



ADMINISTRATIVE CONFERENCE OF THE UNITED STATES

**ARTIFICIAL INTELLIGENCE IN FEDERAL AGENCIES**  
**Bias and Government Artificial Intelligence**

July 29, 2020

TRANSCRIPT  
(Not Reviewed for Errors)

**Panelists**

David Super, Carmack Waterhouse Professor of Law and Economics, Georgetown University Law Center

Kristin Johnson, McGlinchey Stafford Professor of Law, Tulane University Law School

Alex Givens, President and Chief Executive Officer, Center for Democracy & Technology

**Moderator**

Chai Feldblum, Partner, Morgan Lewis & Bockius; former Commissioner, U.S. Equal Employment Opportunity Commission; Public Member, Administrative Conference of the United States

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AUDIO TRANSCRIPTION OF  
Administrative Conference of the United States  
Artificial Intelligence in Federal Agencies:  
Bias and Government Artificial Intelligence

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1 MR. WIENER: Well, good afternoon. I'm  
2 Matt Wiener, the Vice Chair and Executive Director of  
3 Administrative Conference of the United States. And I'd  
4 like to welcome you to this panel. This is the third  
5 panel of our symposium on Artificial Intelligence in  
6 Federal Agencies, sponsored by the Administrative  
7 Conference, or ACUS for short, and the Institute for  
8 Technology Law and Policy at Georgetown Law School.

9 Today's panel is on bias and artificial  
10 intelligence. As far as I'm concerned, there's no more  
11 important topic in the artificial intelligence area than  
12 bias. And we have an outstanding panel to address the  
13 topic this afternoon. I'm especially pleased that our  
14 panel is being moderated by Chai Feldblum. There's no  
15 one more qualified to moderate the panel. And you'll  
16 note on her -- in our program materials that it lists  
17 her many affiliations, which includes now as a partner  
18 at Morgan Lewis. And before that she was a Commissioner  
19 at the EEOC for nine years. And before that, a very  
20 distinguished law professor at Georgetown Law School.  
21 And she also happens to be a member of the  
22 Administrative Conference of the United States. And we  
23 are very, very happy to have her as a member and she's a  
24 very good friend to the Conference. And having said  
25 that, let me turn it over to you, Chai, for what I think

1 will be an outstanding and interesting discussion.

2 MS. FELDBLUM: Great, thank you, Matt. And  
3 I thought you were going to start with; among the  
4 various things she's a public member of ACUS, which I  
5 would have started with, because really, I just as you  
6 know, I think ACUS just plays an incredibly important  
7 role in thinking through tough issues. And I think this  
8 panel is one example in the whole series on "Artificial  
9 Intelligence" shows that role that ACUS is playing.

10 So I'm very excited to be moderating. I'm  
11 very excited that you-all are going to hear from really  
12 three incredible folks. And instead of me reading three  
13 sentences from their bios, what I'm going to do is just  
14 ask each of them to tell you, obviously, their name,  
15 where they are and just a few sentences about how they  
16 got into this area of AI and bias.

17 So Kristin Johnson, we'll start with you  
18 and then Alex, go to you, and then David. So Kristin?

19 MS. JOHNSON: Great. Thanks so much, Chai.  
20 I am Kristin Johnson, the McGlinchey Stafford Professor  
21 of Law and Associate Dean of Faculty Research at Tulane  
22 University Law School. I am delighted to join you and I  
23 have to join Chai in thanking Matt Wiener, Todd Phillips  
24 and Todd Rubin as well as Jeff Gary and ACUS as well as  
25 the Georgetown Institute for Technology in the Law for

1 organizing this summer symposium in general and this  
2 panel in particular.

3 I'm tremendously grateful for the report  
4 that was distributed last February, "Artificial  
5 Intelligence in Federal Agencies" that explores the role  
6 that artificial intelligence has or plays -- machine  
7 learning plays in the context of federal agency  
8 adjudication, rulemaking and other regulatory  
9 activities. I was delighted that the organizers  
10 committed time in their report and this symposium for a  
11 discussion of what Matt correctly describes as one of  
12 the most critical and concerning areas in the adoption  
13 and employment of artificial intelligence technologies.  
14 Specifically today, I'll be focused on algorithms --

15 MS. FELDBLUM: Wait, wait, wait, wait.  
16 Kristin, I'm going to stop you, because I was like, wow,  
17 that's more than an introduction. I'm just going to  
18 stop you before you head into your substance, okay. I  
19 just want Alex and David to introduce themselves and  
20 then we'll get into substance. So Alex?

21 MS. GIVENS: Sure. Thank you so much. So  
22 I'm Alex Givens. I'm the CEO of the Center for  
23 Democracy and Technology which is a civil society  
24 organization based in Washington, D.C., that for 25  
25 years has worked to fight employees' individual rights

1 in the center of the digital revolution. We focus on a  
2 very wide range of issues from consumer privacy to  
3 preserving an open and accessible Internet to security  
4 and surveillance issues to platform governance, which is  
5 to say that everybody I usually work with are staring  
6 intently at their screens as we speak, and they are not  
7 listening to me, they're listening to the House hearing  
8 that is happening right now.

9           So I'm very grateful to those of you who  
10 have dialed in and to join this conversation. I will  
11 say that most relevant for our conversation today, we do  
12 a lot of work focusing on how data is collected and used  
13 to make decisions that impact people's lives. And  
14 that's the crux of the conversation we're having today.  
15 So I'm thrilled to join you-all.

16           MS. FELDBLUM: Great. And David Super?  
17 Oops, David, make sure your video is on. I mean, make  
18 sure your audio is on. That's what we didn't -- okay.  
19 You know what I'm going to do, David, in terms of time,  
20 I'm going to tell people how awesome you are, and you're  
21 going to figure out the audio, because David is a law  
22 professor at Georgetown Law School who does lots of  
23 incredible stuff including, as you will hear, some  
24 issues around AI and government. And the way we're  
25 going to do this is Kristin, Alex and David are all

1 going to tell you about some specific issues they've  
2 been working on; it's sort of like case studies.

3           And our goal for this panel for what we  
4 hope you walk away with this panel from, one, hopefully  
5 having learned something new and interesting. Two, if  
6 you're a in-government agency or a lawyer working with  
7 these issues, that you come out with some concrete ideas  
8 of what you might want to do. And third, especially if  
9 you're in academia that you have some new and  
10 interesting ideas that you might want to research.

