



ADMINISTRATIVE CONFERENCE OF THE UNITED STATES

**ARTIFICIAL INTELLIGENCE AND ADMINISTRATIVE LAW
DOCTRINES**
Challenges and Opportunities

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TRANSCRIPT
(Not Reviewed for Errors)

Panelists

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Moderator

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AUDIO TRANSCRIPTION OF
Administrative Conference of the United States
Artificial Intelligence and
Administrative Law Doctrines:
Challenges and Opportunities

1 MR. WIENER: Well, welcome everyone. I'm
2 Matthew Wiener, the Vice Chair and Executive Director of
3 the Administrative Conference of the United States.
4 Welcome to the second panel of our Symposium on
5 Artificial Intelligence in Federal Agency Programs,
6 which the Administrative Conference, or ACUS for short,
7 is cosponsoring with the Georgetown University Law
8 Center of Technology -- excuse me, Institute For
9 Technology Law and Policy.

10 Today's panel is on the relationship
11 between artificial intelligence and administrative law
12 doctrines. We have an outstanding panel lined up this
13 afternoon, which our moderator will introduce in a
14 moment. Today's panel will be -- is being recorded and
15 it will be transcribed. The recording will appear on
16 our Web site before not too long, along with the
17 transcript, and I hope everyone makes good use of the
18 transcript.

19 With that, let me turn it over to David
20 Vladeck, who's not only a distinguished member of the
21 Georgetown Law School faculty but also a Senior Fellow
22 of ACUS and a longstanding and very good friend of our
23 agency. David?

24 MR. VLADECK: Well, thank you, Matt. On
25 behalf of the Administrative Conference and Georgetown

1 Law School's Institute For Technology Law and Policy, I
2 want to welcome everyone to today's discussion of the
3 impact of the government's growing use of artificial
4 intelligence on our administrative state. The
5 Administrative Conference's commissioned report
6 government by algorithm, artificial intelligence in
7 federal administrative agency drives home that the use
8 of AI tools raise fundamental questions about how
9 agencies will perform their vital functions.

10 The report gives a clear-eyed understanding
11 about both the benefits and challenges caused by the
12 government's increasing use of AI. The report finds
13 that in many areas, AI tools are already substantially
14 increasing the efficiency and quality of government
15 decisionmaking and the delivery of services, but there
16 are still questions to be answered. And they include
17 the following: Algorithms are only as good as the data
18 they're trained on. They may fail to detect new
19 sophisticated frauds, perhaps significant error rates.
20 So one question is, what are the impacts of these
21 limitations?

22 Next, decisions made by algorithms are
23 opaque. There's an answer, but there's never really an
24 explanation, but reason giving is at the heart of the
25 traditional notions of due process and fairness. Should

1 agencies refrain from using AI in making decisions
2 involving individual rights until decisions can be
3 adequately explained? Algorithms need data. Much of
4 the data these days that's being collected by government
5 is personal data. Some of this is biometric data, can
6 be uniquely associated with an individual.

7 We tried China by becoming a surveillance
8 state, what impact will AI have on the United States?
9 Artificial intelligence tools such as border controlled
10 by AI machines and not the border patrol agents suggests
11 that AI may displace thousands of government employees.
12 Is that an acceptable tradeoff? AI technology is often
13 hard to use and there's often a mismatch between the
14 expertise of existing agency staff and the need for a
15 technology-proficient staff. Is this a temporary
16 problem or is this endemic?

17 And last but hardly least, the AI
18 technology government employs is often not government
19 generated or government owned. Increasingly, government
20 contractors are going to carry out core governmental
21 functions. What are the implications of government by
22 contractor? So these issues and more are the subject of
23 today's discussion.

24 We are fortunate to have the foremost
25 thought leaders on this issue as our panelists. You

1 will first hear from Cary Coglianese who is the Edward
2 B. Shils, Professor of Law and Political Science at the
3 University of Pennsylvania. He is also the founding
4 director of the Penn Program on Regulation and he's also
5 authoring yet another report on AI for the
6 Administrative Conference.

7 Next up is Professor Deirdre Mulligan who
8 is a professor at the School of Information at the
9 University of California at Berkeley. She's also
10 affiliated with Berkeley Centers on Long-Term
11 Cybersecurity and its Center For Technology, Society and
12 Policy.

13 Last, but hardly least is Arti Rai, who is
14 the Elvin R. Latty Professor and Founding Director of
15 the Center for Innovation Policy At Duke Law. She also
16 holds an appointment at the Duke-Margolis Center for
17 Health Policy.

18 So each of the panelists is going to take
19 about 5 minutes to introduce topics that they are
20 particularly interested in working on, and then we'll
21 open this up to some questions. So Cary, you're first.

22 MR. COGLIANESE: Okay. Thank you very
23 much, David, and thank you to the Administrative
24 Conference for hosting this session. I am a public
25 member of the Administrative Conference, and as David

1 said, I'm working on a report right now commissioned by
2 the Chairman on Artificial Intelligence and its use by
3 government agencies. I'll talk -- some of my remarks
4 certainly will make its way into the report and
5 certainly my report will be greatly informed by the
6 comments that Deirdre and Arti share as well.

7 Let me try to make four main points here at
8 the outset, just really points that I think are
9 fundamental to keep in mind and provide a good
10 foundation for discussion about the use of artificial
11 intelligence tools. So the first point is just
12 definitional. What is it that we're talking about here?

13 Algorithms, some people say, is what we're
14 talking about, but we're really talking about a very
15 small category of algorithms. And algorithms have been
16 with us since the dawn of humanity. Two plus two equals
17 four is an algorithm. My peach cobbler recipe is an
18 algorithm. Section 553 of the Administrative Procedure
19 Act is an algorithm for how an agency creates a rule.
20 Statistical analysis, regression models and all of that,
21 those are algorithms, too.

22 What at least what I'm talking about when
23 I'm talking about artificial intelligence is the use of
24 machine learning algorithms. This is a particular type
25 of algorithm that is very good at forecasting, making

1 predictions. And I think, like with other kinds of
2 statistical tools that make predictions, the point is to
3 try to identify something that's likely to happen in the
4 future or to give some kind of probabilistic assessment
5 of that event happening.

6 Unlike traditional statistical tools,
7 machine learning has, I think, two qualities that make
8 this conversation important to have. One quality of a
9 machine learning algorithm is that it is autonomous in
10 the type of variables that are selected and how -- and
11 then even sometimes the mathematical relationships
12 between them. It's not the variables that are selected,
13 the weights to be given to them, the mathematical
14 relationships between them, are autonomously generated
15 by the algorithm itself, rather than specified by humans
16 in advance as with a traditional regression model.

