okay, so these more automatic forms of bias than explicit, and we replicated this finding across other types of bias, other types of actors. With this case, it's medical doctors demonstrating more negative treatment with patients based on their political affiliations based on age.

153
00:28:37.740 --> 00:28:48.030
Jennifer Richeson: And if you look across these studies, you just do a meta, a mini meta analysis- what you find is that this accountability effect is small but it's actually quite robust

154
00:28:48.780 --> 00:29:04.050
Jennifer Richeson: And the somewhat smaller but still robust significant effect on punishment, meaning people punish the those less severely when they're discrimination is said to be due to implicit versus explicit bias.

155
00:29:05.970 --> 00:29:14.040
Jennifer Richeson: So unconscious bias is actually often a really feeble excuse for the discrimination we see. There's lots of evidence in the accounts of

156
00:29:14.310 --> 00:29:27.870
Jennifer Richeson: Explicit bias, but it's the one that we go to, we think in part, because of this story we have about the causes and meanings of discrimination in our current moment. Okay, but it seems to be an effective excuse

157
00:29:29.550 --> 00:29:37.470
Jennifer Richeson: So the last one I want to talk about is one that we've been considering more recently, and that is this belief that sort of decisions are- be better

158
00:29:37.830 --> 00:29:50.010
Jennifer Richeson: Made by technology, especially decisions will be less biased if it's made by, you know, technology or AI are than humans. OK, so the technology will save us as our new sustaining myth.

159
00:29:51.060 --> 00:29:56.460
Jennifer Richeson: And obviously there's awesome evidence that this is not true, even by people on this call.

160
00:29:57.330 --> 00:30:11.970

Jennifer Richeson: And we started to ask, Well, you know, who's to blame for when algorithms discriminate? Right, we see that there are these discounts of attribute of accountability for implicit versus explicit bias. Do we see something similar for automated discrimination?

161
00:30:12.480 --> 00:30:23.790
Jennifer Richeson: So here, we did a very similar set of studies, I'll just present one, where we talk about a case of mortgage lending, discrimination in the mortgage lending enterprise which is attributed to one

162
00:30:24.870 --> 00:30:25.320
Jennifer Richeson: Bank.

163
00:30:26.790 --> 00:30:27.210
Jennifer Richeson: In this

164
00:30:29.640 --> 00:30:39.390
Jennifer Richeson: And just to skip ahead either explicit bias, implicit bias, or algorithmic bias. And what we find is that replicating our past work, you see

165
00:30:40.080 --> 00:30:54.990
Jennifer Richeson: Less perceived accountability for implicit bias versus explicit bias, okay, when the bank manager was said to discriminate based on his explicit versus implicit bias. But what about when there's an algorithm, and the bank manager just uses the algorithm?

166
00:30:56.400 --> 00:31:00.690
Jennifer Richeson: You see there's even less accountability attributed to him. Okay.

167
00:31:02.370 --> 00:31:09.630
Jennifer Richeson: So just to close, I just want us to think carefully about, you know what, not just what data we're producing

168
00:31:09.930 --> 00:31:18.450
Jennifer Richeson: But what are people doing with the data? How are they thinking about it? Because I think we're going to need both to consider both of these facets, in order to actually render

169
00:31:18.780 --> 00:31:29.550
Jennifer Richeson: The, the inequality, the disparities visible and to usher in any type of efforts to dismantle the systems that put them in place or to readdress them. Thank you.

170
00:31:31.110 --> 00:31:47.640
Beth Mynatt: Thank you, Jennifer. That was terrific. And I think at least certainly by the volume of conversation we've got going on a lot of interesting questions are being raised. So I think Tiffany, you're also going to pick up on a number of these seems so I'm going to pass it straight to you.

171
00:32:03.150 --> 00:32:04.470
Tiffany Veinot: Making it difficult for me to change.

172
00:32:07.980 --> 00:32:09.300
Tiffany Veinot: Can you see my slides right now.

173
00:32:09.660 --> 00:32:10.710
Beth Mynatt: Yep, perfect.

174
00:32:11.130 --> 00:32:20.820
Tiffany Veinot: Wonderful. Hi everybody, my name is Tiffany Veinot, and I'm a professor and associate dean at the School of Information and School of Public Health at the University of Michigan.

175
00:32:21.210 --> 00:32:30.660
Tiffany Veinot: And I'm also a director of our community health informatics lab and a founding member of our Masters of Health Informatics Program, which is, in its core, interdisciplinary

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00:32:31.920 --> 00:32:38.040
Tiffany Veinot: So I'm going to talk to you today about health disparities. I think it's a phenomenon that many of you will be familiar with, if not most of you.

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00:32:38.400 --> 00:32:48.510
Tiffany Veinot: But essentially, it can be measured by looking at various forms of inequity with regards to health, ranging from disease prevalence to mortality and survival rates.

178
00:32:53.580 --> 00:32:54.780
Tiffany Veinot: This is not advancing

179
00:32:57.330 --> 00:33:07.410
Tiffany Veinot: Okay, so we know that there are a number of health disparity populations. And it really depends on the indicator, but we do know that people's health is highly correlated

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00:33:07.740 --> 00:33:24.780
Tiffany Veinot: With their socioeconomic status, their race or ethnic status, whether they're women or men, depending on the indicator rural and urban residents, LGBTQ people, and people with disabilities are all disparity populations, depending on the health indicator in question.

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00:33:26.400 --> 00:33:37.470
Tiffany Veinot: And we know that a lot of the things that we have done historically to try to address health disparities or health issues in general have actually been characterized by what we

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00:33:37.800 --> 00:33:46.470
Tiffany Veinot: Call intervention generated inequality. And this is when interventions disproportionately benefit advantaged groups and one of the most

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00:33:47.190 --> 00:33:54.030
Tiffany Veinot: obvious examples of this are all the various anti-smoking campaigns which have taken place since the 1950s

184
00:33:54.810 --> 00:34:08.400
Tiffany Veinot: In which we've basically seen that people with higher levels of education are quitting smoking at a much faster rate, creating a- an education-related disparity in smoking where none existed before.

185
00:34:10.470 --> 00:34:28.770
Tiffany Veinot: I'm arguing today that health inequalities related to intervention so IGI or intervention-generated inequalities can emerge at any of four stages of an intervention cycle. And we can see that in each of these stages we might see a- how baseline health inequality can be worsened

186
00:34:30.360 --> 00:34:36.480
Tiffany Veinot: So one of them-- the beginning stage would be access to technology. And this is something that I think we're seeing

187
00:34:37.140 --> 00:34:48.660
Tiffany Veinot: very acutely now in the COVID-19 pandemic era where we see that so many of our-- so much of our lives have moved online but technology access is differential so

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00:34:49.290 --> 00:34:59.190

Tiffany Veinot: The Pew data that I've shared here shares different information, information about socioeconomic status specifically income and technology ownership and we see that

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00:34:59.610 --> 00:35:06.420
Tiffany Veinot: There's more use with regards to mobile only access to the Internet in lower income populations.

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00:35:06.960 --> 00:35:20.160
Tiffany Veinot: And we also see that not only do-- are there particularly issues with regards to having devices to begin with, but also quality of Internet access and the kinds of technologies that people have might vary.

191
00:35:20.550 --> 00:35:29.970
Tiffany Veinot: And as a result, there may be a need for us to be looking at technologies that function on older devices if we're thinking about disparities.

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00:35:30.480 --> 00:35:43.590
Tiffany Veinot: And one of the areas in which we, I think, we see this very acutely now is in the massive transition to online virtual care as a part of the COVID-19 pandemic. Many of these implementations have rolled out overnight.

193
00:35:44.550 --> 00:35:50.760
Tiffany Veinot: And I've had difficulty with regards to access for low SES and other populations.

194
00:35:52.500 --> 00:36:02.880
Tiffany Veinot: We also see that, historically, there's been major disparities, with regards to uptake when we're looking at technology. So in the area of patient portals, which are

195
00:36:03.720 --> 00:36:15.570
Tiffany Veinot: Patient facing electronic health records that are a part of healthcare organizations, at this point, there have been over 100 studies now that have shown disparities in uptake of these technologies

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00:36:16.140 --> 00:36:25.590
Tiffany Veinot: Related to rural residents' race and socioeconomic status, age, and number chronic conditions. So this is a

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00:36:25.920 --> 00:36:34.050

Tiffany Veinot: pervasive problem. And this particular study that I'm sharing the results from here is based on a national survey (HINTS) that looks at

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00:36:34.500 --> 00:36:46.230
Tiffany Veinot: uptake of a patient portal in the previous year. And we see those significant relationships in this particular study, but again this has been reproduced over 100 times now.

199
00:36:48.840 --> 00:37:06.600
Tiffany Veinot: We also see that technologies are can might be used differently depending on people's socio demographics. So one of the more enduring findings across multiple studies now is that when we're looking at patient facing consumer health technologies we very often see

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00:37:07.710 --> 00:37:13.410
Tiffany Veinot: A type of persistence that is greater in people with higher levels of education.

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00:37:14.100 --> 00:37:26.310
Tiffany Veinot: So this has been found in interventions related to mental health, smoking, alcohol consumption, pediatric care, physical activity, and nutrition, so

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00:37:26.820 --> 00:37:38.880
Tiffany Veinot: All of these that I presented here are studies in which they found that people with lower levels of formal education dropped out earlier, and therefore did not persist in the intervention.

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00:37:39.660 --> 00:37:47.550
Tiffany Veinot: There might be a number of reasons for this, ranging from people having many competing demands in their lives to usability challenges

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00:37:48.060 --> 00:38:02.040
Tiffany Veinot: With technologies which are exacerbated when there are health literacy challenges, but this is, I think, something that is really important because it's very difficult to benefit from a digital intervention if you don't persist in using it.