11           So that's our overall goal. We're going to  
12 do sort of the case studies, I'm going to then ask the  
13 panelists to ask each other questions or make  
14 observations. And then we're going to open it up for  
15 questions. So please go ahead and write your questions  
16 in the questions box. I'm sure a lot of you have been  
17 doing lots of these Webinars so you would know that.

18           Okay. So Kristin, I'm going to move it  
19 over to you to talk about a very interesting piece in  
20 terms of credit and government agencies. So on to you.

21           MS. JOHNSON: Great. Thanks so much. So  
22 the use case I'll present initially, and I'm happy to  
23 follow up with a little bit of a discussion regarding  
24 how regulatory agencies might directly integrate AI into  
25 their platforms, but the use case I'll open with in

1 terms of our panel is a credit scoring use case. In  
2 other words, my discussion for the next few minutes will  
3 focus on the integration of algorithms, or more  
4 specifically, machine learning algorithms into consumer  
5 credit scoring platforms.

6 This will pair quite neatly with what I  
7 believe Alex will discuss in the employment context.  
8 And in fact, one of the examples I will offer for the  
9 purpose of setting the stage for those of you who  
10 haven't joined for the entire series, and maybe new to  
11 AI, involves an employment related algorithm.

12 So let me set the stage by describing the  
13 background for this research. In a co-authored paper  
14 with Frank Pasquale and Jennifer Chapman and during my  
15 testimony this time last summer before the House  
16 Financial Services Committee Artificial Intelligence  
17 Task Force, I outline a number of concerns arising from  
18 the integration of nonconventional types of data in the  
19 consumer credit scoring -- or credit underwriting  
20 process.

21 More specifically, my research is focused  
22 on the integration of what I will describe as  
23 alternative data in the consumer finance phase. I'm  
24 focused on legal and ethical implications of the  
25 commodification of this type of data and the outcomes



1 for our society.

2           Many of you will be familiar with what I'm  
3 going to describe, because personally, you may know your  
4 credit score, right? And that's why I like this use  
5 case, it's immediately accessible. So what I'll do in  
6 my remaining time is describe the integration of  
7 alternative data into innovative financial services  
8 platforms. I'll explore some concerns regarding the  
9 potential for technological advances to deliver on the  
10 promise of including many who historically have been  
11 excluded from the financial services space as well as  
12 raising some concerns and offering up some questions or  
13 suggestions for research that we may explore as  
14 academics or that consumer advocacy agencies have -- or  
15 advocacy organizations have undertaken more careful  
16 research and thoughtful analysis.

17           And finally, a few reflections that may be  
18 generally applicable across government agencies that  
19 interface with the public. As you may well know,  
20 individuals and families increasingly rely on credit to  
21 finance household purchases and overcome significant  
22 unanticipated expenses. Without access to credit on  
23 fair and reasonable terms, it can be extraordinarily  
24 expensive to be poor. For families with fragile  
25 financial circumstances, credit may serve as a lifeline

1 enabling consumers to make short-term debt obligations  
2 and to pay for education, transportation, housing,  
3 medicine, child care and even food. And in today's  
4 pandemic, these concerns are especially poignant.

5           Two critical developments create promise  
6 for the 26 million Americans who are credit invisible,  
7 meaning they do not have credit histories. And the 19  
8 million Americans with thin, impaired or stale credit  
9 histories. We would describe these as unscorable  
10 citizens. The birth of big data, the collection,  
11 storage and analysis of vast volumes of consumer data  
12 fuels artificial intelligence are automated  
13 decisionmaking platforms.

14           Similar to the proliferation of AI  
15 platforms and healthcare, education, employment and  
16 criminal law enforcement, the rise of AI in finance  
17 monetizes consumer data. Together consumers Web  
18 browsing data, click stream data, social media data and  
19 other bits of information aggregated through the  
20 consumers interaction with the world, and in the  
21 Internet more broadly, creates consumers' digital  
22 interface.

23           This consumer digital interface reveals  
24 intimate details about consumers' financial transactions  
25 including their checking and savings cash flows, their

1 credit and debit card transactions, data that has  
2 tremendous value. Data mining engenders a new set of  
3 behavioral scoring criteria for evaluating credit  
4 worthiness. We describe this criteria as alternative  
5 data. Early studies reveal three significant challenges  
6 that arise as we integrate alternative data and in our  
7 endeavor to regulate the integration of this  
8 information.

9           First, alternative data may advantage or  
10 disadvantage. It is not immediately and implicitly  
11 clear that one outcome is more likely than the other,  
12 but both are probable. Particularly for those who are  
13 legally -- who are part of legally-protected classes or  
14 who are marginalized or vulnerable as a result of, for  
15 example, their immigration status or other personal  
16 financial circumstances or attributes.

17           Under the behavior scoring model, your  
18 friends on Facebook, the people in the pictures you post  
19 on Instagram, all of this, whether or not you  
20 participate in protests, may influence the interest rate  
21 that you receive on your next mortgage or car loan or  
22 whether or not you're eligible for an education loan.

23           Second, learning algorithms evaluate  
24 facially neutral alternative data. Facially neutral  
25 being the descriptor but maybe, in fact, not completely

1 accurate, yet the results of automated decisionmaking  
2 processes may unintentionally use variables that  
3 function as proxies for protected traits or  
4 characteristics. As a result, the use of machine  
5 learning algorithms or these highly sophisticated  
6 algorithms may lead to disparate impacts for members of  
7 legally- protected classes.

8           Consider, for example, Amazon's experiment  
9 with the learning algorithm tasked with reviewing  
10 resumes for a software programmer position. Armed with  
11 thousands of resumes from previous hires and general  
12 instructions regarding qualification, the algorithm went  
13 rogue. Because previous hires had predominantly been  
14 men, the algorithm began to discount any reference to  
15 women or women's colleges. So in other words, those who  
16 had preferences to serving as a women's chess club  
17 president or having participated in women's tennis clubs  
18 or women's teams, were unfortunately discounted in the  
19 algorithm's calculation regarding which resumes might be  
20 preferred among the class of resumes. Unknowingly, the  
21 algorithm replicated historic discrimination and hiring  
22 biases.

23           Third, machine learning algorithm engage in  
24 machine learning. And by "machine learning", because  
25 I'm the first speaker up to bat, I'll just describe

1 quickly, applies inductive techniques to large data sets  
2 to enable the algorithm to learn rules that are  
3 appropriate to a particular task. In other words, the  
4 intelligence of machine learning is oriented to  
5 outcomes, not process. A smart algorithm is designed to  
6 consistently reach accurate results based on a chosen  
7 task and designated parameters. Like a calculator  
8 multiplying 15 digit numbers faster than any human brain  
9 could, in a narrow, well-specified area it can reach  
10 conclusions faster than humans might be able to.  
11 However, the reality is that the dimensions are  
12 difficult and the issues here are nuanced.