17 That automaticity, if you will, that
18 learning nature is one reason why it's -- the machine
19 learning algorithm has a second quality in that it's
20 more opaque. It's not as easily or intuitively obvious
21 how to explain the results that the algorithm achieves.
22 Unlike with a regression model, where you could look at
23 statistical weights on each coefficient and describe how
24 much of the variation is explained by a particular
25 variable, that's not as easily accomplished with a

1 machine learning model.

2 Machine learning typically also, I should
3 add, is really about correlation, not causation. And
4 that's another reason why it's hard to explain. It's
5 not possible, usually, to be able to say; because of A,
6 B occurs with a machine learning model. But these are
7 very highly accurate in many context, they're being used
8 a lot in the private sector, in the medical fields and
9 in many contexts have been shown to be much more
10 effective and accurate in making these predictions. So
11 that's the first point, just sort of what we're talking
12 about.

13 The second point that I think is fairly --
14 should be fairly obvious is that the kind of concerns
15 that David and other -- you know, David outlined for us
16 at the introduction and that we'll talk about here
17 today, are not distinctive or unique to machine
18 learning. So again, other kinds of statistical or
19 analytic tools have errors in them. Can they have
20 biases in them that come in through data? Yes, they
21 can. Can other statistical tools be used to support a
22 surveillance state, you know, raise privacy concerns?
23 Absolutely. Will there be other things that cause the
24 loss of jobs for people in society? Sure. I mean,
25 modern computers have done that. There's a lot fewer

1 typists employed by the government today than there was
2 50 years ago.

3 So that's really the second point is just
4 to say that we're not moving to a completely new world
5 with artificial intelligence. The problems that we're
6 going to talk about here today are problems that can
7 exist and have existed with other types of statistical
8 tools or methods of decision making.

9 Third point is that there is really, I
10 think, nothing at its core about machine learning that
11 should pose any insurmountable legal obstacles to its
12 use by government officials, assuming they're acting in
13 a responsible manner and careful about their development
14 of these tools in the same way that they should be
15 careful about their deployment and use of any other
16 tools. This is an argument I'm happy to get into
17 further, but I've made this in a couple of articles
18 recently; transparency and algorithmic governance in the
19 Administrative Law Review regulating by robot in the
20 Georgetown Law Journal work that I did collaboratively
21 with David Lehr.

22 So I'm happy to go into that, but I think
23 the basic idea here is that if you take any of the legal
24 concerns that people have raised about artificial
25 intelligence, it is, I think, possible to justify its

1 use with a careful work and analysis.

2 For example, let me just briefly say that
3 we're probably going to talk a lot about explainability
4 and the obscurity of algorithms. The standards that we
5 have for transparency right now under due process or
6 arbitrary and capricious review are pragmatic and not
7 absolute. And you can give an adequate reasons for why
8 a decision is made under a machine learning model, okay?
9 And I'm happy to get into that further.

10 Fourth and final point that I want to make
11 here at the outset is that when we are thinking about
12 the legal issues and the policy issues about artificial
13 intelligence, we need to always keep in mind; compared
14 to what? Artificial intelligence compared to what?
15 Well, if I were to tell you, you know, that we're going
16 to have governmental decisions made in a process that's
17 prone to error, fatigue, racial bias, delay,
18 inconsistency, you would probably say, if that's the
19 world that you want to advocate, we want to be very
20 cautious, we want to resist that kind of world. But
21 that actually is the world we have today with human
22 beings and their decision making.

23 So it is not as if the status quo is
24 perfect nor necessarily acceptable, especially today as
25 the nation realizes, even more acutely than perhaps ever

1 before in a more widespread fashion, the problems of
2 systemic racism, the implicit bias that human beings can
3 have. If we can -- if we can develop technological
4 tools that can overcome some of the inherent biases and
5 errors and inconsistencies that exist in human decision
6 making, I think we ought to be open to that, and again,
7 should not necessarily think about artificial
8 intelligence tools or machine learning algorithms as
9 some kind of brave new world, but actually as an
10 opportunity when used well to improve on the status quo.
11 Thank you.

12 MR. VLADECK: Thank you. Deirdre?

13 MS. MULLIGAN: Hi, thank you so much for
14 having me here today. I want to start just a little bit
15 more broadly. So I've been interested in the questions
16 of how technology embodies policy and what that means
17 for the mechanisms through which technology is brought
18 into government processes in a lot of different domains.
19 And to give a like non-machine learning example, I was
20 part of a team that had a National Science Foundation
21 grant for many years looking at the security, accuracy,
22 privacy and other sorts of implications of the move to
23 electronic voting systems.

24 And one of the things that came up there is
25 that counties were procuring machines that really didn't

1 meet public policy objectives. And to give a really
2 crystal-clear example, the early direct record
3 electronic voting systems basically collapsed casting
4 and counting. And so normally, right, we think about
5 marking a ballot and then that ballot is logically
6 independent of the system of counting, right, whether
7 it's individuals counting the ballots or it's a optical
8 scan system counting the ballot, we know we can audit
9 the counting process because we have the fixed ballots
10 to go back to.

11 Because there was no concrete description
12 of what it meant to be a ballot, when the developers
13 designed these direct record electronic voting system
14 what would happen is it would render a ballot on a
15 screen, you would select your inputs, and it would
16 incrementally add them to the counter, and then discard
17 the ballot, right. So if the purpose of having an audit
18 was to audit the counting process, the design of these
19 systems made it completely impossible. So if you said
20 could we have a recount, they'd say, sure, let's put the
21 button and we'll get the same answer, right.

22 And you could look at that as a real
23 failure of the technologist, or you could look at that
24 as a kind of failure at an institutional level for us to
25 kind of thought through, what were the assumptions in a

1 paper-based world and what were the new -- the way in
2 which we needed to kind of think through the design
3 implications in this new electronic world so that we
4 would still have the same level of kind of logical
5 independence between casting and counting that's
6 required for a meaningful audit, right.

7 And I just offer that as an example that,
8 while the questions around machine learning models and
9 the way in which they embed policy, I think, are really
10 driving this conversation about how do we think about
11 administrative law and technology. There are a lot of
12 other areas where we adopt technology where they embed
13 really profound policy choices that, I think, bypass
14 many of the mechanisms that we normally rely on for
15 scrutinizing them to make sure that they comply with or
16 embody the policy choices that we need them to reflect.

17 So I come to this conversation, at least in
18 part, by the Loomis decision which I think many of you
19 are probably familiar with, it involved the use of a
20 risk recidivism tool. I'm not going to go through all
21 the details, but the case ends up being appealed to the
22 U.S. Supreme Court. And the Solicitor General weighs in
23 on this case and basically says that the challenge to
24 the use of this compass tool is not a suitable vehicle
25 for looking at the question of whether or not risk

1 recidivism tools can basically be used -- be normed
2 differently for male and female offenders, because it's
3 completely unclear from the record below about how the
4 compass tool accounts for gender.