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00:38:04.500 --> 00:38:13.680
Tiffany Veinot: And the last stage of the intervention cycle and which we might see that this kind of inequality emerge (interventions inequality) is

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00:38:14.010 --> 00:38:20.010
Tiffany Veinot: Related to effectiveness. So effectiveness differences might be found because of those earlier

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00:38:20.460 --> 00:38:34.680
Tiffany Veinot: differentials that I talked about in terms of access, uptake, and adherence. But then we also see that depending on the technology and it- the way it's designed and the way that it's implemented, we do see differential

208
00:38:35.160 --> 00:38:47.730
Tiffany Veinot: Impacts with regards to health equity. So in the area of clinical technology, so we're thinking about clinical informatics the areas of things like electronic health records decision support systems, etc.,

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00:38:48.360 --> 00:38:55.950
Tiffany Veinot: Theoretically speaking, one of the ways in which we might try to address disparities, a way that technology could theoretically help us would be

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00:38:57.000 --> 00:39:09.870
Tiffany Veinot: harkening back to the earlier talk. We could try to reduce bias. So we could, for example, try to make more things default. We could try to prompt actions in particular situations we could try to

211
00:39:10.200 --> 00:39:20.190
Tiffany Veinot: Prompt providers to use self regulation capabilities in order to improve outcomes. So these are different ways that we could try to achieve,

212
00:39:21.090 --> 00:39:31.500
Tiffany Veinot: To reduce disparities with regards to the technology. And looking at the example of diabetes care, which is a condition in which there are significant disparities

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00:39:31.890 --> 00:39:38.670
Tiffany Veinot: already, we look at some of the work related to clinical reminders with regards to diabetes care.

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00:39:39.150 --> 00:39:50.040
Tiffany Veinot: We see that in studies that have looked at race and gender related equity effects, there have been three studies that have looked at equity related issues in these areas, and we see that

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00:39:50.460 --> 00:39:58.890
Tiffany Veinot: There have been mixed effects. So one study found it to favor disparity groups. There are also studies have found that there was no effect.

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00:39:59.610 --> 00:40:10.200
Tiffany Veinot: We also saw that- see that with regards to prompting treatment actions, the results have been neutral or mixed. And there's been no impact on intermediate health outcomes in that they've only been looking at process outcomes.

217
00:40:12.660 --> 00:40:28.020
Tiffany Veinot: If we look at the idea of default actions as a potential way to try to reduce disparities in healthcare, we could look at things like order sets or care pathways as a way to try to reduce bias. So

218
00:40:28.860 --> 00:40:35.550
Tiffany Veinot: Here we see a bit more of a positive story. We see positive intervention effects for targeted interventions

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00:40:35.850 --> 00:40:46.680
Tiffany Veinot: In which providers are asked to put more energy into working with disparity groups. So in one case, this was South Asian immigrants and another was Cambodian immigrants and refugees.

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00:40:47.040 --> 00:41:00.030
Tiffany Veinot: And both of these studies which were created at the practice level, there was a positive effect with regards to healthcare process related, as well as in the second one, there were effects related to

221
00:41:01.380 --> 00:41:03.840
Tiffany Veinot: More diagnosis of depression and PTSD.

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00:41:06.690 --> 00:41:17.010
Tiffany Veinot: And then if we look at interventions related to audit and feedback, which is a major class of interventions with regards to healthcare as a way to try to prompt quality improvement,

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00:41:17.580 --> 00:41:24.480
Tiffany Veinot: Very, very few studies have ever looked at any equity issues and the one that I was able to locate that did

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00:41:24.990 --> 00:41:35.880

Tiffany Veinot: Was one which favored advantage groups so it was found that whites benefited more than blacks, white non-Hispanics benefited more than Hispanics and low SES people

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00:41:36.480 --> 00:41:53.580
Tiffany Veinot: Benefited less than high SES people. Now this one is a descriptive study at 198 primary care practices, looking at health outcomes. And I think that this makes it clear that it's quite possible for there to be unintended outcomes with regards to clinical interventions.

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00:41:55.380 --> 00:41:59.910
Tiffany Veinot: So in conclusion, I want to argue and assert strongly that

227
00:42:00.240 --> 00:42:12.180
Tiffany Veinot: Health technologies do pose a risk of intervention-generated inequality and I've outlined how they might emerge at four different stages and shared some examples with you related to internet access,

228
00:42:12.690 --> 00:42:20.370
Tiffany Veinot: related technologies, internet quality, patient portals, consumer facing interventions and clinical informatics interventions.

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00:42:20.910 --> 00:42:28.650
Tiffany Veinot: And we see that it is possible for there to be positive equity effects. We saw that in relation to the targeted interventions for immigrant populations.

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00:42:29.070 --> 00:42:43.950
Tiffany Veinot: But we also very often see some form of inequity. And I would argue that we don't always understand why this emerges or how to effectively prevented and we don't know enough about how to use technology to enhance health equity.

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00:42:45.630 --> 00:42:55.230
Tiffany Veinot: So my recommendations would be that I believe we need more collaborative research and I think that we need to involve health disparity communities themselves more

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00:42:55.560 --> 00:43:04.350
Tiffany Veinot: And in particular, I think we need funding mechanisms that permit the meaningful engagement of nonprofits and marginalized communities in research.

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00:43:04.770 --> 00:43:11.520
Tiffany Veinot: And I think the community based participatory research model offers a really excellent model and i- i think i would say that

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00:43:11.910 --> 00:43:19.260
Tiffany Veinot: We probably need to change some of our funding mechanisms. I can point to an NSF grant that I have in which it was actually impossible

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00:43:19.530 --> 00:43:27.840
Tiffany Veinot: To find community based involvement as well as fund everything else that we needed to do in the project. So we need some mechanism for that.

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00:43:28.470 --> 00:43:34.290
Tiffany Veinot: I think we also need more joint efforts with regards to technology design and implementation.

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00:43:34.890 --> 00:43:41.400
Tiffany Veinot: And systematic study of equity effects at each of these four stages with some comparisons of approaches. So, for example,

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00:43:42.090 --> 00:43:53.610
Tiffany Veinot: Do we find that universal interventions that focus on removing barriers are better or worse than those that target disparity populations? I don't think we know about what general strategies work.

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00:43:54.240 --> 00:43:58.440
Tiffany Veinot: And I think we need to understand it- differential impacts looking at different groups.

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00:43:59.130 --> 00:44:06.840
Tiffany Veinot: And specifically, I think this is all the more important when we're looking at the COVID-19 pandemic. When we have so many health technologies

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00:44:07.110 --> 00:44:15.360
Tiffany Veinot: That are increasingly playing a role in virtual care and many of the face to face services upon which people have historically relied have been withdrawn,

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00:44:15.690 --> 00:44:32.610
Tiffany Veinot: And that makes the access to these technologies and effective use of them all the more important. And with regards to some

specific recommendations I want to highlight a workshop report that came out of a Computing Community Consortium Workshop

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00:44:33.720 --> 00:44:42.600
Tiffany Veinot: That took place in 2017. This was a workshop involving more than 50 individuals from the fields of behavioral medicine,

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00:44:43.350 --> 00:44:47.400
Tiffany Veinot: Health Disparities, Health- Health Informatics, and Computing.

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00:44:47.880 --> 00:45:01.350
Tiffany Veinot: And this lists a number of recommendations with regards to funding research to try to address disparities. I'll also highlight that Katie Siek who is on this, at this meeting as well, co-chaired this meeting as did

246
00:45:01.980 --> 00:45:12.780
Tiffany Veinot: Beth Mynatt who is facilitating our work today. Also, I just wanted to share with you this particular screen. I think that this is a very nice summary of some of the

247
00:45:13.470 --> 00:45:28.230
Tiffany Veinot: ongoing challenges that we face in trying to conduct research with marginalized populations in the health domain and some suggested solutions that we could try to address with regards to funding opportunities and mechanisms and I will leave this on the screen.

248
00:45:29.670 --> 00:45:32.040
Tiffany Veinot: If you, if we have questions. Thank you.

249
00:45:33.570 --> 00:45:44.760
Beth Mynatt: Thank you, Tiffany. And for those of you who are screen capturing as quickly as you can. This is a reminder that our- that the speakers presentation slides are also available to you on the website in PDF form.

250
00:45:46.230 --> 00:45:53.520
Beth Mynatt: Again, fantastic presentation. Really love the questions that are being raised, and I'm going to ask

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00:45:54.990 --> 00:46:00.390
Beth Mynatt: If Tiffany stop sharing the screen because Suresh is going to come in and be our closing panelist.

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00:46:11.460 --> 00:46:12.720
Suresh Venkatasubramanian: All right. Can you all hear me?

253
00:46:13.260 --> 00:46:13.620
Yep.

254
00:46:14.670 --> 00:46:14.790
I'm

255
00:46:17.550 --> 00:46:20.760
Suresh Venkatasubramanian: Trying to get into full screen mode and my laptop is thinking about it.

256
00:46:21.930 --> 00:46:24.420
Beth Mynatt: It's considering it. You're in Presenter view just

257
00:46:24.420 --> 00:46:25.140
Beth Mynatt: flip the views.

258
00:46:26.070 --> 00:46:30.450
Suresh Venkatasubramanian: Yeah, actually don't know how to do that. Let me hold on a sec. Oh, I think I

259
00:46:35.490 --> 00:46:35.850
Suresh Venkatasubramanian: Can

260
00:46:36.060 --> 00:46:39.150
Suresh Venkatasubramanian: Do. There you go. Well, thank you all for having me here.

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00:46:40.350 --> 00:46:47.730
Suresh Venkatasubramanian: I appreciate the chance to talk with you all. This is a topic that's near and dear to my heart because of the work I've been doing and my attempts to sort of

262
00:46:48.450 --> 00:46:57.030
Suresh Venkatasubramanian: Learn about, from a CSI, all the ways in which social scientists think about the world and society at large. I'm going to

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00:46:57.930 --> 00:47:10.560

Suresh Venkatasubramanian: Rather than give a broad overview of some of the thoughts I've had on this matter, we're actually going to go deep into two specific case studies, if you wish, of work that I've done and try to draw some sort of larger insights from it.