13           As I described earlier in the context of  
14 credit scoring algorithms, the data shared with the  
15 algorithm can make all the difference. The process of  
16 planning, selecting, storing and partitioning data among  
17 other concerns might lead to data sets that deeply  
18 influence how the algorithm learns. Unintentionally,  
19 leading developers have released algorithms trained to  
20 be neutral only to discover that the algorithms  
21 performed in blatantly discriminatory ways.

22           In the narrow context of consumer finance,  
23 federal agencies exercising oversight of fair consumer  
24 lending practices such as the CFPB, the OCC, the FDIC or  
25 the FTC and others who have historically focused on the

1 enforcement of the Equal Credit Opportunity Act, and  
2 other laws ensuring fair lending, would want to be  
3 exceptionally thoughtful about the firms they regulate  
4 and their integration of algorithms. In particular, in  
5 the context of adverse notices where an algorithm has  
6 been deployed by a third-party credit rating agency, or  
7 acquired by a credit agency from a third party, it will  
8 be imperative for the credit rating agency to describe  
9 why and how the credit rating agency has taken a  
10 particular perspective on an applicant's credit rating  
11 or an applicant's credit score.

12 MS. FELDBLUM: You need to -- one minute  
13 warning.

14 MS. JOHNSON: Down to the last three  
15 sentences. In the modern context of federal agencies'  
16 adoption of machine learning algorithms, we might note  
17 that integrating historic law enforcement or  
18 prosecutorial data may lead to efforts -- may lead us to  
19 direct efforts and resources to areas that have been  
20 historically heavily policed, right, sort of replicating  
21 the pattern in our society.

22 Similarly, law enforcement agencies that  
23 use facial recognition technology in a variety of  
24 context may discover as did the authors of the darker  
25 shades or gender shades study that those with darker

1 skin tones may not be as easily identified using facial  
2 recognition technology.

3           These kinds of implications of bias by the  
4 algorithm that's presumed to execute based on neutral  
5 data are issues that we must continue to explore,  
6 carefully evaluate and effectively regulate which may  
7 mean submitting impact statements requiring regulated  
8 entities, impact statements regarding the algorithms'  
9 use and integration or other interventions to ensure  
10 fairness.

11           MS. FELDBLUM: Thank you. Clearly, we're  
12 enough on the way (unintelligible) in terms of where we  
13 are on time. So David Super, let's see how your audio  
14 is doing. And it's not. And I sent an e-mail. So  
15 would anyone on ACUS please see about e-mailing or  
16 calling David and seeing whatever you can do in terms of  
17 helping? And sometimes, as people know who are  
18 listening, I'm sure who have been on these, I don't know  
19 if sometimes it helps to sign off and sign back on, but  
20 as a panelist, you may not want to do that. So sending  
21 out the request to ACUS to help David.

22           Okay. So Alex, I'm going to go to you  
23 instead and take it away, and actually, we'll follow  
24 very nicely on what Kristin has been talking about.

25           MS. GIVENS: Sure. And David, feel free to

1 say "test, test" while I'm speaking if you need to keep  
2 testing your audio. I won't be distracted. So I'm  
3 going to turn us -- I'm actually covering two different  
4 topics in my remarks today. One is going to focus on  
5 benefits determinations and then the second is going to  
6 pick up on employment, which draws on the example that  
7 Kristin just talked about.

8           In the benefits section, the piece that I  
9 will focus on is the increasing use of algorithms to  
10 help inform eligibility determinations for benefits  
11 programs. This is happening at an increasing number of  
12 state programs both in the United States and around the  
13 world. And in many instances we're seeing devastating  
14 effects from errors and miscalculations in how these new  
15 tools are developed and deployed.

16           For those of you who are looking for  
17 further reading or kind of a user- friendly guide to  
18 this, one of the most detailed accounts of these types  
19 of issues can be found in Virginia Eubanks' book  
20 "Automating Inequality". And I'm going to touch on one  
21 of the case studies that she raises there, because it's  
22 a very useful illustration.

23           She writes very powerfully about how the  
24 massive systemic problems that arose in Indiana in the  
25 mid-2000s when the state moved to automate all of their



1 welfare eligibility processes. There were record  
2 numbers of errors in the transition, for example, people  
3 being required to resubmit all of their documentation  
4 establishing eligibility for services. And if there  
5 were errors in the patients's record as a result of  
6 that, it created a finding of failure to cooperate which  
7 led to automatic termination of benefits.

8           From 2006 to 2008 the State of Indiana  
9 denied more than one million applications for food  
10 stamps, Medicaid and cash benefits, which is a  
11 54-percent increase in rejections compared to the three  
12 years prior to the switch to automation. It's a really  
13 important number when you actually think about what the  
14 human impact is in, not just outright rejection, but  
15 even delays in issues like food stamps or Medicaid or  
16 other cash benefits. These are vital services that  
17 people depend on. And what we see is a really serious  
18 human impact that comes from these changes.

19           The Indiana story is one of experiment.  
20 We're seeing an increasing number of these issues  
21 reported in various programs in the United States and  
22 the United Kingdom, Australia and around the world. I  
23 think it's hopeful as we talk about things to think  
24 about a brief taxonomy of how problems can arise. Some  
25 problems arise from shared flaws in data entry or

## \*Not Reviewed for Errors\*

1 database linkage. So errors in systems transition from  
2 one system to another.

3           These are perhaps inevitable, but when they  
4 scale into massive problems when the systems lead to  
5 automatic suspension or termination of benefits. And  
6 when we think about who is most impacted by those, they  
7 are the most vulnerable members of our communities. But  
8 there were other problems beyond just those technical  
9 questions of translating data from one set to another.  
10 Other problems arose from design flaws that come when  
11 you formalize benefit policies into the code that these  
12 programs need to operate in.

13           For example, in the mid-2000s there was an  
14 instance in which a California program cancelled  
15 Medicaid for over 5,000 qualified beneficiaries because  
16 they failed to obtain annual redeterminations of their  
17 eligibility. In that instance, neither Federal Law nor  
18 State Law required annual redeterminations for some  
19 individuals, but it had been coded into the system. So  
20 what you had was people being penalized even though they  
21 were in compliance with the law.