5 And for me, you know, that means this case
6 has gotten all the way up to the Supreme Court and
7 there's a lack of clarity in the record about how gender
8 is being used, right. And the debate was about was it
9 actually an attribute that was being used in the model,
10 or were there different scales being used for men and
11 women, right, both of which raise interesting questions,
12 but the problem is like there was no clarity in the
13 record, right. And this is a tool that had been put in
14 use in the system of justice, right. And to be that
15 raises such enormous questions about how we are
16 unboarding technology into various processes, whether
17 they're in the courts or in other administrative
18 agencies.

19 And that might not have been so troubling
20 if you viewed it as an outlier, but then there was some
21 additional work by Brauneis and Goodman in 2018 where
22 they looked at the way in which states and counties were
23 coming to use different sorts of algorithmic assessment
24 tools. And they found that government simply did not
25 have many records concerning the creation and

1 implementation of algorithms, either because those
2 records were never generated, or because they were
3 generated by contractors and never provided to the
4 governmental clients.

5 And this meant there were no records that
6 modeled design choices, data selection, factor
7 weighting, validation designs, and at a really -- at the
8 most basic level the governments didn't even have a
9 record of what problems the models were supposed to
10 address and what the metrics of success were.

11 And I think when we read the ACUS report
12 most recently, we see a similar strain here where there
13 was a -- there's a finding that for most government
14 applications, 61 percent, there was insufficient
15 publicly-available technical documentation to determine
16 with precision what methods were employed. In some
17 cases the agency description appears more like marketing
18 language or concerns of tools still under development.
19 In other cases agencies describe use of neural networks,
20 natural language processing or facial recognition
21 technologies, but do not provide enough technical
22 details to discern whether a use case is a simpler or a
23 more sophisticated version thereof, right.

24 And so we see like a lack of information
25 about what tools are being used. Now, the ACUS report

1 finds, I think, different variations of expertise in
2 different agencies, and it was really interesting to me
3 in the Brauneis and Goodman work at the state and county
4 level they find that most tools are being outsourced.
5 And I think one of the really interesting findings in
6 the ACUS report is that many of these tools aren't being
7 developed in house. But similarly, there's some real
8 questions, I think, about the extent to which both
9 agencies have the level of expertise available to make
10 good decisions about base models.

11 And secondly, the extent to which things
12 that are really core policy issues, and I would say
13 things, questions about how we operationalize target
14 values, the choice of model to use, thresholds, the
15 training data, where it is sourced from, how it is
16 cleaned, when it is updated, all of these issues require
17 both a profound level of expertise, but also because
18 they are essential policy choices, we also need
19 techniques to make sure that they are visible both to
20 the public in ways that allow for public participation
21 about such choices, as well as for agency staff, because
22 one of the things that we know if we want to maintain
23 some discretion in engagement is figuring out how agency
24 staff understand the outputs of models, understand the
25 reasoning of models, even if they can't understand the

1 inner workings of them, are essential for them to kind
2 of align well with agency mandates.

3 So I think an important part of this
4 question is not like what are the problems, but really
5 where can we look for solutions. And what I want to
6 suggest is that I really, at this point, think that we
7 need to figure out a way to create more centralized
8 communities of expertise within the government. The
9 rise during the Obama Administration of the U.S. Digital
10 Services and 18F, which provides kind of a skunkworks
11 effort that can be both developing resources and
12 guidance documents and methods for sharing expertise
13 across agencies is very important, coupled with the use
14 of things like impact assessments, but I also want to
15 suggest prototypes and other things that allow the
16 public to understand some of the policy choices that are
17 so knitted into the technical designs of these systems
18 are really essential for us to think about developing.
19 And I know my time is up. So I'm going to sit down.

20 MR. VLADECK: Thank you so much. Arti,
21 you're next.

22 MS. RAI: Well, thanks so much to my fellow
23 panelists and to the Administrative Conference and to
24 Georgetown Law for inviting me to this event and to
25 David for moderating. So I think that both Cary and

1 Deirdre have spoken eloquently and at a very acute way
2 about the ways in which database machine learning may or
3 may not raise challenges that are different from other
4 technologies, because as they've both pointed out, we've
5 had algorithms forever, including secret algorithms,
6 including somewhat opaque algorithms.

7 So Loomis, which involved an algorithm was
8 not a machine learning algorithm as far as I'm aware.
9 Now, we don't know for sure, because it was secret, but
10 most commentators believe it was not, repeat, not a
11 machine learning algorithm. So these issues, in lots of
12 ways, are not new.

13 I want to spend just a few minutes
14 highlighting some issues that do arise that are perhaps
15 a little bit newer, even in relatively utilitarian
16 contexts, that don't implicate individual rights and
17 bias to the same extent that some of the context to
18 which Deirdre was speaking, do implicate such concerns
19 of rights and bias. And I think these issues are not
20 entirely new, but they have to do with the fact that
21 database machine learning does involve such extremely
22 high levels of expertise. And in the context that I'm
23 going to focus on on the part of the private sector that
24 is going to agencies to get various rents; the economic
25 term for the types of things that the private sector

1 seeks from agencies.

2 So I'm going to focus on the patent system
3 of which I am extremely well versed in, but I think that
4 the context that I'm talking about, the patent context,
5 is not dissimilar from other contexts where very highly
6 learned, highly expert entities can seek a rents
7 including by using machine learning from agencies.

8 So let me, again, as I said, mention the
9 patent office as my specific use case. And then -- but
10 first show the general principles of the patent use case
11 illustrates and then get into, dive a little bit into
12 the specific case which was, by the way, in the ACUS
13 report. And so if you want to read it in greater
14 detail, the ACUS report has a chapter that draws from my
15 work on the patent office.

16 So I think the case study of the patent
17 office highlights two points that are generalizable in
18 commercial context that involve sophisticated players.
19 First, and this is in keeping with what's already been
20 said, effective use of machine learning by the public
21 sector will require real expertise, not necessarily
22 expertise to protect individual rights in all cases, but
23 actually expertise to deal with the expertise on the
24 other side that the agencies are faced with, because the
25 commercial context has involved very sophisticated

1 players on the other side. So that's one thing.

2 Then second, even in these cases that don't
3 involve individual rights in the same way as some of the
4 cases upon which Deirdre was focussed, the use of
5 machine learning will raise opacity issues, multiple
6 opacity issues, that can be flags for what, at least
7 some would say, are due process problems. Now, we may
8 not necessarily, all of us may not necessarily think
9 that these are particularly salient due process
10 problems, but certainly lawyers will raise them as due
11 process problems even when the entities that are being
12 affected are, you know, large, sophisticated
13 corporations.