264
00:47:13.500 --> 00:47:18.750
Suresh Venkatasubramanian: I don't know if I would call this a qualitative analysis of my research on what I'll do, I'll let others decide that

265
00:47:19.050 --> 00:47:31.920
Suresh Venkatasubramanian: But I will let me start with this. So I want to talk about two kinds of disparities and the first kind of disparity I want to talk about is disparities in representation. So this was inspired by a wonderful talk that Kate Crawford had given at the NeurIPS machine learning conferences.

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00:47:34.530 --> 00:47:43.920
Suresh Venkatasubramanian: Oops, sorry. Yeah, a few years ago where she was trying to compare and contrast the work in algorithmic fairness around what she called harms of allocation.

267
00:47:44.550 --> 00:47:48.150
Suresh Venkatasubramanian: The idea of looking at how decisions might affect different groups differently.

268
00:47:48.570 --> 00:47:54.870
Suresh Venkatasubramanian: And all the research that has been done on coming up with metrics for unfairness and skew in decision making.

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00:47:55.200 --> 00:48:01.740
Suresh Venkatasubramanian: And then she made this very important point that none of this research really speaks to another important problem, namely harms of representation

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00:48:02.310 --> 00:48:11.790
Suresh Venkatasubramanian: This is important because from a, from a technology point of view, we often sort of take data of people and represent it in some way and the representations themselves are learned representations

271
00:48:12.270 --> 00:48:18.540
Suresh Venkatasubramanian: And how we learn those representations itself can cause harm in a way that is hard to quantify because there is no actual decision being made.

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00:48:18.930 --> 00:48:28.920
Suresh Venkatasubramanian: So, for example, she brought up the idea that notions like stereotyping of groups, ex-nomination, under-representation, and denigration are examples of things that can happen when you represent people

273
00:48:29.400 --> 00:48:40.290
Suresh Venkatasubramanian: For downstream analysis by a system in a way that is skewed. And so this sort of inspired the question that I've been pondering since then, how do you identify and measure disparities in representation?

274
00:48:41.580 --> 00:48:43.830
Suresh Venkatasubramanian: So there's been some work on this in the sort of

275
00:48:44.250 --> 00:48:54.690
Suresh Venkatasubramanian: Mostly in the natural language processing field. The idea of looking at bias in learned representations and how we might correct it. So one of the classic examples of many of you heard of series of papers that developed this

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00:48:55.080 --> 00:49:02.220
Suresh Venkatasubramanian: Was this idea that if we take words in a corpus- text corpus and you embed them as we do in sort of some high dimensional space.

277
00:49:02.610 --> 00:49:15.750
Suresh Venkatasubramanian: Then by looking at where the points are looking at in the space, you can infer some sense of bias, in this case a bias towards assuming that a doctor must be male and a nurse must be female by looking at the way the words are embedded

278
00:49:16.410 --> 00:49:25.440
Suresh Venkatasubramanian: And so there's been a lot of work and trying to understand the way in which the geometry of the representation encodes some kind of bias, unstated unclear bias.

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00:49:26.430 --> 00:49:33.420
Suresh Venkatasubramanian: But there's been also follow up work that shows that geometry as a definition of bias isn't quite enough because

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00:49:33.810 --> 00:49:42.420

Suresh Venkatasubramanian: Merely looking at the representations in the in the sort of learn space doesn't really give you a full indication. And in fact, they often hide our true forms of bias.

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00:49:43.050 --> 00:49:49.050
Suresh Venkatasubramanian: And in a sense of what you need to do is go back to the original sources of the way people are

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00:49:49.890 --> 00:49:56.760
Suresh Venkatasubramanian: Represented in biased ways in, in sort of the source material in text or in media in general. And if you take one example of this

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00:49:57.270 --> 00:50:05.160
Suresh Venkatasubramanian: so stereotyping, which came up earlier in Tiffany's talk as well, there are many different ways one can define stereotyping. One definition that we are looking at from the

284
00:50:06.030 --> 00:50:12.810
Suresh Venkatasubramanian: Handbook talks about associations and beliefs about the characteristics and attributes of a group of its members that shape how people think about and respond to the group.

285
00:50:13.590 --> 00:50:20.940
Suresh Venkatasubramanian: And then you can think about what a mechanism for stereotyping might be. It's a tendency to assign characteristics to all members of group based on stereotypical features shared by a few

286
00:50:21.990 --> 00:50:31.560
Suresh Venkatasubramanian: So now if you say, well, if this is a way in which you can think of an essentially a cultural attack on representation in a way that people's representations are modified or distorted

287
00:50:32.010 --> 00:50:38.640
Suresh Venkatasubramanian: in, in media in text and video and film, how would you try to capture this? So, this is so in

288
00:50:39.090 --> 00:50:50.310
Suresh Venkatasubramanian: This has also been looked at in the psychology literature. There's been some interesting work asking how people tend to absorb stereotypes of what other groups and that tends to be in the same way as described that essentially

289
00:50:51.060 --> 00:50:59.550

Suresh Venkatasubramanian: When we're thinking about this is that stereotyping is a process by which groups experience non-uniform variance reduction. Now this seems, maybe, maybe a little bit too mathy,

290
00:50:59.910 --> 00:51:09.990
Suresh Venkatasubramanian: But what you're basically saying is that you can imagine stereotyping as a way in which you don't allow one group to express its full variation, whereas another group is allowed to do so.

291
00:51:10.800 --> 00:51:19.470
Suresh Venkatasubramanian: And once you have that formalism, you can start trying to ask questions like, is there, can you look at unusual patterns and data that may be a result of stereotyping?

292
00:51:19.950 --> 00:51:31.320
Suresh Venkatasubramanian: And even if there are ways to correct for it and you can show that this kind of effect, this attack on the data, will itself cause problems and downstream costs, things like classification or clustering, or what have you. So in other words, distortions,

293
00:51:32.070 --> 00:51:45.390
Suresh Venkatasubramanian: Understood sort of in a social context, can once formalized in some way actually have a measurable effect on decisions in a way that you would not be able to appreciate if you weren't actually looking for the way representations are distorted.

294
00:51:46.830 --> 00:51:54.180
Suresh Venkatasubramanian: So that's one example, and the sort of the broader research effort here is to understand our different forms of representation attacks on

295
00:51:54.600 --> 00:52:06.690
Suresh Venkatasubramanian: The source media, the source data used to build learned representations can actually distort the representation themselves. So this is one example of a disparity in representations. Let me search for another small case study

296
00:52:08.580 --> 00:52:13.200
Suresh Venkatasubramanian: Of disparity in access and we talked about, again, Tiffany was talking about this a lot in the context of health disparities.

297
00:52:13.800 --> 00:52:22.860
Suresh Venkatasubramanian: So you know we understood for a long time that social standing within some kind of network. And I'm very ashamed to give this talk in the presence of Duncan Watts, and I'm also, you know, hope,

298
00:52:23.220 --> 00:52:33.000
Suresh Venkatasubramanian: Hoping that this will, you know, this will be of interest to to to his work as well. So social selling in the network confers utility on an individual and social position is a class marker

299
00:52:33.600 --> 00:52:41.190
Suresh Venkatasubramanian: defined by the network and not the individual. And this is interesting because of a question that Boyd, Marwick, and Levy asked some years ago saying

300
00:52:41.670 --> 00:52:52.440
Suresh Venkatasubramanian: Should we be worried about discrimination based on social position? And this is interesting because it's a marker that is not associated with an individual, but is sort of emergent out of a network itself.

301
00:52:53.160 --> 00:52:57.030
Suresh Venkatasubramanian: And to do this we need to understand what it means to even think about social "position" in a network.

302
00:52:57.900 --> 00:53:02.430
Suresh Venkatasubramanian: So we were trying to look at a much simpler version of this problem, namely disparity in access

303
00:53:02.880 --> 00:53:10.260
Suresh Venkatasubramanian: To think about the idea how information flows through network. This is, in fact, particularly important right now in the context of COVID and the way we're trying to spread information about

304
00:53:10.680 --> 00:53:15.510
Suresh Venkatasubramanian: Care and about access to testing and so on in the context of the, of the, of the pandemic.

305
00:53:16.320 --> 00:53:23.820
Suresh Venkatasubramanian: We know that because that network position confers advantage and access to information that improves your position relies on your position itself.

306
00:53:24.450 --> 00:53:35.100
Suresh Venkatasubramanian: And you can think of edges in a social network as biased input data because of privileges in how the edges are created. How do we ensure that information is delivered to everyone who needs it?

307

00:53:36.120 --> 00:53:49.170
Suresh Venkatasubramanian: Now, in the world of sort of influence maximization, the way we talk about how it's- information is spread, in fact how epidemics are spread, this has been studied for a long time. You think of propagation from a node to other nodes' network. This is not an unusual thing.

308
00:53:50.280 --> 00:53:51.000
Suresh Venkatasubramanian: However,

309
00:53:52.230 --> 00:53:57.390
Suresh Venkatasubramanian: And you can have different models for how nodes and information on each edge. And there are different ways to think about this.

310
00:53:58.170 --> 00:54:05.730
Suresh Venkatasubramanian: But the way this has been talked about is in terms of what I call welfare functions, you think of the probability that a node gets a bit of information and don't worry too much about the notation here.

311
00:54:06.120 --> 00:54:16.380
Suresh Venkatasubramanian: The ideas that nodes get information from probability and you want to optimize some function of these properties and the typical optimization is some kind of average you want to maximize the number of people who get information.

312
00:54:17.730 --> 00:54:22.260
Suresh Venkatasubramanian: But that's not necessarily what you want if you want to make sure that everyone gets information. In fact,

313
00:54:22.740 --> 00:54:32.880
Suresh Venkatasubramanian: What we want- in this work, what you're trying to quantify is the idea of an access gap that there's one group of people who do not have access to information, compared to another group because of the structural properties of the network.

314
00:54:33.480 --> 00:54:38.430
Suresh Venkatasubramanian: And then we formulate an idea of the rich getting richer that even if you do some intervention, you provide information,

315
00:54:38.880 --> 00:54:45.330
Suresh Venkatasubramanian: The people who have access to information get more access to it and the people who don't get less and so the access gap increases.