22           We can call this a design error in some  
23 instances, but a more accurate statement is to really  
24 reflect that new policy decisions can be embedded into  
25 code sometimes unintentionally. And that can have

1 really devastating results, and in this area in  
2 particular that agencies and people that care about  
3 administrative law really need to focus on and care  
4 about.

5           If you indulge me, I'm going to go deep on  
6 one more case study to illustrate the use and the  
7 benefits system. The area that we have a particular  
8 project focused on at CDT is the use of algorithms and  
9 benefits determinations and how that impacts disabled  
10 people.

11           This example focuses on the use of home and  
12 community-based services, credits under the Medicaid  
13 system. And in this instance, there are actually a  
14 surprising number of cases that are already being  
15 brought around the country of people having significant  
16 reductions in benefits, sometimes having their  
17 eligibility revoked altogether after the adoption of new  
18 systems.

19           In the Armstrong case out of Idaho, a  
20 series of decisions that came out in 2016 and 2017,  
21 Plaintiffs were a class of adults who had developmental  
22 disabilities who were eligible for home and  
23 community-based services that were funded through  
24 Idaho's Medicaid Program. In 2011 Idaho switched their  
25 system to a new algorithm-driven program that worked

1 like this. So a human would visit the individual and  
2 complete an assessment form with track boxes  
3 representing the individual's needs.

4           So for example, the form would asked about  
5 feeding and ask the assessor to rate the person's need  
6 for assistance in feeding on a scale of 1 to 4. The  
7 person would then manually enter that data into a  
8 digital budget tool which automatically calculates what  
9 Medicaid would pay to cover the need. The budget tool  
10 would calculate a total assigned budget amount and  
11 generate an automatic notice that would tell the  
12 beneficiary recipient how much money they are permitted  
13 to use under their care plan.

14           The person could appeal that budget amount  
15 to a human, but the exception to the decision was  
16 granted only if they show an immediate threat to health  
17 and safety, which is a very high standard and a term  
18 that was undefined. And more importantly, that appeal  
19 was very lengthy, took months, people couldn't see the  
20 assessment forms where their needs were actually  
21 assessed, because the company asserted a copyright  
22 interest in it and trade secret interests as well. And  
23 then most importantly, when we think about who the  
24 recipients are in this instance, people with  
25 developmental disabilities, there was no support

1 provided for or financially covered for pursuing those  
2 appeals.

3           You can see the superficial appeal of  
4 adopting a program like this. There are arguments about  
5 how it helps ground determinations in data, about how  
6 this creates a more objective measure of translating  
7 needs into a budgetary amount that is allocated. But  
8 the switch had a significant impact on participants in  
9 the home services program.

10           On appeal, 62 percent of the decisions were  
11 increased following reconsideration. Again, what I say  
12 what is interesting about these programs is that these  
13 have actually gone to court, so there are judicial  
14 opinions analyzing what went wrong after extensive  
15 discovery. And in this instance, the discovery revealed  
16 really telling an interesting facts about the program  
17 that need to be on people's radar if you look in its  
18 face.

19           One is that there were very significant  
20 design errors, so the budget tool was developed based on  
21 3,500 participant records from earlier years, but of  
22 that sample, one-third were discarded for sample or for  
23 facial errors. So the data in there that was driving  
24 the algorithm was really egregiously flawed.

25           What the Court then found was that there

1 were also instances of very significant input errors.  
2 So the person that was in the home doing the assessment  
3 had to manually transfer their scores from a number of  
4 different pages to three separate worksheets that then  
5 went in to form the budget tool. There were huge --  
6 there were significant findings of human error in doing  
7 this, but remember, because the proprietary concerns  
8 that were raised by the company that developed this  
9 tool, Plaintiffs weren't allowed to review their sheets  
10 if it looked like there may have been an error in the  
11 system.

12                   Finally, there was no updating or auditing  
13 of this system, so the Court observed that, although  
14 Idaho knows that the tools needs to be recalculated  
15 annually, basically to appropriately match needs to what  
16 the budgetary allowance should be, Idaho wasn't doing  
17 that. And really importantly, no auditing. So Idaho  
18 had never checked to determine how many participants  
19 were actually assigned insufficient budgets.

20                   Because these cases are going to court,  
21 we're starting to see a body of case law develop around  
22 this. It's grounded in the Goldberg v. Kelly precedent  
23 establishing that welfare recipients have a right to  
24 adequate hearing before their benefits can be terminated  
25 and that that process includes timely and adequate

1 notice and fair hearing.

2           So this has given Medicaid recipients a  
3 hook to challenge the programs that are being adopted  
4 when these types of flaws are being found. Sadly, a  
5 remedy has been much harder to come by, so thinking  
6 through how do we actually get these tools to work well  
7 still seems to be alluding many people and their smart  
8 minds that are really working on hard on this. But  
9 again, for those of you who work in relevant government  
10 agencies and also for administrative law professors,  
11 this is a fascinating area of the law, a fascinating  
12 series of cases that are unfolding that I highly commend  
13 to your attention.

14           And I should say that CDT will be  
15 publishing a report on this exact issue analyzing this  
16 range of cases in the coming months. And so that will  
17 be out there as a resource for folks to reference.

18           I'm going to pivot, Chai, if you'll allow  
19 me -- or should I pivot to employment now or should I  
20 wait for David?

21           MS. FELDBLUM: Let's see about getting  
22 David on and then we'll see our time. And by the way,  
23 folks, I see one question on the question check box.  
24 Please go ahead and put in your questions so that we can  
25 make sure to answer them. And David, I see we've got

1 the old-fashioned phone here calling in. So let's see  
2 about hearing you.

3 MR. SUPER: Can you hear me?

4 MS. FELDBLUM: Yes, we can. Go right  
5 ahead.

6 MR. SUPER: Great. Well, I apologize for  
7 all these technical difficulties. My computer says I'm  
8 on, the application says I'm on, but I wasn't on. In  
9 any event, I want to talk about a particular problem in  
10 SNAP, the Supplemental Nutrition Assistance Program,  
11 that replaced food stamps. And it concerns something  
12 called SNAP trafficking. This is the idea of trading  
13 SNAP benefits for something other than eligible food at  
14 an eligible store, because people have severe food needs  
15 but also severe needs for other things like toilet paper  
16 and soap and whatever that SNAP doesn't cover.