14 All right. So let me talk about that
15 opacity piece in particular, because I think that is a
16 little bit new. And it's not that secrecy is new, it's
17 not that complexity is new, but I do think that database
18 machine learning combined with secrecy raises the stakes
19 to an even greater level of opacity. So here I'll bring
20 in my intellectual property background a little bit and
21 note that reverse engineering database machine learning
22 algorithms is, for the most part, a little bit harder
23 than reverse engineering ordinary algorithms.

24 And so as a consequence, if you can't
25 reverse engineer very readily and you don't have access

1 to any of the training data and the decision making is
2 very complex, that's going to create perhaps a slightly
3 greater level of opacity than we've seen in the past.

4 And that's where I think it's sort of the
5 combination of all the different types of opacity. It's
6 the complexity of opacity plus the secrecy of opacity,
7 neither of which individually was unique, but in
8 combination, I think, that level of opacity becomes a
9 little bit different from what we've seen in the past.
10 So the synergy is what I'm really interested in. And
11 this synergy really does come out in the patent case
12 that I have focussed my initial research, at least, on.
13 So let's turn to this patent examination case study.

14 So the patent office faces a really
15 difficult challenge. It gets hundreds of thousands of
16 patent applications a year and it has a very small labor
17 force to deal with those applications. And because it's
18 completely funded by user fees, not very much money
19 either, because users don't want to pay very much money.
20 All right. Unless you think, by the way, that bad
21 patents are an arcane issue that doesn't -- don't have
22 real-world social consequences, let me just throw out
23 one statistic that relates to drug pricing and bad
24 patents.

25 There's a recent study from Health Affairs

1 just came out in June 2020 that examined the extension
2 of patent term caused by questionable patents on just a
3 few drugs. And it found that patent term extension on
4 just five key drugs cost Medicaid programs about half a
5 billion dollars from 2010 to 2016. So questionable
6 patents on just five drugs; half a billion dollars. And
7 that's just Medicaid which is a very small part of total
8 health care spend.

9 So you know, these are real issues with
10 real social welfare consequences where the commercial
11 states are extremely high and we have extremely
12 sophisticated players on all sides, well, really on the
13 private sector side and then the public sector side has
14 to sort of strive to keep up, in other words, the public
15 examiner core.

16 Okay. So how does this work in terms of
17 trying to integrate machine learning into what the
18 Patent Office does. So there's pretty good evidence.
19 And one of my colleagues at Duke, Michael Frakes is
20 responsible for generating most of it, quite frankly.
21 But poor quality patents are granted, because examiners
22 just don't have the time to search for the prior
23 invention to determine whether the application covers
24 territory that is either not new or is obvious. So
25 that's where some of these bad drug patents come from,

1 for example, and he's got a recent paper on that as
2 well.

3 So machine learning could automatically
4 help find this prior invention to help with the time
5 problem. But it's going to be opaque, perhaps, what the
6 prior -- and how it finds the prior invention. And as a
7 consequence there are good patent attorneys who are
8 already very much in the mode of telling the patent
9 office you can't have anything that's opaque, because
10 that's a due process violation, and we are going to be
11 very suspicious if you try to implement any of that.

12 And as a consequence, the Patent Office,
13 which has been working on trying to implement machine
14 learning immediately put out this statement saying that,
15 oh, no, no black box for us, we're going to be
16 completely transparent. Well, of course being
17 completely transparent also means that you create
18 opportunities for gaming by the very sophisticated
19 players on the other side.

20 So what's happened? Well, the Patent
21 Office was, to its credit, very much on top of the idea
22 that machine learning -- could you believe these things
23 called concept semantic tools could be used. And so
24 they came up with this homegrown, so that Deirdre's
25 point is well taken that this was homegrown, it was

1 actually pretty good. It was a latent semantic analysis
2 tool called Sigma. Multiple problems.

3 First, it wasn't as transparent as the
4 Patent Office, the lawyers who prosecute patents before
5 the Patent Office, wanted. And that was probably for a
6 good reason, but nonetheless, that was a problem.

7 Second, the -- and this goes to expertise on the patent
8 examination core side. The algorithm was difficult to
9 use even by the geeky people at the Patent Office,
10 because those who were geeky but not in computer science
11 didn't -- couldn't use it well. So the biochemists of
12 the world weren't able to use it well.

13 So multiple problems, and as a consequence,
14 their homegrown algorithm, good as it was, didn't really
15 get off the ground. So then they have to try to
16 contract with the private sector and then the private
17 sector then adds the layer of trade secrecy on top of
18 complexity and opacity caused just by a complexity. And
19 they couldn't end up contracting with the private sector
20 contractor that was willing to give away all its trade
21 secrets essentially. And as we've just discussed, the
22 Patent Office had announced that it wasn't going to take
23 anything that had trade secrecy protection, because
24 that's not what the patent lawyers -- or they weren't
25 going to allow the Patent Office to do that.

1 So the Patent Office found itself in a box,
2 and I think this is a real problem for these
3 sophisticated commercial contexts where the public
4 sector is just racing to keep up with what the privacy
5 sector is leaps and bounds ahead in doing, including for
6 purposes of gaming the system. And so that is my
7 intervention for my 5 minutes. Thank you very much.

8 MR. WIENER: Okay. So this is a nightmare
9 for the moderator, because there's a consensus about too
10 many things. There's a consensus that the status quo
11 isn't great and that machine learning algorithms can
12 help. I think there's a consensus that there's an
13 expertise issue in government; that existing staffing
14 may not have the expertise to actually use these tools
15 to their best advantage. And third, there's an opacity
16 issue. You know, you can't interrogate a machine
17 learning algorithm, you just can't. They won't talk,
18 and you can't make them talk.

19 So I think what I'd like to get comment on
20 and we'll do 3-minute rounds this time, and we'll start
21 with Arti because she was so patient the last time
22 around. What impact does that have on how government
23 audit will follow? Do we need to have as some,
24 including Deirdre, have suggested, sort of a common core
25 of people who are expert who can then sort of help out?

1 Do we need to have embedded expertise in every agency?
2 Sort of how do we deal with that and how do we deal with
3 the opacity problem? Because again, machine learning
4 algorithms may be very expert in forecasting or making
5 predictions, but they also, you know, they may be wrong
6 or they may not be accurate at times. So Arti, you go
7 first.