316
00:54:45.960 --> 00:54:52.560
Suresh Venkatasubramanian: And one very surprising fact is that some of the metrics that are used to try and optimize the flow of information

317
00:54:53.220 --> 00:55:00.540
Suresh Venkatasubramanian: All have this property that the rich get richer. So a summary of this dilemma is saying that under any welfare function you might come up with, or any reasonable one

318
00:55:00.870 --> 00:55:11.460
Suresh Venkatasubramanian: the rich always get richer. So you actually don't really get the information access equity that you need. And so we tried to look at a more relaxed version notion, again, the notation and the

319
00:55:12.360 --> 00:55:20.340
Suresh Venkatasubramanian: Notion is a bit more complex, but in summary what you can show is that if you try to improve the minimaxes, make sure that the people who have the least access get better.

320
00:55:20.820 --> 00:55:28.980
Suresh Venkatasubramanian: Then you can actually show that this is in some sense the right thing to do. It prevents the rich from getting richer at the same level and no other measure would satisfy this.

321
00:55:30.120 --> 00:55:36.960
Suresh Venkatasubramanian: And this measure of improving minimum access isn't some kind of new measure. It hasn't been looked at an influence maximisation sort of community, broadly speaking,

322
00:55:37.440 --> 00:55:42.660
Suresh Venkatasubramanian: And it presents very different challenges for how to spread information, but also present interesting questions about how to do this.

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00:55:44.280 --> 00:55:52.020
Suresh Venkatasubramanian: So I want to take a step back in the, in the time I have left and sort of I've spent a lot of time, sort of, again, working on problems of the sort of boundary of

324
00:55:52.290 --> 00:55:56.190
Suresh Venkatasubramanian: Computer Science and sort of where we need insight from the Social Sciences and

325
00:55:56.550 --> 00:56:07.350
Suresh Venkatasubramanian: One thing I think is very interesting to keep in mind about a lot of the basic computer science work is that we tend not to have a critical perspective on our work, we don't question the frame very much, but we are seeing more of it now.

326
00:56:08.460 --> 00:56:14.160
Suresh Venkatasubramanian: To- a paper that I wrote last year, this is also what I like to refer to this as a punch line to the joke.

327
00:56:14.580 --> 00:56:21.120
Suresh Venkatasubramanian: What happens if two computer scientists, a lawyer, and two social scientists walk into a bar or a conference room. This is a paper that ends up

328
00:56:21.750 --> 00:56:26.430
Suresh Venkatasubramanian: We looked at how, you know, some of the- some of the ways in which we implicitly make choices about

329
00:56:27.270 --> 00:56:37.350
Suresh Venkatasubramanian: Designing of systems even if they're quote unquote, fair machine learning systems have don't actually capture the or recognize the true complexity of a social tactical system.

330
00:56:37.830 --> 00:56:41.610
Suresh Venkatasubramanian: Other work from folks at Cornell argue for how

331
00:56:42.030 --> 00:56:49.080
Suresh Venkatasubramanian: Computer science with- through a more critical examination of its own work and actually play a role in social change. And that's something that's new that's happening now, which I think is an encouraging

332
00:56:49.560 --> 00:56:51.210
Suresh Venkatasubramanian: Effort on the side of computer science.

333
00:56:52.110 --> 00:57:02.880
Suresh Venkatasubramanian: And the other thing that's important to keep in mind is that a lot of the view of how computer science can work as a more of like a "have data, compute" kind of model where the CS contribution involved in doing quantitative work.

334
00:57:03.390 --> 00:57:09.330

Suresh Venkatasubramanian: But I'd like to argue that the computational lens itself is valuable in and of itself, it allows for certain kinds of precision,

335
00:57:10.500 --> 00:57:17.340
Suresh Venkatasubramanian: And it allows us to articulate limits on our system. So two examples of this, there's a, a paper that we wrote a couple of years ago that's

336
00:57:17.760 --> 00:57:24.120
Suresh Venkatasubramanian: going to be published soon. Talks about how when you input values, the value systems that you have

337
00:57:24.450 --> 00:57:32.370
Suresh Venkatasubramanian: Need to be stated explicitly in order to make sure the different mechanisms for fair decision making in fact achieve even some notion of fairness that you might want

338
00:57:32.670 --> 00:57:43.530
Suresh Venkatasubramanian: That without the right choice of value system, these notions are incompatible. And of course, you may have heard of a well known paper on how fairness notions themselves are mathematically incompatible with each other.

339
00:57:43.980 --> 00:57:50.820
Suresh Venkatasubramanian: And the point of these papers is not sort of, sort of say that you know all formalization are useless. It's to say that

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00:57:51.090 --> 00:57:58.920
Suresh Venkatasubramanian: There are, there's an interface between how we formalize and what our values are. And we have to identify what that boundary is and that's what these precis, precise methods can do

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00:58:00.480 --> 00:58:03.840
Suresh Venkatasubramanian: Finally, there was a lot of critique, valid critique of the idea

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00:58:03.870 --> 00:58:09.600
Suresh Venkatasubramanian: Of technology and I'm almost done, that of technology being problematic and how we have to work around technology or replace it.

343
00:58:10.440 --> 00:58:16.410

Suresh Venkatasubramanian: This this, often I find, assumes a fixed formulation of technical questions like the examples I gave earlier show that

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00:58:16.860 --> 00:58:26.370
Suresh Venkatasubramanian: You can actually change the questions you ask in a way that actually facilitates a more insightful and more sort of a valuable way to think about

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00:58:26.880 --> 00:58:31.650
Suresh Venkatasubramanian: Helping people who are being harmed by technology, rather than sort of just assuming the technology itself was bad.

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00:58:32.190 --> 00:58:41.160
Suresh Venkatasubramanian: And many folks have called this and I call this sort of decentering the technology and centering the people who are, may potentially be harmed by technology and that there are ways to formulate research questions

347
00:58:41.400 --> 00:58:44.220
Suresh Venkatasubramanian: In computer science that do the decentering for us.

348
00:58:44.790 --> 00:58:52.500
Suresh Venkatasubramanian: I'll end with a slide. This is how I see a lot of work that I do that there is sort of the stuff in dark blue is more stuff that's very CS focused

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00:58:52.680 --> 00:58:57.150
Suresh Venkatasubramanian: But there's a lot of stuff involving values, how we think of what society and culture, legal frameworks, and policy,

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00:58:57.480 --> 00:59:09.720
Suresh Venkatasubramanian: And a critical and reflective process that puts all these things together. And I think any attempt to, any attempt at collaboration should celebrate the fact that all of these notions interact with each other in complicated and sort of exciting ways, and I'll stop there. Thank you very much.

351
00:59:11.550 --> 00:59:13.230
Beth Mynatt: Terrific Suresh. Thank you.

352
00:59:15.090 --> 00:59:20.970

Beth Mynatt: Wow, what a fantastic set of panelists and talks. Thank you so much.

353
00:59:22.590 --> 00:59:33.270
Beth Mynatt: I think Alondra and I have accumulated quite a set of a collections coming from the chat longer. Alondra, do you want to chime in first, and I'll ask all of our panelists to please

354
00:59:34.380 --> 00:59:35.910
Beth Mynatt: Put your video back on.

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00:59:37.050 --> 00:59:42.120
Alondra Nelson: I'll ask Jennifer and David to come back on video and Tiffany as well. Thank you so much. And thank you all for being here.

356
00:59:42.900 --> 00:59:47.490
Alondra Nelson: I know many of us have been having bits and pieces of this conversation in our communities for

357
00:59:47.910 --> 00:59:59.400
Alondra Nelson: Quite a long time and to be able to be all together and have you know 70ish moreover to be in this conversation is just tremendously fruitful and generative so I wanted to get us started

358
01:00:00.180 --> 01:00:07.740
Alondra Nelson: By way of kind of bringing together some of the questions on some of the presentations. I wanted to ask a question first to

359
01:00:09.000 --> 01:00:13.410
Alondra Nelson: About I think about mixed methods, what might be one way we can put Tiffany And David

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01:00:14.010 --> 01:00:24.090
Alondra Nelson: David's presentations together. And so, you know, David, the the sort of casual way we use mixed methods and sociology is sort of a little quant, a little qual, but you're talking about something that's

361
01:00:24.600 --> 01:00:27.030
Alondra Nelson: Much more nuanced that I think takes up

362
01:00:27.750 --> 01:00:33.090
Alondra Nelson: The scale of problems we're trying to deal with the kind of social dynamics we now know that we're encountering

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01:00:33.300 --> 01:00:44.070
Alondra Nelson: So I wanted you to kind of think about what it is you're saying, say a little bit more about what it is you're asking us to do and how maybe NSF can be fruitful and thinking that through that, helping us think about that.

364
01:00:44.760 --> 01:00:55.080
Alondra Nelson: And then, Tiffany, there's the issue of, for you of mixed methods with sort of mixed roles and really bringing the community so that it's not just academic experts and academic researchers, but there's a role for

365
01:00:55.500 --> 01:01:04.320
Alondra Nelson: Community members that make our mixed, methods mix that stop just community members as users or people who give us data but but you're imagining something else and

366
01:01:04.560 --> 01:01:14.220
Alondra Nelson: What would you advise you know NSF to sort of do and think about, and what were some of the, if you want to say a little bit more about the hurdles you faced in trying to bring a

367
01:01:15.240 --> 01:01:24.840
Alondra Nelson: participatory research focus and your work. And then of course for Suresh and Jennifer, the sort of issues around bias, of course, are the things that tie you together.

368
01:01:26.550 --> 01:01:28.830
Alondra Nelson: You know, I was struck very much by Jennifer's

369
01:01:29.910 --> 01:01:38.790
Alondra Nelson: Helping us to think through how implicit bias has been really taken up as the language of discrimination in this time. So there's one question that's asking us to

370
01:01:39.240 --> 01:01:53.730
Alondra Nelson: I think tease out the differences between bias, discrimination, statistical discrimination, and you know also thinking about, I don't know if you know Michael Mu√±iz's work at Northwestern about how

371
01:01:54.780 --> 01:02:08.220
Alondra Nelson: How social scientists talked about demography in the past about the growing majority minority nation has sort of had this feedback

loop, much like implicit bias and how we think about what's happening in the world.