17 This is something that happens in small  
18 numbers, people's benefits are so small that they're  
19 generally used up on food. USDA studies show that the  
20 trading of benefits for something else is rare, but it  
21 does happen and the program tries to stamp it out. And  
22 the story I want to tell, I think, has two basic lessons  
23 to it. One is how algorithms can be unfair, and the  
24 second is how an algorithm that is unfair but not very  
25 important can become a lot more important and do a lot



1 more damage with its unfairness.

2           The starting point is that with the  
3 conversion of food stamps into SNAP and everyone having  
4 electronic benefits is an enormous volume of data about  
5 transactions made with SNAP and stores and recipients.  
6 USDA obviously can't investigate everything and everyone  
7 so they have used algorithms to narrow in on what are  
8 thought to be suspicious transactions. Unfortunately,  
9 what this ends up doing is identifying transactions that  
10 are abnormal, that are outside the usual patterns, but  
11 not necessarily in suspicious or dishonest ways.

12           For example, someone drives past a large  
13 supermarket, a Kroger or Safeway or whatever, to go to a  
14 smaller store and buys a lot of their food there. That  
15 is seen as potentially trafficking, that they know  
16 someone at the smaller store who will buy their SNAP  
17 benefits for cash. Possible, but it also may mean that  
18 that store is the one that stocks the food that their  
19 ethnic group enjoys and values and that the supermarket  
20 doesn't.

21           So it identifies people, some people who  
22 probably are trafficking, but it also identifies  
23 immigrants, it identifies people from racial and ethnic  
24 minorities, it identifies people who are relatively  
25 informal and value shopping from someone who maybe

1 speaks their language if their first language isn't  
2 English or who understands other cultural preferences  
3 that they have.

4           Many of the other items in these  
5 trafficking-prone profiles that USDA's developed have  
6 similar dual purposes. They're not irrelevant to  
7 trafficking, but they also identify informality or  
8 people with ties to subcommunities rather than to the  
9 broad mainstream that shops at Kroger's. And this was,  
10 I think, has always been a problem, it has -- it is not  
11 helpful to have any algorithms in government that target  
12 people who are doing nothing wrong other than being  
13 members of a subgroup, such as immigrants or an ethnic  
14 minority, but it's gotten a great deal more significant.

15           Originally, this was used at the very  
16 beginning of the process to identify stores that would  
17 be investigated. A store that had a large number of  
18 transactions that were seen as suspicious under these  
19 algorithms would have an undercover investigator sent  
20 in, they'd try to sell food stamps or SNAP benefits for  
21 cash. If they were successful, they'd criminally charge  
22 the store, and part of the plea bargaining they'd get  
23 the store to name the people who had sold food stamps  
24 there. Now, I mean, not a flawless process, but a sane  
25 one, a sensible one, one that one can start with.

1                   However, after the 911 attacks U.S.  
2 attorneys around the country lost interest in SNAP  
3 trafficking and were no longer willing to bring criminal  
4 charges in these cases, and without criminal charges  
5 there is no plea bargain. So the program ended  
6 upstanding on its head.

7                   And now, someone being flagged, an  
8 individual recipient being flagged for these  
9 transactions and shopping at a store that is believed to  
10 be trafficking is used as a basis to disqualify people  
11 from SNAP. And often, because trafficking is criminal,  
12 what happens is not even a Goldberg hearing, as was  
13 mentioned before, but rather a fraud investigator often  
14 armed, often wearing a badge, tells the recipient on the  
15 basis purely of the algorithm having flagged them as  
16 doing things that are suspicious, that the government  
17 has been (inaudible) that they will have to sign a  
18 confession unless they want to be prosecuted criminally.

19                   In almost all of the country, criminal  
20 defense lawyers do not understand SNAP, do not  
21 understand trafficking, do not understand the  
22 algorithms. And if people are prosecuted criminally,  
23 they will almost certainly have to plead to something  
24 and get a criminal record. So people say, oh, you're  
25 only going to throw me off the program I use to feed my

1 family for a year? Well, that's pretty bad, but it's  
2 better than a criminal record. Where do I sign?

3           So the bulk of these things don't go to any  
4 sort of hearing. If they did go to a hearing, people  
5 are not represented, and even if they are represented,  
6 the government refuses to share information underlying  
7 these algorithms that could be used to impeach them. In  
8 essence, the fraud investigator says I am an expert in  
9 fraud, I trust the algorithm and the algorithm says that  
10 Mr. Super here is guilty, and that's the end of it.

11           MS. FELDBLUM: Not -- not a good story,  
12 right, in terms of any of these stories. So actually  
13 we're going to end with -- I mean, I want to leave 15  
14 minutes for the question and discussion. So Alex is  
15 going to have a few things to say about employment  
16 issues and then Kristin, a few things to say about  
17 commenting on regs which is, of course, our favorite  
18 activity for many of us on this call. So Alex.

19           MS. GIVENS: Sure. Well, we're in luck  
20 because Kristin teed this up really beautifully talking  
21 about the Amazon example. So yes, to pivot from my  
22 earlier remarks about benefits, another area that we  
23 work on is the use of AI in hiring. There's an  
24 increasing amount of reliance on AI in various aspects  
25 of the employment life cycle. So this can range from

1 determining who sees certain job ads on social media  
2 services to screening resumes and assessing candidates  
3 to reviewing employee performance on the job and far  
4 more as well, assigning shifts, et cetera.

5 I'm going to focus on the use in hiring  
6 because hiring, of course, is a gateway to economic  
7 opportunity -- is the gateway to economic opportunity.  
8 And there is an increasing use of these tools. To give  
9 it a little bit more of a flavor, Kristin used the  
10 example of resume screening tools that can be used to  
11 help reduce the stack from a thousand applicants for a  
12 job to a more manageable level for humans to review, and  
13 some of the problems that can arise there.

14 There are also examples like assessments  
15 that are based on interactive games so where people will  
16 go through a series of exercises on a computer screen  
17 and their performance on that exercise will be compared  
18 to a sample set, a pool of ideal candidates as to how  
19 the test thinks a person should respond. That also  
20 comes up in the realm of video interviews, so there's at  
21 least one company that's marketing video interviews and  
22 then purporting to run AI analysis on your vocal  
23 modalities and your facial expressions in the course of  
24 that recorded interview, and other examples besides this  
25 as well.