8 MS. RAI: Great. So I'm glad you brought
9 up Deirdre's point about expertise, concentrating
10 expertise or at least having core expertise resources.
11 And I think that idea is a very good one. It seems to
12 me that having both centralized expertise and more
13 agency-specific expertise would be useful. Of course,
14 that's expensive and that's part of the problem --

15 MR. VLADECK: Right.

16 MS. RAI: -- that, you know, all of this
17 would be very expensive to generate, because as would
18 be, I think, as obvious to many people, individuals who
19 have this expertise are highly sought after in the
20 private sector. They can earn maybe 10X what they could
21 earn in the public sector in the private sector. And so
22 this is a very -- and I've seen personally and engaging
23 with various agencies situations where the person with
24 whom I was engaging left for a much higher-paying job in
25 the private sector. And so it's, you know, dispiriting.

1 I do wonder whether there's a possibility
2 of doing something that's a little bit just outside the
3 public sector, some sort of third-party certification
4 model, at least for certain machine learning areas. So
5 this comes to me because of some work I've been doing in
6 the healthcare space where the physicians and other
7 healthcare providers are thinking about how to set up
8 third-party certification organizations at least for
9 some types of machine learning systems so that every
10 hospital doesn't have to have that level of expertise.
11 And I wonder if that could happen in a way that would be
12 useful for government agencies as well.

13 As for the opacity issue, so yes, I think
14 opacity a really unique issue in terms for all the
15 reasons of secrecy plus complexity that I noted. I
16 think it's a trickier issue when you're talking about
17 sophisticated commercial players though than when you're
18 talking about individual rights, because a full
19 transparency with sophisticated commercial players gives
20 them opportunities to game the system, and that, I do
21 worry about. And that is where I wonder if, you know,
22 the fact that you have to contract out for trade secret
23 protected stuff is a good cover for -- at least in
24 certain contexts -- basically being able to hide that
25 algorithm from those who might use it to game the

1 system.

2 MR. VLADECK: Thanks. Deirdre?

3 MS. MULLIGAN: So I wanted to jump in, I
4 guess, first on -- there's another piece in the ACUS
5 report and they say that no agency examined in the
6 report had established systematic protocols for
7 assessing the potential for an AI tool to encode bias.
8 And to me, one thing that centralized expertise could
9 provide is some background knowledge about different
10 ways to think about bias and different ways to think
11 about its relationship to fairness, right.

12 So we know fairness can mean lots of
13 things, right, there's the dignitary interest, there's
14 you know, different ways of thinking about fairness at a
15 legal level, right. When we get into how to translate
16 that into the design of a technical system, we get into
17 all these tricky issues about how fairness is measured.
18 Is it by group level, demographic parody, equal positive
19 predictive values, equal negative predictive values,
20 yada, yada, yada, yada, right. It goes on and on and
21 on. And right now, like I'm not particularly surprised
22 that no agency had established systematic protocols for
23 assessing.

24 My guess is that no agency has yet
25 established systematic ways to think through how to

1 consider kind of biases that are in the data, in the
2 model selection, in the selection of target variables.
3 And so it's not just how to measure it and audit it over
4 time, but it's even like what to aim for and how to
5 build towards that goal. And so to me, I can't imagine
6 a world in which every single agency is going to be
7 expected to do all of that detailed work on their own
8 without some scaffolding at a central level.

9 Now, the one other thing I want to say
10 about expertise though is a lot of the conversation
11 tends to be, oh, we need data scientists, we need
12 machine learning experts, we need people who do neural
13 networks. And I would suggest that I think a lot of the
14 relevant expertise is actually bridge players. So
15 people who understand statistics and understand enough
16 about machine learning and understand enough about the
17 law that they often tend to be these hybrid players.
18 And for them to facilitate good reason decision making
19 about the use of machine learning, they need what are
20 called, and what we like to call, boundary objects to
21 bring other people along in the conversation.

22 So if we want to have a conversation about
23 bias and its relationship to fairness, we need ways to
24 tease out, are we talking about the bias embedded in the
25 system or embedded in the overall system of justice and

1 how it relates to that? Are we looking to root out
2 particular forms of bias in the data? How can we do
3 that? What sorts of techniques do we have? So I just
4 want to like slightly problematize the kind of expertise
5 in that I think it's not just about machine learning
6 experts. It's about kind of which teams that can do a
7 lot of boundary spanning and provide meaningful advice
8 to other government agencies.

9 And then the second question that you asked
10 about, opacity. I think Arti's absolutely right that I
11 think like we might have different tolerances for
12 different levels of opacity in different domains and in
13 different areas, depending upon whether or not we're
14 talking about the deployment of enforcement or the
15 allocation of benefits and the extent to which the use
16 of the tool constrains agency discretion.

17 And I think when we're talking about
18 something that's used to surface patterns that can
19 inform decisions about enforcement priorities that's
20 used in a decision assistance manner, right, that's very
21 different than, for example, if you have a tool that is
22 kind of being used in a more formulated way and where
23 there are real costs to agency personnel for deviating
24 from the output of a technical outcome.

25 MR. VLADECK: Thank you. Cary?

1 MR. COGLIANESE: Well, Arti and Deirdre
2 have laid out a lot of great points as I will try not to
3 repeat those. I would just want to make -- I guess say
4 three things. First, on the expertise issue. It's much
5 bigger than just the need for expertise to use machine
6 learning and we have, I think, a denigration of
7 expertise in our larger culture today and certainly in
8 certain levels and parts of the government as well. And
9 so we need to think about expertise more broadly.

10 We need to think about it more broadly, I
11 think, also not just because government might want to
12 use artificial intelligence tools, but because the
13 private sector is using them. And in an article I wrote
14 called optimizing government for an optimizing world, or
15 "Optimizing Regulation for an Optimizing Economy", we
16 have increasingly private sector actors who are using
17 these tools, and government is called upon to think
18 about how to regulate and oversee those private sector
19 uses. So the government needs to get that expertise in
20 house whether it's using the tools or just overseeing
21 private sector harms that might come about from these
22 tools.

23 Second point is that the type of oversight,
24 the type of public engagement, all of the best practices
25 that I think Deirdre has outlined very nicely, I think

1 those are going to vary, though, depending upon the type
2 of use. And this may be just restating it in a little
3 bit different way something that Deirdre was just
4 saying, but we might care a little bit more about having
5 robust transparency and public participation for systems
6 that really make a tangible difference and actually
7 override human decision making in areas of great
8 consequence to people.

9 But maybe we don't need all of that if the
10 National Weather Service, as it does, is using machine
11 learning tools for weather forecasting, or the Postal
12 Service which was actually one of the first parts of the
13 Federal Government to use machine learning, is using it
14 to read handwriting on envelopes and deliver mail. You
15 know, these more banal uses maybe even today with the
16 FDA, perhaps relying on machine learning tools to scour
17 the 30,000 papers that have been written so far just
18 since January 1 in the scientific literature on
19 COVID-19, for example. These are important uses, but
20 they're tools for finding things and helping humans make
21 decisions and that may be different than actually
22 substituting for human decisions.