372
01:02:09.690 --> 01:02:21.300
Alondra Nelson: And then Suresh for you as well, I mean, I think it would be helpful. I mean, one of the things certainly we need to bridge across the fields is how we talk together about bias. And so, you know, just wanted to offer you and Jennifer an opportunity

373
01:02:21.840 --> 01:02:33.630
Alondra Nelson: To kind of talk to each other and then you know maybe speculatively if you two were going to work together, how could NSF support and incentivize you to work together on the question of bias?

374
01:02:45.150 --> 01:02:47.520
David Grusky: Did you want us, Alondra, to jump right in?

375
01:02:49.770 --> 01:02:51.660
Alondra Nelson: Yeah David please jump in, thank you.

376
01:02:52.530 --> 01:03:02.040
David Grusky: Okay, well, I'm happy to take on the question that you, you put, a tough one. And I think, I think it's important to distinguish between the different types of mixed methods that are in play.

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01:03:02.400 --> 01:03:09.180
David Grusky: I think there are three types in particular that that are usefully distinguished. What you might call type one is where you have the same researcher

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01:03:09.480 --> 01:03:16.560
David Grusky: Doing two separate studies like one quantitative, one qualitative, and the idea is that you can approach the same problem through different angles.

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01:03:17.970 --> 01:03:23.670
David Grusky: And one researcher is responsible in effect for completing two separate studies.

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01:03:24.780 --> 01:03:32.070
David Grusky: That's a very conventional model. And of course you know we ramp it up and put it on steroids. And now the expectation is you shouldn't do two separate studies, but three, four, five,

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01:03:33.840 --> 01:03:40.500
David Grusky: And I think that's what, that's one model and it can be productive but but I think there are two other models that I was talking about a bit more that are also productive.

382
01:03:40.980 --> 01:03:49.980
David Grusky: The second type two mixed methods studies where you you have the same researcher, but it's an integrated studies. So with the American Voices project, most of it's all about qualitative

383
01:03:50.220 --> 01:03:56.190
David Grusky: Immersive interview data, but in addition respondents are asked if they would consent to link to administrative data.

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01:03:57.060 --> 01:04:03.330
David Grusky: The vast majority when you explain the terms under which that consent could be given agree to do so. And that then

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01:04:03.630 --> 01:04:18.210
David Grusky: opens up the possibility of, of carrying out a combination of rich immersive qualitative data with with quantitative data. And so it's a single study same researcher model. That's type two, and I think that can be very fruitful kind of fuses two methods together

386
01:04:18.660 --> 01:04:22.980
David Grusky: With, with data on the same individual that's both quantitative and qualitative.

387
01:04:23.340 --> 01:04:27.810
David Grusky: Um, and then, then there's a third type, though, that I was also advocating for which I think is important. It kind of

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01:04:28.050 --> 01:04:30.240
David Grusky: cherishes, celebrates the division of labor.

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01:04:30.450 --> 01:04:39.420
David Grusky: It says that, you know, it's not the case that a single researcher has to do all types of research, both qualitative and quantitative, we can have one stream of the qualitative research, it's very valuable,

390
01:04:39.600 --> 01:04:49.020
David Grusky: That carries up, that allows for these holistic understanding subsystems. And then you should have another stream of

research that is quantitative and then you can have people who whose job is to diffuse those two.

391
01:04:49.320 --> 01:04:59.910
David Grusky: And you don't have to necessarily have a single researcher doing both at once, but we just have to have data systems that allow us to do both really well. So I think those three types all valuable, and I was kind of advocating, advocating for types two and three.

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01:05:03.360 --> 01:05:10.530
Beth Mynatt: And David just to jump in with a quick follow on and then back to Alondra's impressive list of questions. There was some chatter about

393
01:05:11.460 --> 01:05:17.970
Beth Mynatt: The ethical implications of secondary use of qualitative data that a number of us coming from those traditions,

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01:05:18.300 --> 01:05:27.330
Beth Mynatt: You know, that is not the norm, but it's more about kind of the trust and relationship when you set up doing that work, which doesn't lend itself to secondary use. Can you can you speak to that?

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01:05:29.400 --> 01:05:33.660
David Grusky: Sure, yeah. I mean, that's obviously the critical issue and and

396
01:05:35.280 --> 01:05:45.270
David Grusky: First and most most most critical one is you need informed consent. You need to be completely transparent about the secondary uses to which the data will be used. Make sure that the respondents understand

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01:05:46.500 --> 01:05:52.950
David Grusky: That and and have full and informed consent to the extent that that's possible in the world, such as it is, um.

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01:05:53.820 --> 01:06:08.460
David Grusky: The other really critical part of it is that the same sort of infrastructure that we use to ensure confidentiality for quantitative data can be deployed for for qualitative data. That is, you can identify you can have disclosure review, you can carry out analyses in in

399
01:06:08.970 --> 01:06:16.920
David Grusky: secure facilities. Federal Statistical research data centers have, you know, are a treasure of the of the of the of the

400
01:06:17.730 --> 01:06:25.950
David Grusky: Quantitative world in terms of protecting data quite quite quite successfully, I would say, relative to the standards that propel the private world

401
01:06:26.430 --> 01:06:35.400
David Grusky: Or private sector and that same sort of infrastructure can principle, then I think should be used to to protect confidentiality for qualitative data as well.

402
01:06:36.840 --> 01:06:37.440
Beth Mynatt: Thank you.

403
01:06:38.310 --> 01:06:38.790
Tiffany?

404
01:06:41.070 --> 01:06:58.890
Tiffany Veinot: So with regards to trying to engage community members and research. So I've been doing community based participatory research for a long time. And I think that there is a need for dedicated funding sources specifically for that kind of work.

405
01:06:59.970 --> 01:07:12.180
Tiffany Veinot: My experience with other funders has been that there are mechanisms that are better for dealing with community groups in the sense that you can have subcontract, you can pay for stuff, you can cover overhead.

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01:07:12.750 --> 01:07:21.720
Tiffany Veinot: In my experience with an NSF grant that I had recently, we could not, after we actually paid for our students,

407
01:07:22.680 --> 01:07:30.390
Tiffany Veinot: And our various kind of hard costs around building technology, we couldn't afford to put anything in for our community organizations.

408
01:07:30.720 --> 01:07:45.930
Tiffany Veinot: So that was a problem. They agreed to participate anyways, but it's quite difficult with nonprofits and other organizations, healthcare, that have so many competing priorities to command an organization's attention

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01:07:46.320 --> 01:07:52.890
Tiffany Veinot: If you don't actually have a way to pay them. And I would also say that with regards to nonprofits, there's also

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01:07:53.550 --> 01:08:02.910
Tiffany Veinot: Because they're not funded necessarily securely, etc., sometimes there is a need to even try to bring money into stabilize them because there's so much turnover of staff,

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01:08:03.210 --> 01:08:15.210
Tiffany Veinot: They might be facing difficulties financially and so I feel like in some ways, trying to fund a sort of nonprofit infrastructure to support research organizations in which

412
01:08:15.510 --> 01:08:21.570
Tiffany Veinot: there's actually a certain amount of people's time ready and able to participate in research

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01:08:21.870 --> 01:08:30.540
Tiffany Veinot: Would be a way to go. And it could also really help to stabilize and build skills in our nonprofit sector in the country as well. And I think we should

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01:08:30.900 --> 01:08:41.580
Tiffany Veinot: Understand that that actually could be a very powerful mode of diversifying our workforce by being able to reach out to community activists from a host of

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01:08:42.270 --> 01:08:50.760
Tiffany Veinot: Communities. I mean, I myself with somebody working in a nonprofit organization who got involved in CVPR research and decided to go back and do a PhD.

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01:08:51.480 --> 01:09:01.440
Tiffany Veinot: There's lots of folks who can get the research bug if the- or technology bug if they are given those opportunities through funded projects. Thank you.

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01:09:02.310 --> 01:09:09.090
Alondra Nelson: Thanks a lot. So let's turn to the question of bias. So there's been a lot of chatter about implicit bias. Jennifer's kind of

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01:09:09.570 --> 01:09:19.230

Alondra Nelson: Blown some lines as has Suresh and the way that they're kind of laying out, how they're thinking about the problem. So I would just, you know, if you guys want to talk to each other about each other's

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01:09:20.400 --> 01:09:23.220
Alondra Nelson: Presentations to start and then we've got some specific questions.

420
01:09:25.950 --> 01:09:40.320
Jennifer Richeson: Okay. Well, I mean, I guess I'll say two things. One, just generally about the question of sort of bias broadly as an umbrella term for lots of different things and lots of different forms, you know, in psychology

421
01:09:41.460 --> 01:09:45.750
Jennifer Richeson: Bias actually can mean stereotyping, it can mean discrimination,

422
01:09:49.410 --> 01:10:02.430
Jennifer Richeson: It can mean attitudes. Right. So when I'm using, in this case, I'm using bias either explicit or implicit, I'm using it as the

423
01:10:02.460 --> 01:10:05.280
Jennifer Richeson: Attitudes or stereotypes that that

424
01:10:05.430 --> 01:10:16.290
Jennifer Richeson: Presumably the actors in the articles that we're talking about have, right, toward whatever outward. So being, having negative attitudes toward

425
01:10:16.950 --> 01:10:29.610
Jennifer Richeson: People who own guns, which was one of the scenarios, and the political bias one, or toward older adults among doctors, right, and then in the in our work attributing

426
01:10:30.210 --> 01:10:41.790
Jennifer Richeson: So basically saying that we found that these doctors are treating older adult patients worse than their younger counterparts in a variety of ways.