1                   In each of these instances the algorithmic  
2 piece of this, and where the AI fits in, is in analyzing  
3 these tools against an idealized set of traits or a  
4 profile that's been associated by the designers with  
5 good fit for the job. The appeal for the employers is  
6 clear, right, so vendors market these tools as  
7 evidence-based hiring assessments. They claim that they  
8 make the process more objective than human review and  
9 may even help reduce bias. For example, the gamified  
10 assessments really are very aggressively marketed as  
11 being alternatives to traditional in-person interviews  
12 where human bias can skew the outcome.

13                   In our work we look at this and say that  
14 that may be while in theory, but is still very  
15 problematic in terms of the execution for many of the  
16 reasons that Kristin alluded to in the Amazon example.  
17 When you think about what the training data set is for  
18 these tools, in very many instances what companies are  
19 doing is drawing on a sample from their existing  
20 employees. That means that existing patterns of  
21 inequality discrimination are perpetuated into the  
22 future in ongoing hiring decisions.

23                   In addition, not only do you have the risk  
24 of an individual HR interviewer having bias, but we are  
25 now thinking about testing at scale. So value judgments

1 about what skills and what abilities are required of  
2 somebody are now being applied at a large grand scale,  
3 sometimes not just at a company level, but when it's a  
4 vendor that is selling very similar products across  
5 companies, across entire industries or fields. That is  
6 a very dangerous recipe that I find we need to focus on  
7 very significantly.

8           The last piece I'm actually going to cut my  
9 remarks short just because I know you want to have time  
10 for discussion. The last piece that I will flag on  
11 this, and I think it's a good one for discussion, is  
12 that there is a lot of conversation around testing for  
13 bias in these tools. The hiring area is one where we're  
14 hearing probably the most about it, because the vendors  
15 are very eager to reassure employers that they have  
16 heard the Amazon example, they've heard other instances  
17 and they're taking corrective measures. I'll just put a  
18 flag in there that it's far more problematic than it  
19 sounds. There isn't an easy way to test who your  
20 algorithm is screening out and what the consequences  
21 are. And so we need to be really careful when we think  
22 about that dynamic as well.

23           MS. FELDBLUM: Thank you so much. Last  
24 sort of case study example, Kristin, talk to us about  
25 reg tech.

1                   Nope, unmute yourself. Very good to mute  
2 when you're not talking. I try to do that.

3                   MS. JOHNSON: Apologies. Finding it when  
4 you have a thousand apps open complicates it, right. So  
5 now I've revealed what you would see in the closet of my  
6 computer desktop if I shared my screen. But Alex's  
7 comments perfectly dovetail what the reflections I will  
8 share here at the end of the panel.

9                   So my reflections will focus on  
10 highlighting the tensions, if you will, that we've  
11 talked about today, that algorithms, in particular  
12 machine learning algorithms, offer many and efficient  
13 and arguably accurate and effective mechanisms of  
14 executing a rote task (inaudible) in the context of  
15 algorithms, it is imperative that we are thoughtful  
16 about the effects of applying or deploying the  
17 algorithms.

18                  And the final example that I will describe  
19 today relates to several points, that Alex just  
20 mentioned as well, that sort of grow out of some of the  
21 concerns that Alex described. So the final case study  
22 I'll reference is administrative agencies' integration  
23 of algorithms or artificial intelligence in the machine  
24 learning tools in the context of customer service or,  
25 more broadly, we might describe it as the notice and



1 comment period of the rule-making process. We could  
2 also imagine similar platforms being deployed in the  
3 context of complaints.

4           Earlier in my comments, I referenced the  
5 CFPB, the Consumer Finance Protection Bureau, and the  
6 platforms that we can imagine they will deploy that  
7 would solicit comments from consumers raising flags  
8 regarding sort of predatory practices, for example, in  
9 the lending -- in the consumer lending space, right. So  
10 how would artificial intelligence be integrated into  
11 platforms for these two purposes?

12           Well, in the context of the notice and  
13 comment period in the rule-making process, we could  
14 imagine agencies soliciting directly from consumers in a  
15 way historically that was delayed or at least slowed by  
16 the need to receive the comments from the consumers or  
17 from various regulated entities directly, whether they  
18 be by letter or whether they be directly by telephone  
19 commentary. In either case, we can facilitate the  
20 development of thoughts that would essentially  
21 efficiently review thousands of comment letters or  
22 review thousands of consumer complaints instantaneously  
23 almost, and sort of attempt to categorize those  
24 complaints or comments in a way that is machine  
25 motivated, right.

1           So the machine learning algorithm would  
2 carefully review each of the comments or letters and  
3 attempt -- or complaints -- and attempt to classify them  
4 in the first instance based on the substantive remarks  
5 that are made in those comments or complaints and  
6 attempt to produce a report that would enable the agency  
7 to more efficiently review what the concerns of the  
8 citizens might be or regulated entity might be.

9           Well, a number of challenges arise  
10 immediately with this type of automated customer service  
11 interface. So much like Alex was describing earlier in  
12 the context of screening interviews, first, the training  
13 data set that was used to train the algorithm may not  
14 effectively capture the comments, concerns or complaints  
15 of certain groups in our citizenry.

16           So if someone's first language is not  
17 English, if the person's lexicon isn't sort of  
18 consistent with what we would expect them to use in  
19 terms of commonly-adopted language to describe a  
20 concern, those concerns might be under-included, right.  
21 So we can imagine immediately that deploying the bots  
22 that might facilitate customer service or receive  
23 comments or complaints as being unlikely to include or  
24 possibly -- sorry, likely to exclude and, therefore,  
25 under-inclusive of some of the concerns from certain

1 groups within our community.

2           They may also misread sort of volumes of  
3 information. So were grassroots groups mobilized to  
4 disburse a significant number of similar comment  
5 letters, the bots that facilitate classifying complaints  
6 or comments might misread that as data that has been  
7 generated by a bot, in fact, faking a comment, letter or  
8 faking a complaint or faking concern. So carefully  
9 distinguishing between what is a community grassroots-  
10 based movement and what might otherwise be some type of  
11 campaign deployed by a third party that isn't generally  
12 reflecting what citizen concerns is one of the kinds of  
13 issues we can imagine arising.

14           And therefore, as a result, we are worried  
15 or concerned that there may be over-inclusion, right, of  
16 certain groups because the bot is unable to effectively  
17 distinguish between the kinds of concerns that are the  
18 types that we want to include and integrate into our  
19 thoughtful analysis in these context, and those that we  
20 would exclude because they are the results of automating  
21 a process and permitting others in our society to deploy  
22 technology in responding to that process.