23 Third point. Third point here is just with
24 respect to the obscurity and particularly the issue
25 about private contractors who are doing a lot of this

1 work. I just think we need to be more thoughtful about
2 government procurement when engaging private contractors
3 and making sure that legitimate trade secrets can be
4 protected. I don't think that the source code needs to
5 be disclosed to withstand procedural due process or
6 arbitrary and capricious review.

7 But do you need to be able -- does the
8 government need to be able to disclose the outcome
9 variables that are being used? Does it need to disclose
10 the objective function that the algorithm is designed to
11 optimize for? Sure. Those things -- but neither of
12 those things should be -- we should worry about trade
13 secrets about. Even with validation runs and the like,
14 I think, can be insisted on in the procurement process
15 when government is relying on private consultants to
16 make sure that that's disclosable down the road to be
17 able to withstand any concerns about adequate
18 transparency.

19 MR. VLADECK: Well, thank you. Because
20 that's the bridge to the next set of questions that I
21 want to ask. So Arti recounted an effort by the Patent
22 Office to develop its own machine learning algorithmic
23 tool and ultimately had to resort to the private sector.

24 Do we worry about government increasingly
25 relying on tools that are not generated by government?

1 Just take one example which is drawn from the ACUS
2 report. You know, the CBP, the border folks are trying
3 to use face recognition to substitute for boarding
4 passes. And they've contracted with a number of outside
5 organizations and, you know, not surprisingly, because
6 face recognition technology is not perfect, there have
7 been all sorts of problems.

8 And but one of the ironies here, and this
9 is sort of driven home in the ACUS report, was CBP
10 wasn't able to explain any of the problems that it was
11 facing, because most of the sort of intellectual
12 property there was bought and used to some extent by
13 third-party contractors. And so the question is, what
14 do we do about that? Is that okay? Is normatively, is
15 it okay for government to essentially outsource core
16 governmental functions? We've done it in other spheres,
17 I mean, we have private prisons that now, you know, hold
18 lots of federal inmates. But here, when we're making
19 these kinds of choices, is it okay to rely on outsourced
20 government contracting. And Cary, you go first on this
21 one and we'll go back around.

22 MR. COGLIANESE: Again, I don't see that
23 there's anything necessarily different here than in any
24 other context except for the fact that, at the end of
25 the day, you have to keep in mind that the output of a

1 machine learning model will not be a set of coefficients
2 that can allow the government, very intuitively and
3 easily, to explain why a forecast was made or what
4 proportion of a variance is explained by particular
5 variables. That's just not the way machine learning
6 works.

7 But can the government, even if they're
8 relying on a private contractor to disclose what I think
9 are the essential elements to withstand due process,
10 describe the system, how is it structured, what is its
11 goals, what are the data that are being used, what were
12 the validation tests that were done, what were the
13 results of those validation tests, can we show that
14 there's some, you know, increase in accuracy?

15 Under Mathews v. Eldridge that's one of the
16 three factors in the balancing test that the Court uses
17 for procedural due process in particular. And machine
18 learning, generally speaking, when designed well has the
19 potential to really improve accuracy and reduce errors.
20 That doesn't mean it will eliminate errors, and the
21 errors that machine learning and algorithms make will
22 often be ones that humans would not make, and maybe we
23 can't even understand why they were made, but if we can
24 get fewer errors, you know, you just need to be able to
25 make sure at the end of the day that you contract in

1 such a way that the government will be able to have
2 access to those essential elements to demonstrate what
3 it did, why it was designed the way it did.

4 The ineffable sort of black box nature of
5 machine learning, you know, is not something that I
6 think current law requires government to somehow be able
7 to address. I mean, I think of machine learning tools
8 as just tools. And just as, you know, it's sufficient
9 for government to be able to explain if it's using a
10 thermometer if this thermometer has been validated to
11 read certain temperatures accurately and not necessarily
12 provide some kind of, you know, phenomenal logical
13 explanation of why mercury does what it does or why the
14 physics underlying the thermometer. It's a tool, it's
15 been designed for a certain purpose, it's been
16 validated, it works well.

17 And if you could think about that as the
18 way of explaining what a machine learning algorithm
19 does, I think we're basically going to be fine. Just
20 make sure that when you go through the procurement
21 process with third parties, firms, that you are going to
22 be able to have enough information at the end of the day
23 to demonstrate that. And I don't think that requires
24 them giving up the precise, you know, innovations that
25 they have for the particular kind of machine learning

1 algorithm, because there's lots of different types of
2 machine learning algorithms. They don't have to
3 disclose that, but just give us enough about how this
4 thing is working.

5 MR. VLADECK: So Deirdre, Cary used the
6 magic word "procurement". Do you want to talk a little
7 about that as you respond more generally?

8 MS. MULLIGAN: Sure. First, I want
9 to respond, like I think the use of the example of a
10 thermometer is just like really misleading, right.
11 Thermometers, we have a whole set of standards, we
12 understand what we're trying to measure, we understand
13 not just that there's testing and validation and we do a
14 whole bunch of different things to make sure that they
15 are doing the task that we want and actually doing it in
16 the right way.

17 And these machine learning tools, we need
18 to be concerned, not just that they're giving the right
19 answer, but that they're giving the right answer for the
20 right reasons, right, if we're thinking about using them
21 for making important decisions. And as we've been
22 discussing, you know, what machine learning does
23 typically, it's used not to learn from detailed decision
24 trees that experts put out and say, here's how we
25 reason. What it is used to do is to try to look at past

1 decisions by agency or other experts and to, from that,
2 develop its own logic that it uses, right.

3 So it is displacing logic in some way, it's
4 coming up with its own reasoning. And as we know,
5 because machines are good as detecting patterns that we
6 don't see, it's often not intuitive to us and it often,
7 you know, like all the classic examples of identifying
8 the sheep rather than the wolf, right, like we know it's
9 actually reasoning wrongly. And that, you know, the
10 known unknowns I think here, we know that it is
11 reasoning based on things that we wouldn't reason on.
12 And those can be super dangerous. And so I think it's
13 really important to keep that in mind here.

14 So I think that the same way we think about
15 like security, right, we understand we're not going to
16 be able to like root out security, but what we want to
17 do is locate it in places where we can best manage it.
18 And I think when we're thinking about something like
19 bias and a lot of the issues that come up in
20 relationship to facial recognition systems are concerned
21 about different performance on different segments of the
22 populations, different distributions of false positives
23 and false negatives and what that might mean in practice
24 for the population.

25 I think there's a broader set of questions

1 that I actually think are more important about whether
2 or not using surveillance technologies given the racism
3 and other issues in our criminal justice and policing
4 system generally poses particular kinds of systemic
5 risks that suggest that we shouldn't be using those
6 kinds of tools at all in the current environment, but
7 kind of cabining those off and just talking about kind
8 of a performance of these algorithms.