427
01:10:42.300 --> 01:10:50.310
Jennifer Richeson: And we attribute that differential behavior, which in psychology is discrimination, that's all that discrimination is in psychology--

428
01:10:50.760 --> 01:11:01.410
Jennifer Richeson: Differential behavior based on some group membership-- to either explicit bias, meaning attitudes and stereotypes about from the doctor so they know that they have them,

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01:11:02.370 --> 01:11:15.450
Jennifer Richeson: Or implicit bias. So they are maybe not so aware that they hold these negative attitudes and stereotypes about older adults and/or they're not aware that they

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01:11:15.990 --> 01:11:25.050
Jennifer Richeson: That those attitudes influence their behavior, right. So it can be either of those. And so, but I do think yes, it's very important to think through

431
01:11:25.560 --> 01:11:37.230
Jennifer Richeson: Not only these these processes and what's at play because it certainly matters, and you know in the chat, Mahzarin Banaji made a really important point that it was very necessary to

432
01:11:37.740 --> 01:11:53.100
Jennifer Richeson: Bring the concept of implicit bias and actually sort of formalize that study and understand how it impacts our decision making into the for, certainly for any number of legal decisions because we know that intentional explicit, overt

433
01:11:54.360 --> 01:11:56.040
Jennifer Richeson: Forms of bias, attitudes,

434
01:11:56.220 --> 01:12:00.210
Jennifer Richeson: Stereotypes are not the only thing that's affecting behaviors. That's really important.

435
01:12:00.390 --> 01:12:06.330
Jennifer Richeson: What our work suggests is that it's almost this concept has become so popular

436
01:12:07.260 --> 01:12:25.230
Jennifer Richeson: In the public imagination that it seems to be the go to default explanation for evidence of discrimination in any number of domains, and there's often evidence that actually discrimination is due to regular ordinary explicit, overt

437

01:12:25.950 --> 01:12:31.560
Jennifer Richeson: Biases. And so it's really important to not misattribute the source.

438
01:12:31.620 --> 01:12:34.680
Jennifer Richeson: And to think about what the implications of these different sources of

439
01:12:34.680 --> 01:12:38.070
Jennifer Richeson: Biases, bias, and algorithmic bias are for

440
01:12:38.310 --> 01:12:39.180
Jennifer Richeson: Accountability.

441
01:12:39.570 --> 01:12:40.800
Jennifer Richeson: You know, so

442
01:12:42.240 --> 01:12:45.450
Jennifer Richeson: Kind of capping that and sort of thinking about Suresh's

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01:12:45.780 --> 01:12:47.640
Jennifer Richeson: Framework, I think is useful because

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01:12:48.090 --> 01:13:02.910
Jennifer Richeson: All of this work in this conversation focuses, you know, too much on the perspective of the so-called perpetrator. Right? And so we're like looking for, 'Okay, well did they mean it?

445
01:13:03.300 --> 01:13:16.290
Jennifer Richeson: Was it intentional? Where did it come from? What can we do?' and not enough attention, I think, on the harms to the victims and what it means for them and does it matter for them if

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01:13:16.590 --> 01:13:23.850
Jennifer Richeson: It was intentional or not or due to an algorithm or not. And I think that shift to the harm to the

447
01:13:24.510 --> 01:13:34.530
Jennifer Richeson: Victim in in our work and I think in this general discussion is one that I think is really important and also important, just in our public conversations about

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01:13:35.160 --> 01:13:43.290
Jennifer Richeson: Bias and discrimination. So I'll stop there except to say some of this work was thankfully, we're grateful for support from the National Science Foundation.

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01:13:50.910 --> 01:13:56.220
Suresh Venkatasubramanian: So thanks for that. And Jennifer, I remember listening to your interview with Ezra Klein on Vox and

450
01:13:56.640 --> 01:14:05.430
Suresh Venkatasubramanian: And being very depressed by the by the tail of the of the political dynamics and sad a bit, but that's okay. I get depressed a lot nowadays which stinks. So

451
01:14:06.420 --> 01:14:15.000
Suresh Venkatasubramanian: I want to highlight two things. I think so. One is, sort of, sort of a history of the work we were trying to do in understanding stereotyping and

452
01:14:15.330 --> 01:14:18.720
Suresh Venkatasubramanian: What happened was we were talking with Danah, Danah Boyd, and we're trying to

453
01:14:19.170 --> 01:14:23.490
Suresh Venkatasubramanian: Piece out what it might mean to think about, you know, even what it means to talk about stereotyping and

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01:14:23.790 --> 01:14:29.520
Suresh Venkatasubramanian: We very quickly came to the conclusion that we don't you know as computer scientists, we don't understand what stereotyping means so

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01:14:29.880 --> 01:14:32.880
Suresh Venkatasubramanian: This sort of necessitated a six month long deep dive into

456
01:14:33.240 --> 01:14:44.100
Suresh Venkatasubramanian: Some of the early works on sort of Lippmann's original sort of definition of stereotyping and all the literature in that area. This distinction between stereotyping between prejudice and discrimination and how they're all very different things--

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01:14:44.610 --> 01:14:54.690
Suresh Venkatasubramanian: To the point where, you know, we had at least semblance of a beginnings of an inkling of a handle on on what what one

version of stereotyping might represent, and not even all of it, one version of it.

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01:14:55.680 --> 01:15:02.280
Suresh Venkatasubramanian: And it's funny because in the time since I've been talking with colleagues, especially those who do NLP and I've been pointing out sort of thing that you know

459
01:15:02.550 --> 01:15:14.520
Suresh Venkatasubramanian: What they referred to as biases is a very packed term that has to be unpacked in many different ways. And there isn't much of, you know, an understanding yet of that fact. And I think one of the points of contact between

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01:15:15.660 --> 01:15:22.860
Suresh Venkatasubramanian: Life found between the computer science and the social sciences is this ability is this need to unpack notions that we

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01:15:23.490 --> 01:15:33.720
Suresh Venkatasubramanian: Are using in some sense carelessly. But if we had the rich nuance that comes with a deep understanding of bias, of explicit bias, of implicit bias, so the implications of these things,

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01:15:34.230 --> 01:15:39.150
Suresh Venkatasubramanian: We would be able to fully understand both the ramifications of the technology we're using and maybe

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01:15:39.810 --> 01:15:47.130
Suresh Venkatasubramanian: Design remedies or other forms of technical interventions that might be helpful in this context. So I think that that point of interaction that's been true for a lot of the work I've done

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01:15:47.430 --> 01:15:51.630
Suresh Venkatasubramanian: Being able to unpack just, you know, words that have a loaded meaning

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01:15:52.230 --> 01:16:00.510
Suresh Venkatasubramanian: by by by the appropriate direction has been very helpful. And I should mention that my work also, together with Danah, has been funded by the National Science Foundation. We are the ground together so

466
01:16:00.840 --> 01:16:07.920

Suresh Venkatasubramanian: It's, it's, it's the by the big data programs that was great. The other thing I think this when you bring up sort of the, the harms to the

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01:16:08.760 --> 01:16:15.060
Suresh Venkatasubramanian: To the victims and this is another common theme and a lot of computer science work in this topic, there's this

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01:16:15.690 --> 01:16:26.880
Suresh Venkatasubramanian: Understanding that something must be done because algorithms by themselves have all kinds of problems, but there is a resistance to doing anything that might sound like it's trying to

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01:16:28.260 --> 01:16:34.320
Suresh Venkatasubramanian: Address inequities, which is odd, right? Because if you think you want to address inequities, you should be going in and addressing them.

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01:16:34.590 --> 01:16:42.270
Suresh Venkatasubramanian: But there's a sense of, 'No, no. All we want to do is make sure we have a level playing field,' and of course as many people have observed, you can't have a level playing field when it's been skewed for so long.

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01:16:42.960 --> 01:16:46.650
Suresh Venkatasubramanian: And I think trying to focus on harms and not, and

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01:16:47.190 --> 01:16:54.510
Suresh Venkatasubramanian: I think we do spend a lot of time worrying about, well, what was the intent? Was there a bad intent? Is that something, you know is it our job just to sort of worry about the intent? And

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01:16:54.960 --> 01:16:57.360
Suresh Venkatasubramanian: This reframing this around: it doesn't matter.

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01:16:58.350 --> 01:17:05.370
Suresh Venkatasubramanian: That the harm is the point. And that's what you have to focus on and centering, and I think a lot of people have been talking about this idea of, you know, centering

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01:17:05.760 --> 01:17:11.640

Suresh Venkatasubramanian: The, the people who are harmed by the technology or harmed by the system, whether it's, you know, technical system or not.

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01:17:12.300 --> 01:17:17.700
Suresh Venkatasubramanian: That's something that we still have to get used to. And, you know, again, we've talked a bit in the past about, so in the

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01:17:18.360 --> 01:17:29.880
Suresh Venkatasubramanian: last hour about security concepts, this idea of threat modeling, of threats to peoples as harms is a useful way to sort of align the computer science viewpoint of thinking about this, along with

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01:17:30.360 --> 01:17:37.170
Suresh Venkatasubramanian: This larger perspective on on harms that in a security language, it's actually possible to think about specific harms, specific vectors of harms

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01:17:37.380 --> 01:17:44.160
Suresh Venkatasubramanian: Without having to worry about trying to solve the problem in some sense. And I think that's another point of where we can actually overlap in some way

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01:17:45.210 --> 01:17:47.880
Suresh Venkatasubramanian: if we, if we write this grant together that the NSF is going to fund us for, Jennifer.

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01:17:51.510 --> 01:17:52.740
Alondra Nelson: Thank you so much. Beth?

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01:17:53.760 --> 01:17:58.230
Beth Mynatt: Yeah, we're looking for attribution for this roundtable for all the grants that are going to come,

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01:17:58.770 --> 01:18:01.080
Beth Mynatt: grant applications that are going to come out of these discussions.

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01:18:01.380 --> 01:18:14.010
Beth Mynatt: And in particular, there's just a recent thread that has shown up in the chat that I want to grab because I think it connects to what Suresh and others have been speaking to you, which is how do we, what, what is the

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01:18:15.450 --> 01:18:28.680
Beth Mynatt: The goal around impact for the research that we're doing? Because in terms of what, you know, what type of standard should NSF be setting, should it be a higher setting

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01:18:30.090 --> 01:18:40.560
Beth Mynatt: To have a societal impact in terms of the research that we do, which would, would maybe draw in kind of the need for the sustained community partnerships that Tiffany and others have pointed to?