23           So these are just some high-level thoughts  
24 and concerns about what could happen if we integrate  
25 artificial intelligence technology into the notice and

1 comment or complaint processes as they currently exist.  
2 But I think they illustrate a number of the concerns in  
3 the context of the agencies' actual deployment of  
4 artificial intelligence as we've talked about over the  
5 course of our panel today.

6 MS. FELDBLUM: Thank you. And we got these  
7 case studies by 2:45. So we're going to be able to do  
8 15 minutes of conversation. And I'm going to pull out  
9 one of the questions that was asked. And then before  
10 you answer, I'm also going to make a few observations  
11 from when I was a Commissioner at EEOC and we were  
12 dealing specifically with employment issues.

13 So the question is; what are the thoughts  
14 about setting up a federal agency for oversight of these  
15 AI/ML, you know, machine learning artificial  
16 intelligence algorithmic black boxes? Okay, so that's  
17 the question.

18 And I want to make these three observations  
19 and get your comments on these observations. One is  
20 that companies are going to use AI, right. So in terms  
21 of the issues that you raise as concerns, in terms of  
22 possible responses, well, I just made that as an  
23 assertion but I guess I want to ask it also as a  
24 question. Do you think that one of the facts on the  
25 ground, people who care about these issues have to take

1 into account is that you're probably not going to be  
2 able to deal with it by not having these AI/ML  
3 approaches being developed?

4           The second piece is so much of this is from  
5 bias that's been there before -- you know what and David  
6 (echo/unintelligible) -- your phone is muted.

7           Okay. So the second is they have to use  
8 what is already there. That's what they're going to  
9 tell you. So what are the approaches that you can do to  
10 undo that, right. And then finally, my observation  
11 again, from EEOC is that there's really not a lot of  
12 conversation between the people who are substantively  
13 trying to use these AI tools and the tech people who are  
14 building it. I mean, it's just they're different worlds  
15 and different conversations. So what are the  
16 possibilities for overcoming that?

17           So I guess that's my three questions (echo)  
18 when we think about this thought of federal agencies.  
19 So Alex, I'm going to maybe start with you. Kristin and  
20 then David.

21           MS. GIVENS: Sure. I want to answer all  
22 your questions but I'm not going to. I'm going to  
23 restrict myself. So first, on the AI commission. In my  
24 mind we need an all-of-the-above approach. We need more  
25 expertise and the benefit of centralized expertise

1 thinking about the challenges raised by AI. But we also  
2 need to think about AI's impact in specific sectors. So  
3 to me, the EEOC has to be thinking about the use of AI  
4 in hiring and it can't outsource that to a central AI  
5 commission that's going to do the thinking for it. You  
6 need the agencies, whether it's HUD, whether it's CFPB,  
7 you name it, you need the individual agencies that  
8 police these silos on the ground.

9 I can think of far greater understanding of  
10 how algorithmic systems are impacting the issues that  
11 they are here to serve the American people on. And that  
12 is kind of Core Mission Number 1. I do think there are  
13 benefits to coordination across agencies in some manner.  
14 Historically, the Office of Science and Technology  
15 Policy in the White House would help play that type of  
16 role. There are other commission structures that have  
17 been suggested in Congress that could help play a  
18 coordinating function so that agencies can learn from  
19 one another.

20 That conversation is happening. ACUS  
21 itself is doing a wonderful job helping agencies think  
22 about it. But I do think we need a more robust  
23 infrastructure, and very importantly, one that is  
24 thinking not only about affirmative uses in AI, right,  
25 so a lot of the narrative right now coming out of the

1 executive branch is around just how do we win the race  
2 for AI and how are we kind of encouraging strengthening  
3 these tools. We also need the agencies that are the  
4 cops on the ground, policing for bias, policing for  
5 discrimination to have a far better grounding in how AI  
6 is affecting their work.

7           On your three questions, I may just engage  
8 with Question 2, because I want to hear what the other  
9 panelists have to say, which was about how do we get  
10 over the fact that systems, of course, just replicate  
11 the bias in the systems that they learned from, right,  
12 that's kind of an inherent flaw built in here is that if  
13 you're reliant on teaching assistance based on training  
14 data, garbage in leads to garbage out.

15           So there are a couple different ways to  
16 think about that. I think, first of all, in the reg  
17 tech example, there needs to be really thoughtful  
18 efforts on how you approve the range of training data so  
19 what natural language processing looks like. If you are  
20 learning from Twitter in general or from Facebook  
21 streams, you're going to get access to a far broader  
22 range of dialogs and conversational techniques than you  
23 will if you are just studying, you know, the Oxford  
24 English dictionary, right.

25           And so I think there's creative work to be

1 done there and there are movements in the computer  
2 science field that are working about these issues. But  
3 the other piece of that, I think, is a really thoughtful  
4 conversation about when we need to rely on these tools  
5 and when there should be more thoughtful intervention.  
6 And employment is a perfect example of this. I really  
7 question whether the right way to hire employees is to  
8 see how your current employers are doing on a game and  
9 then hire people that play the game like they do, right.

10           Where is the analysis that is actually  
11 looking at what are the essential functions of the job?  
12 Like a real job analysis of what are the skills that are  
13 needed to perform this role, how do we measure whether  
14 somebody has these skills, and how do we do that in a  
15 focused and applied way. So when we work on these  
16 issues, one of the things that we really caution people  
17 against is just the shiny object of somebody, you know,  
18 they're descending from heaven telling you they're going  
19 to fix all of your hiring problems, because here's just  
20 a tool that will magically sort through people.

21           We don't get that, like you don't have that  
22 luxury as an employer. The responsibility's on you to  
23 really think through what are you testing people for,  
24 what are the skills that you need and how do you measure  
25 those. And I would argue that AI may be a small piece



1 of that sometimes, but it cannot be the full answer and  
2 employers and vendors need to be far more thoughtful  
3 than they currently are.

4 MS. FELDBLUM: Great. So we have about 8  
5 minutes left. So Kristin, if you could give us some  
6 thoughts and then David on these issues.

7 MS. JOHNSON: Hi. So I am so grateful for  
8 those questions, Chai. I want to start with your first  
9 question which essentially asks whether we could  
10 anticipate that the businesses and other institutions in  
11 our society have adopted various forms of algorithms and  
12 that the movement toward adopting those types of  
13 platforms is one that is here to stay; not likely to go  
14 away in the near future. And I think that that's a fair  
15 observation.