9 I think questions that we need to ask is,
10 who do we think is going to be more attentive to the
11 issues of over and under inclusion in training data,
12 who's going to be in the best position to understand and
13 to do the testing and validation to understand different
14 performance on different populations? And what level of
15 transparency do we want around both the standards being
16 set both for the data and for the technology and for the
17 audits of that technology?

18 And so I think as in, you know, Jody
19 Freeman's famous, "The Private Role in Public
20 Governance", yes, right, there's -- there are different
21 ways to structure private and public relationships
22 around important governmental functions, but I think
23 here we really need to be attentive because of the level
24 of opacity, as Arti described, that's not just at the
25 trade secrecy level but at the technical level itself.

1 And I think that like the last issue is
2 kind of the brain drain from government. And we see a
3 data drain from government, and I think that's very
4 problematic. I was on the Oakland Privacy Advisory
5 Commission for a while here in Oakland and we have a
6 surveillance ordinance that we were applying to
7 different kinds of technologies. And one of the things
8 that seems to become the norm is that private sector
9 comes in, says we'll do this function for you, we're
10 going to suck up all the public data and then we're just
11 going to give you reports, right. And that means that
12 governments aren't even able to assess whether or not
13 something is performing well, because they don't end up
14 with the raw data to do their own validation, right.

15 So I think we also need to be concerned
16 about kind of how expertise and how raw assets end up
17 being redistributed in these public/private
18 arrangements.

19 MR. VLADECK: Thank you. Arti, you want to
20 weigh in?

21 MS. RAI: Yes. So I'm going to weigh in
22 with my intellectual property hat on, because I've been
23 doing a lot of research recently into what sorts of
24 things private sector firms consider their core trade
25 secrets and what can be disclosed either fully publicly

1 or to trusted parties, quote/unquote, which might
2 include the government agency but not necessarily the
3 whole public.

4 So you know, one thing that is relevant, I
5 think, to this discussion is that summaries of training
6 data, demographic characteristics, you know, how it was
7 collected, all of those procedural issues surrounding
8 training data, I have not heard anyone say from any of
9 my private sector interviews that that is something they
10 consider a trade secret. So summaries of training data,
11 they get into some relative detail about demographics
12 and the like.

13 And also -- and this gets a little more
14 tricky with respect to labeling, you have to label the
15 data in order for it to be good training data. Labeling
16 is a little more tricky, but you can -- you know, that
17 can be publicly disclosed to some extent. So I think
18 that mitigates some of the concerns that one might have
19 in these contexts where individual rights and bias are
20 really very salient, which I do think is a really
21 important context even though, for the most part, you
22 know, I had not been talking about those context.

23 So I think that's one way to do it with
24 respect to training data, because the training data does
25 seem to consider, you know, the secret sauce or the real

1 gold for these private sector firms. One can talk about
2 training data without reviewing the training data even
3 perhaps to the government agency, although ideally, I
4 think a government agency should be trusted enough with
5 the training data that they should be able to get the
6 training data.

7 They may not have the expertise to know
8 what to do with it exactly, but at least given that
9 their FOIA exemptions and all the rest of it, I don't
10 see why a government agency can't get the training data,
11 or even the source codes so long as it's exempt from
12 FOIA. But fully public information can be made
13 available regarding summaries.

14 And then everything that Cary said with
15 respect to the reasoning of the model, it seems to me,
16 nobody with whom I have spoken in the private sector has
17 disagreed with the idea that the key factors, confidence
18 intervals with respect to predictions, that sort of
19 thing, that's all really good best practices.

20 And then finally, last but not least, in
21 terms of validation, some of the bias and other concerns
22 about which we are rightly focused -- on which we are
23 rightly focused, can be addressed by making sure that
24 your model is tested -- well, is created on really
25 diverse populations and all the rest of it, but then

1 also tested on a totally separate data set from the data
2 set from which the training data was devised, so you get
3 performance measures before it's even put out into the
4 wild on a totally independent data sets. Again, that's
5 all expensive, but it's not trade secret, it
6 shouldn't -- none of that should be trade secret.

7 MR. VLADECK: Okay. So we have a question
8 from the audience that I'd like to read to each of you.
9 And Arti, you get the first crack at this.

10 The question is this: IT systems in use in
11 government agencies tend to be entrenched -- become
12 entrenched and obsolete. Given limited AI experience
13 and the high cost of labor, how is this tendency not to
14 become exacerbated for AI systems?

15 And when I was in government we were using
16 the computer system that, you know, I think there were
17 still Kaypro computers around. So you know, any
18 thoughts about that question, which I think is a serious
19 question?

20 MS. RAI: Yeah, I completely agree. When I
21 was at the Patent Office we were still, believe it or
22 not, there were faxes being used which --

23 MR. VLADECK: Oh, yeah.

24 MS. RAI: -- faxes still existed. So yeah,
25 so the -- I think this is a really serious issue which

1 is why I do think that the private sector has to be
2 involved. I don't see how this can be a completely
3 homegrown effort at the end of the day. I mean, at the
4 PTO, as I've said, they did come up with a pretty good
5 homegrown effort but it wasn't user friendly. And so it
6 does seem to me that the private sector has to be
7 involved which involves money, which involves these
8 careful, you know, safeguards to make sure that what the
9 private sector is giving you has been properly validated
10 and so forth. So yeah, I think it's a real problem and
11 a real concern.

12 MR. COGLIANESE: If I could jump in?

13 MR. VLADECK: Sure.

14 MR. COGLIANESE: The Government
15 Accountability Office, you know, a few years ago did a
16 study and I guess something on the order of 75 percent
17 of all IT spending in the Federal Government goes to
18 legacy systems. So you know, we are pouring a lot of
19 money into really antiquated technology. So it's not
20 just the expertise, the human capital that we need in
21 government but also the actual hardware systems, and
22 I'll add to that, the data. We have a lot of data, but
23 it's often not organized, there aren't ways of linking
24 up to separate data sets.

25 So there's some work to be done if

1 government is going to take a lead in developing these
2 systems. And I agree with Arti that, at least in the
3 world we're in today, I mean, if we don't make those
4 improvements in the infrastructure, the IT
5 infrastructure and the expertise, government will have
6 to be relying a fair amount on the private sector for
7 help with this.

8 MR. VLADECK: Deirdre?

9 MS. MULLIGAN: I don't know that I have
10 much to add. I do think that it is interesting to look
11 at the way USDS and 18F, for example, their
12 healthcare.gov, 18F, USDS come in and provide some
13 different kinds of expertise and really change outcomes
14 as far as usability and system design. And I think that
15 the positioning of expertise and what we need to bring
16 in house and what we can outsource and the positioning
17 of the technology itself, right, what we can rely on, in
18 the private sector and what agencies need to bring in
19 house is really going to be domain and problem specific.