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01:18:41.100 --> 01:18:52.200
Beth Mynatt: Or are we making things more difficult because, you know, trying to show measurable impact in a world of, you know, a long standing historical disparities

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01:18:52.500 --> 01:19:13.470
Beth Mynatt: you know, may either discourage or shift researchers into, you know, another form of, of proximal impact variable. So how should, how should NSF be thinking about what these collaborative proposals should be trying to achieve above and beyond scholarship, scientific scholarship?

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01:19:20.370 --> 01:19:22.560
Beth Mynatt: Tiffany, I'll put you on the spot.

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01:19:26.040 --> 01:19:27.210
Tiffany Veinot: So I think

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01:19:28.860 --> 01:19:40.920
Tiffany Veinot: I think it's necessary to be thinking about disparities or marginalized populations from the basic from, from the moment of asking the question

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01:19:41.430 --> 01:19:46.710
Tiffany Veinot: On through to assessing the outcomes or evaluating the work.

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01:19:47.460 --> 01:20:02.520
Tiffany Veinot: I think that there are a number of process-oriented things that we could be trying to evaluate things, like who's in our studies? Have, what are the methods we used? How what how equitable or fair was our process?

494

01:20:03.270 --> 01:20:16.950
Tiffany Veinot: Looking at targeting some of these phases of an intervention cycle, where if you could say this approach is one which will be taken up by these marginalized groups that we have worked with that shows

495
01:20:17.370 --> 01:20:26.160
Tiffany Veinot: That that or there's a difference in how people respond to it, I think that one can chip away at the problem.

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01:20:27.510 --> 01:20:32.940
Tiffany Veinot: And I think we could try to have research that through its process actually makes a difference.

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01:20:34.020 --> 01:20:36.480
Tiffany Veinot: So that would be my comment on that.

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01:20:40.890 --> 01:20:43.440
Beth Mynatt: Wise words. Anyone else want to jump in here on this?

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01:20:44.460 --> 01:20:47.160
Beth Mynatt: Again picking up on some of the, the chatter as well

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01:20:50.580 --> 01:20:51.090
David Grusky: I'm happy to

501
01:20:51.180 --> 01:20:52.200
David Grusky: say something if

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01:20:52.500 --> 01:20:54.060
David Grusky: If there aren't others.

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01:20:55.650 --> 01:21:04.650
David Grusky: I would just want to elaborate and say that I think in some of the social sciences, evaluation research has been a bit disparaged and that that's unfortunate.

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01:21:04.980 --> 01:21:11.610
David Grusky: Because we need to know what you know what has worked and what hasn't worked with respect to the disparities. When we have moments of crisis, like this one,

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01:21:11.880 --> 01:21:21.750

David Grusky: We need to have that bank of of evidence upon which we can draw so that the decisions that are made, when the opportunity presents itself, decisions are made on the basis of the evidence and and

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01:21:22.410 --> 01:21:27.450
David Grusky: I also think though that's not enough. It's not enough just to evaluate what's been tried, but we also have to have

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01:21:27.720 --> 01:21:41.490
David Grusky: A very holistic capacity to understand new solutions that go beyond what has been tried, but we need both. And I think sometimes the evaluation research side of the equation hasn't been valued as much as it should be.

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01:21:44.910 --> 01:21:46.410
Beth Mynatt: Thank you. All right.

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01:21:48.150 --> 01:21:54.660
Beth Mynatt: It's looking to, it's kind of like a game show, I can see you take your mic off and it's ready to queue up um

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01:21:55.740 --> 01:22:02.520
Beth Mynatt: It's almost that we knew we'd want to bring the other panel back for this discussion, but there's been a lot of folks asking about the relationship of trust,

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01:22:03.570 --> 01:22:10.260
Beth Mynatt: And how trust plays into the types of disparities and bias

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01:22:12.060 --> 01:22:16.410
Beth Mynatt: That we're seeing within this. So I, I've seen a couple versions of this so

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01:22:17.430 --> 01:22:32.640
Beth Mynatt: For example, you know, could we look at the racial equality myths that Jennifer was unpacking for us in terms of misinformation and disinformation frameworks discussed in the first session? And does that provide, you know is there

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01:22:33.630 --> 01:22:43.140
Beth Mynatt: Perhaps a sweet spot or sort of bringing these two threads together? And then there's another version of this. So starting with Jennifer, but another version

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01:22:44.370 --> 01:22:48.480
Beth Mynatt: queuing up Suresh, Tiffany, and others, which is the relationship of

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01:22:50.640 --> 01:23:05.520
Beth Mynatt: Where authority comes from in its relationship to IT systems and the the the coupling of authority and trust to potential uptake. So, Tiffany I would expect you would see this in some of the health IT work.

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01:23:06.180 --> 01:23:16.200
Beth Mynatt: So first person system where its traditional authority may not have the same level of uptake from communities that don't trust that authority to begin with.

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01:23:16.530 --> 01:23:23.790
Beth Mynatt: So maybe there's some ways of unpacking that so I'm probably you know this is a this is hard though. So the third panel has to answer questions that

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01:23:24.120 --> 01:23:34.410
Beth Mynatt: Go across all of the roundtable so they're going to get ready for that. But, you know, how do we look at these these trust in Information Network questions and bring this into the disparities conversation?

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01:23:36.150 --> 01:23:46.050
Jennifer Richeson: Yeah, I actually think that's a really interesting way to to think about it and frame it, and if there is some level of

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01:23:47.340 --> 01:24:04.740
Jennifer Richeson: Misinformation, if not disinformation, around what Implicit bias is and is not and what types of behaviors and decisions it affords and does not afford and under what conditions? So, there is something there, I think.

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01:24:06.270 --> 01:24:17.070
Jennifer Richeson: We know less about and the question of how they're repeated or probably, but maybe even incidental

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01:24:18.450 --> 01:24:33.240
Jennifer Richeson: attributions of, you know, for instance of policing case that you know, disparate outcomes in policing or in mortgage lending or any number of domains, how making those attributions

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01:24:34.260 --> 01:24:46.980

Jennifer Richeson: To implicit bias. And then perhaps to algorithms, how that actually impacts the trust and I would say large set of emotions of the communities that once again

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01:24:47.460 --> 01:25:01.590
Jennifer Richeson: Are sort of on the downside, right. Are again facing years more evidence of inequality, of discrimination, yet here again, there is no good answer about

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01:25:01.950 --> 01:25:09.180
Jennifer Richeson: Why it's happened and in many times, the answer is something that, as we were saying in our work leads to

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01:25:09.870 --> 01:25:21.000
Jennifer Richeson: inaction, right, and or you know basically excusing the behavior. And so I think, you know, more work we're really investigating that, and again this is

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01:25:21.360 --> 01:25:30.930
Jennifer Richeson: Shifting it to a harm-centered view, I think is, is really important because we are, and I would argue and others have, that our

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01:25:31.470 --> 01:25:41.010
Jennifer Richeson: But our desire to believe that society, people are inherently good and are getting better, right, and our moralization around

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01:25:41.790 --> 01:25:46.680
Jennifer Richeson: Racism, or any of these other biases. This is not just true for racism, I'm just using this account.

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01:25:47.520 --> 01:25:59.430
Jennifer Richeson: If I think it motivates us to want to make excuses for both individual actors and institutional actors, even while they're continuing to produce the very same inequalities

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01:26:00.420 --> 01:26:05.850
Jennifer Richeson: From the past. So I think we really need to, you know, change the way we're thinking about these

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01:26:06.810 --> 01:26:18.210
Jennifer Richeson: These processes. And yeah, perhaps shift to to the side of the story where we're like, you know, actually, maybe it's, we

just need a whole new default. Let's just assume that everybody's biased in some way,

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01:26:18.510 --> 01:26:27.870
Jennifer Richeson: And the- the systems that they create are biased in some way. And why don't we try to preempt those biases on the front end instead of, you know, for instance, that famous case of the

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01:26:28.140 --> 01:26:38.490
Jennifer Richeson: Algorithm on patient care, right, where hundreds of thousands of black patients didn't get the care that they needed because the algorithm had these baked in biases about you know how much

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01:26:38.850 --> 01:26:48.480
Jennifer Richeson: money you're spending on healthcare. Well, you know, that was probably really predictable if you had a different set of people in the room, or even with those people if you started from the

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01:26:48.810 --> 01:26:59.370
Jennifer Richeson: The assumption that there, there there's discrimination and healthy inequalities based on race already in existence, and we need to account for that sort of upfront.

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01:27:04.950 --> 01:27:06.120
Tiffany Veinot: That speaks to, Oh, sorry.

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01:27:07.980 --> 01:27:16.680
Tiffany Veinot: I was going to jump in and speak to the trust issue so, so yes trust is a major factor underlying uptake of technologies.

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01:27:17.070 --> 01:27:29.760
Tiffany Veinot: And that's those we see that in terms of the sociology of trust. We see African Americans in particular are less likely to adopt patient portals that are linked to healthcare, low SES populations are less likely to

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01:27:29.760 --> 01:27:36.690
Tiffany Veinot: adopt, there may be access issues there. But often, when you control for access to technology, these relationships were made.

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01:27:37.410 --> 01:27:47.190
Tiffany Veinot: And I think that we need to be thinking systematically about trust. What this is something I've experienced in my work in Flint related to HIV and STI prevention.

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01:27:48.030 --> 01:27:56.910
Tiffany Veinot: In that particular work, we found that trust was absolutely the most salient factor in the design of our technology and design of our intervention.