16 I think it's a fair observation for some of  
17 the reasons that we've indicated in our discussion  
18 regarding what some of the benefits of artificial  
19 intelligence might be. So we've signalled that there  
20 certainly is something more efficient about relying on  
21 artificial intelligence, and that would be highly  
22 attractive to the average business or institution or  
23 federal agency, right, being more efficient at executing  
24 a task, in particular a rote task, for which the  
25 consequences of relying on the algorithm might be less

1 significant or severe is a highly-attractive pathway for  
2 many types of firms and institutions.

3           The challenge arises, I think, as Alex and  
4 David both point out, and as I hope to highlight as  
5 well, with the consequences of relying without  
6 appropriate checks and balances on science -- or on  
7 algorithms and machine learning algorithms as a form of  
8 science, right, wholly entrusting as the futurists  
9 might, the notion that the platform itself can perform  
10 as desired.

11           And some of the debunking that myth  
12 comes -- in order to debunk that myth we must recognize  
13 that artificial intelligence may not always be as  
14 intelligent as we would like for it to be. Therefore,  
15 the human intervention, the human in the loop really  
16 creates an opportunity for us to carefully evaluate what  
17 the probability in terms of outcomes might be for our  
18 society and the ethical implications in particular.

19           So I'll leave you with one last point of  
20 reflection that really kind of ties some of our examples  
21 together. In the last several weeks a number of  
22 employers and firms have begun to rely on contact  
23 tracing, digital contact tracing executed through  
24 privately-acquired platforms that Alex is describing  
25 that may have been historically deployed or at least

1 were ramping up and focused on hiring or other elements  
2 of the employment cycle are now -- or technologists and  
3 developers focused on those, are now focused on using  
4 this technology in a different way that would impact the  
5 broader citizenry in the context of a public health  
6 pandemic.

7           We have so many questions about the uses of  
8 this technology that, as we begin to think about  
9 deploying it in this type of sphere, it is critical that  
10 we have thought through and began to create appropriate  
11 checks and balances, because the consequences are  
12 certainly likely to be deeply felt by some of the most  
13 vulnerable and those who are marginalized in our society  
14 and our economy. So as we think about integrating this  
15 kind of a technology in additional areas of our society,  
16 we have to appreciate it won't be going away, but there  
17 certainly must be guardrails that direct us in the  
18 appropriate uses of the technology.

19           MS. FELDBLUM: Great. And so David, in  
20 terms of reactions to the questions, as well as your  
21 thoughts about setting up this federal agency for  
22 oversight and probably technical assistance.

23           MR. SUPER: I agree that we need a  
24 all-of-the-above approach, that this is a huge problem.  
25 When I started working on food stamps and antipoverty

1 program, the big obstacle is the lawyers. And as the  
2 lawyers constrained everything that happened, everything  
3 had to be cleared through the lawyer and you had a balky  
4 lawyer and nothing happened.

5           Now, the lawyers are pretty marginal; it's  
6 the programmers. And because what really happens is the  
7 algorithm, which doesn't get cleared through the  
8 lawyers, because how, the lawyers become pretty  
9 irrelevant. They write their rules and everyone thinks  
10 that's nice and no one pays any attention to them. It's  
11 between the operations people and the programmers.

12           Once upon a time, the Federal Government  
13 saw the importance of law and set up a super agency to  
14 deal with that called the Department of Justice. I  
15 think we're rapidly getting to a point where technology  
16 and automated decision making is as important and also  
17 needs a super agency. Not that all wall work is done in  
18 the DOJ, not that all tech work would be done in such an  
19 oversight agency, but it is necessary.

20           The other thing that I think we absolutely  
21 need to do is deal with transparency. There are law  
22 enforcement concerns about what I'm talking about, there  
23 are trademark and -- trade secret rather, and copyright  
24 issues about the in-home services assessment forms. And  
25 we need to make a decision that if this is going to be

1 part of government, and it's going to be so dramatically  
2 outcome determinative that those concerns for secrecy  
3 are simply invalid and need to be overrun. And if  
4 people don't want to expose their products to public  
5 scrutiny, then they're welcome to not contract with the  
6 government.

7 MS. FELDBLUM: Great. So I have one  
8 remaining quick question for Alex and then some  
9 concluding comments, which is one of the questions that  
10 came in Alex is, do you have a date for when that report  
11 is going to be issued that you referenced on employment  
12 in people with disabilities?

13 MS. GIVENS: My team would kill me if I  
14 said yes, because it would put them to a public  
15 deadline, but it is coming soon. We had a wonderful  
16 workshop in January of all of the major litigators that  
17 have been bringing these cases, including the people  
18 that have served as the main plaintiffs which is a major  
19 undertaking when you're kind of taking on this extensive  
20 litigation against the State.

21 So we've done that work. It will be coming  
22 soon. A matter of -- next month, let's say that, that's  
23 safe enough. Right?

24 MS. FELDBLUM: That's safe enough and on  
25 behalf of your staff, thank you.

1 MS. GIVENS: I should just say it'll be  
2 available at cdt.org, not to do a plug, but hopefully  
3 that's useful or useless if people are looking.

4 MS. FELDBLUM: No, no, no. I've known it  
5 since it got started. So and also, I know that ACUS  
6 will be, I'm assuming will be making materials available  
7 and hopefully that among others.

8 So I -- in terms of concluding remarks, I  
9 would come back to where I started. I hope that folks  
10 have learned at least something new that they didn't  
11 know, that you have some ideas, certainly any lawyers  
12 and agencies to say, no, I do need to be relevant and I  
13 do need to be part of this conversation. And then  
14 future ideas for research and including research and  
15 work that ACUS can do.

16 Obviously, ACUS is in it already, but any  
17 other ideas that you have, I think, certainly I, the  
18 other members of ACUS and all the lawyers and academics  
19 who are working on this would appreciate, because this  
20 is a challenge. Just because it's a challenge doesn't  
21 mean that we don't face it and try to do something about  
22 it. So thank you Kristin Johnson, Alex -- and Alex goes  
23 by Alex, Alexandra Givens, and David Super for not only  
24 doing all this work, but sharing it with us in this  
25 panel. Everyone, have a good afternoon or morning

1 wherever you are. Bye now.

2 MS. JOHNSON: Thanks for --

3 (End of audio file)

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I, Carmel Martinez, TX CSR No. 8128, FPR No. 1065,  
do certify that I was authorized to and did listen to  
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that the transcript is a true record to the best of my  
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Dated this 7th day of August, 2020.



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Carmel Martinez,  
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