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01:27:57.210 --> 01:28:04.920
Tiffany Veinot: And we, despite taking it into account through developing as Trust Center design framework which we published, I could share that if you'd like,

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01:28:05.940 --> 01:28:11.100
Tiffany Veinot: But despite doing that and systematically trying to address it, we still found that

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01:28:12.000 --> 01:28:24.900
Tiffany Veinot: We did not have a lot of uptake of our intervention because people were so worried about talking about sexual health on social, in social media type environments because of other experiences that they were having in their lives

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01:28:25.560 --> 01:28:32.160
Tiffany Veinot: That it basically impeded the uptake work. That's work we're going to be publishing soon. Thanks

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01:28:35.130 --> 01:28:35.640
Suresh Venkatasubramanian: They

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01:28:36.420 --> 01:28:56.010
Suresh Venkatasubramanian: The whole interaction between trust, authority, and especially IT systems is is very complicated because like it's a game that's being played out at high speed, at least it seems to me in the last few years as well. Right? So, first there's the rhetorical trust of, you know,

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01:28:57.030 --> 01:29:03.060
Suresh Venkatasubramanian: You should trust the algorithms, because, you know-- this is from a few years ago, right-- trust the algorithms because they're objective and they're free of all the

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01:29:03.480 --> 01:29:06.480
Suresh Venkatasubramanian: All the biases that come with it. And this is an argument that's made to this day, right that if

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01:29:06.750 --> 01:29:15.000

Suresh Venkatasubramanian: We replace human decision making with algorithm decision making it somewhat, it is better because it's free of the biases or it's more transparent. And then of course the counter trust

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01:29:15.390 --> 01:29:22.020
Suresh Venkatasubramanian: Is that, 'No, no. In fact, we know how these algorithms absorb and transmit and magnify all the biases in our system.'

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01:29:22.740 --> 01:29:34.530
Suresh Venkatasubramanian: Which leads us with, which leaves us with a situation where on the one hand, there are attempts to claim that algorithms represent some kind of epistemological standard that is higher.

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01:29:35.400 --> 01:29:40.320
Suresh Venkatasubramanian: And on the other hand, the claim that they're much lower because you can't, because they're not transparent.

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01:29:41.040 --> 01:29:55.890
Suresh Venkatasubramanian: And then you end up with a situation where, in cases, I think the COVID tracking, contact tracing sort of discussions around this is a good example of this, where they're actually might be a value for certain kinds of technology appropriately designed and appropriately centered to help

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01:29:57.090 --> 01:30:04.650
Suresh Venkatasubramanian: People in different communities, but because we've destroyed the trust or we've created enough doubt around where the trust, I think that's the key thing about this situation is that it creates doubt,

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01:30:05.190 --> 01:30:12.060
Suresh Venkatasubramanian: Enough doubt has been created around which technologies are reliable or not, we assume none of them are and nothing is ever valuable, and I think

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01:30:12.840 --> 01:30:23.370
Suresh Venkatasubramanian: I, this is what, you know I was saying this depressed me about the first session that it feels like, you know, we have a huge number of problems. It's not clear how we break out of this vicious cycle that we're in, and I think

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01:30:24.750 --> 01:30:39.690
Suresh Venkatasubramanian: I don't, to be honest, I don't think you know, I don't think computer science is helping much with some of the rhetoric

that we use around this. And I think we need to work harder at being more circumspect about some of the claims that we make. But nevertheless,

561
01:30:41.400 --> 01:30:56.280
Suresh Venkatasubramanian: I think that someone trying to figure out the sweet, the balance point between throwing everything out and and maybe trusting too much is where I don't yet know how how we're going to do it and I will leave the first panel as an answer to this issue.

562
01:30:58.740 --> 01:31:10.080
Alondra Nelson: So let's, where I'm mindful of time, but let's just go to one question that I think now that we've, you know, I think had a really rich conversation about the assumptions and about that go into work,

563
01:31:11.400 --> 01:31:19.710
Alondra Nelson: computational work, social science work. There's a question I think that points a little bit, Suresh, to an answer, but that brings the technical back in so

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01:31:20.280 --> 01:31:37.050
Alondra Nelson: This question is could we benefit from more interdisciplinary research that quantifies impact on the technology of structural bias, not just in its presence or absence, but to measure it, to scale it, how it works exactly, exactly, etc.?

565
01:31:38.340 --> 01:31:50.700
Alondra Nelson: So is there a way that we can think about collaborative projects, for example, across CISe and SBE that that sort of take the strengths of both fields to to kind of make measure and make sense of the problem?

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01:31:56.220 --> 01:32:04.560
Tiffany Veinot: I'll make just one quick point which I feel like we, I think we should be addressing, which is the role of technology in

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01:32:05.010 --> 01:32:13.140
Tiffany Veinot: Creating inequalities and the way that it's changing things like economic opportunity, structures of jobs people have,

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01:32:14.100 --> 01:32:27.720
Tiffany Veinot: And how people socialize. There's, there's just so much that I think we, you talk about the technology of inequality, I think that we actually need to study the ways that technology are contributing to inequality.

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01:32:28.890 --> 01:32:33.600
Tiffany Veinot: And I think that would be a really rich area for research that, across our areas.

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01:32:36.990 --> 01:32:43.890
Suresh Venkatasubramanian: Can I quickly jump in? If you don't mind. So I've been thinking a lot about this, especially in the context of the pandemic and how it feels like

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01:32:44.940 --> 01:32:48.090
Suresh Venkatasubramanian: The pandemic is showing how existing

572
01:32:49.110 --> 01:32:59.820
Suresh Venkatasubramanian: Inequities, existing inequalities, everything gets refracted through that, right. The whole issue of contact tracing, who's going to get tests, who's not going to get tests, where is information coming from? Everything is going through

573
01:33:00.300 --> 01:33:09.960
Suresh Venkatasubramanian: The existing structures of inequality we have. So in that sense I, while I agree that technology amplifies a lot of inequality, I think, at the very least, recognizing, measuring

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01:33:10.380 --> 01:33:18.390
Suresh Venkatasubramanian: Sort of some way identifying the ways in which technology when when pushed through a very, very unequal society creates these effects

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01:33:19.230 --> 01:33:28.680
Suresh Venkatasubramanian: is itself already helpful, even before we start worrying about the amplifying effects. Because I think that's at least that's something I think is not often appreciated

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01:33:29.370 --> 01:33:36.360
Suresh Venkatasubramanian: Among the crowd who wants to use technology to solve problems to say that, just because you have a new technical tool,

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01:33:36.780 --> 01:33:41.910
Suresh Venkatasubramanian: You have to reckon with the fact that you're pushing into a system that already exists, that has all these different barriers in place.

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01:33:42.210 --> 01:33:48.810

Suresh Venkatasubramanian: You're not going to have the effect that you think you have unless you reckon with the system already. And just understand that interaction itself

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01:33:49.290 --> 01:34:00.690
Suresh Venkatasubramanian: Is is is important and it, be- before we start worrying about the amplifying effect. And that's something you know, just as we know, is something that I think it's something that is appreciated the, in the circles that I move in.

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01:34:02.070 --> 01:34:07.770
Alondra Nelson: Thanks that help, that's helpful. Any last words, Jennifer, David? Got a minute or two.

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01:34:14.970 --> 01:34:20.940
Jennifer Richeson: Yeah, I mean no, except for it's, um, you know, I think

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01:34:21.390 --> 01:34:33.990
Jennifer Richeson: It's important to, you know, I talk a lot of my work, I talk about this sort of, you know, unfolding over time and why do we have this you know this mythology and these myths, and I think it's important to not fall prey to that again

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01:34:34.770 --> 01:34:48.210
Jennifer Richeson: In this discussion and recognize that there's there, there have for a long time, right, we've had these struggles and maybe a willful blindness to inequality, inequity,

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01:34:49.110 --> 01:34:54.750
Jennifer Richeson: Discrimination and its sources. And in each moment, where you know there's

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01:34:55.200 --> 01:35:03.000
Jennifer Richeson: You know evidence. So for instance, Elizabeth Hinton, the historian, is writing a new book on the you know '94 Crime Bill and the crack versus powder

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01:35:03.240 --> 01:35:14.430
Jennifer Richeson: Cocaine disparity and how that you know happened at all. And we sort of think, well, at the time, they didn't really realize the disparate impact. It's like no, they realized it then, they talked about it then, it was called out then,

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01:35:15.180 --> 01:35:22.890

Jennifer Richeson: and in every other attempt to get rid of it, it was called out. But people still would not just say it's disparate impact discrimination.

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01:35:23.220 --> 01:35:28.260
Jennifer Richeson: Right. They wouldn't say that or they wouldn't say it's racist. They would say, well, people didn't intend it

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01:35:28.590 --> 01:35:34.110
Jennifer Richeson: To have this impact, and it really is a colorblind policy so it's okay, right. And so I guess I think we need to

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01:35:34.350 --> 01:35:49.140
Jennifer Richeson: Like just be more, maybe this is asking too much from society, but be more like honest and forthcoming about wh- and name things what they are. If it's racial discrimination, if it's racial bias, if it's racism, sexism, if whatever it is, just name it.

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01:35:50.250 --> 01:35:58.020
Jennifer Richeson: Whether it's in algorithms or in people or in systems. So you know if that's my big picture wish, and NSF can't pay for that, though.

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01:35:59.820 --> 01:36:01.050
Beth Mynatt: Thank you, Jennifer.

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01:36:01.080 --> 01:36:14.010
Alondra Nelson: Well you as a panel really model I think what we're all here trying to do. You know, how we can begin to kind of talk across our, our fields in our assumptions and so thank you very much to the panelists, and I'll hand things over to Beth.

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01:36:14.850 --> 01:36:21.720
Beth Mynatt: Again, thank you very much. Terrific, terrific discussions and so we're going to shift into two things.

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01:36:22.110 --> 01:36:32.610
Beth Mynatt: First, if you've noticed from our very first panelist when Claudia was talking about training and talent and labor up into the comments, just a second ago in the chat channel, which is

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01:36:32.910 --> 01:36:39.000
Beth Mynatt: It really matters who's building these types of tools that we're talking about and participation in the labor of creating them.

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01:36:39.570 --> 01:36:46.440
Beth Mynatt: You're not going to be surprised that the questions of, you know, how what it means to have that that that workforce

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01:36:47.340 --> 01:36:55.170
Beth Mynatt: To address these issues is queued up as the third panel. I warned them that they were going to have the hardest job because all of these conversations are rolling to them now.

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01:36:55.620 --> 01:37:04.590
Beth Mynatt: But we all have a 30 minute break. Okay, we'll make it a 27 minute break and we'll be back together at 3pm East Coast time. Thank you so much.

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01:37:05.880 --> 01:37:06.540
Alondra Nelson: Thanks, everybody.