20 And so I don't think we're going to have
21 one size fits all here, but I think there's a constant
22 kind of denigration of government capacity. And I think
23 making government an interesting place where one gets to
24 solve the most important problems facing the world can
25 be a really compelling thing for people who, right now,

1 are trying to figure out how to get you to click on
2 (inaudible). And I think that bringing experts often
3 brings new technology, like the experts are the people
4 who design it.

5 And so I think that there is a real desire
6 roaming in the relevant technical communities to solve
7 important problems. And if we can bring more of those
8 people into government in different ways, whether it's
9 on tours of duty or if it's in specialized skunkworky
10 kind of ways or on agency staff or on expert advisory
11 committees, I think we can bring some technology with
12 it. And so you know, I think there won't be a one-size
13 solution and I'm optimistic about the government.

14 MR. VLADECK: So we have about 8 minutes
15 left. What I'd like you to do in the last quick round
16 here is sort of talk about how government is going to be
17 able to attract and retain people of this kind of
18 sophisticated knowledge.

19 When I was at the Federal Trade Commission
20 when I started in 2009, there was not a single
21 technologist on staff, retention is very difficult.
22 Arti pointed this out earlier, what are we -- you know,
23 do we concentrate our expertise in OTA or something like
24 that, or do we diffuse it among the agencies? If we're
25 going to take advantage of AI, how can government best

1 do this? And you know, in answering it, is outsourcing
2 really the only answer?

3 Your patent example, I think, is a
4 cautionary tale. The agency tried -- the office tried
5 to develop its own algorithm and ended up having to
6 abandon it. So Cary, let's start with you. Each of you
7 have about 3 minutes because we have to wind up at 3:15.

8 MR. COGLIANESE: Well, I think there's not
9 really a, you know, going to be something that these
10 tools inherently by themselves are plug and play in
11 different context. So I do think that agencies need to
12 develop their own inhouse expertise about how to use
13 these tools for the type of problems that they confront.
14 And some agencies are doing that. The Securities and
15 Exchange Commission, for example, has developed an
16 inhouse staff focusing on machine learning tools to
17 identify -- help identify fraud on the market. So
18 that's an example.

19 How do we get there? I mean, I think that
20 we have a need for people in government who do a lot of
21 types of analysis and not just use machine learning
22 tools. And we always have to think about inspiring our
23 younger people, you know, to the ideals of public
24 service and to the real value that people in government
25 can provide and the challenges, quite frankly, too. I

1 mean, I think in some respects if I had to leave the
2 audience with anything is to say that I think the
3 technical issues here are in some sense almost the
4 easiest ones.

5 When it comes to government and government
6 using machine learning tools, the value choices and the
7 policy issues are some of the really tough nuts that we
8 have to crack. You know, inevitably there will be
9 tradeoffs between things like accuracy and fairness, or
10 even within particular context tradeoffs between
11 achieving one goal and not harming people in another
12 way. And how we actually make those choices are policy
13 normative ones where we need -- we need at the end of
14 the day, not just technology, but we need people. We
15 need good people in government who can interface with,
16 interact with people in society overall and help us make
17 those policy choices in a way that will make these
18 systems be viewed as legitimate and not just as somehow
19 technically accurate.

20 MR. VLADECK: Okay, thank you. Deirdre?

21 MS. MULLIGAN: So David, you know this and
22 Cary and Arti and others may know. You know there is a
23 movement right now to try to develop career paths and
24 professional identity for students with a certain level
25 of technical expertise in a stem field, but also with an

1 interdisciplinary orientation. So some understanding of
2 a particular social context, particular discipline along
3 with kind of ethical and legal competence to create a
4 public interest technology field, similar to the way we
5 developed a public interest law field.

6 And I don't think there's a reasonable
7 expectation that the financial rewards of working in
8 government are ever going to be the same as those
9 working in the public sector, and I think all of us on
10 the call right now realize this. And I don't think that
11 should be the goal. I think that there are lots of
12 reasons to want to work in the government on these sorts
13 of problems in helping technical people see themselves
14 as problem solvers of large social problems in teams or
15 as part of, you know, a social justice movement, part of
16 a good government movement that we need them and we need
17 to partner with them and that we want to partner with
18 them and we're making space at the table for them, are
19 really important signals.

20 And so I think it's hopeful that there's a
21 set of universities around the country that are trying
22 to help technical people view themselves in public
23 service, view themselves in social justice. And I think
24 that that can have a real -- just setting the right tone
25 and developing the career pathways can help address some

1 of the lax that we see in government today.

2 MR. VLADECK: Arti, you get the last word.

3 MS. RAI: Oh, great. I do want to end on a
4 more optimistic note, because I think I've been somewhat
5 pessimistic through a lot of my talk here. So I do
6 agree with Cary and Deirdre that there are, I think,
7 there's a significant cadre of people coming up through
8 the ranks who are motivated by the desire to improve the
9 functioning of government. And it seems to me that one
10 way to harness that energy perhaps, perhaps, would be to
11 have something similar to what we've established in some
12 agencies through offices like the Office of the Chief
13 Economist.

14 So those are offices where you can go in
15 and head up the office for a couple years and then go
16 back to wherever you came from, so you don't have to be
17 a permanent, you know, resident of Washington, D.C. for
18 the rest of your life. You can come in and out. And
19 that has been a model that's been used with
20 technologists as well, although perhaps not as robustly
21 as they could. And it seems to me that that sort of
22 model would work very well for technologists as well.
23 And it was -- it has been used, as Deirdre has pointed
24 out, to some extent, but perhaps even more so within
25 each agency would be something worth considering moving

1 forward.

2 MR. VLADECK: Well, the FTC has a chief
3 technology officer. We brought in Ed Felten early
4 on ---

5 MS. RAI: Right.

6 MR. VLADECK: -- and it really transformed
7 the agency, so maybe that's one tool that we might try
8 to use more uniformly. Always have a chief technology
9 officer. Well, thank you all. You've been terrific. I
10 would applaud you, but no one I think can hear. But
11 great job and we've ended on time and so thanks so much.

12 MS. MULLIGAN: Thank you, David.

13 MR. COGLIANESE: Thank you, David.

14 MS. RAI: Thank you.

15 MR. VLADECK: Thank you, guys.

16 MR. COGLIANESE: Thank you Georgetown and
17 ACUS.

18 MS. RAI: Yes, indeed.

19 MR. VLADECK: And Matt.

20 MS. RAI: And Matt.

21 (End of audio file)

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CERTIFICATION

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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
and transcribe the foregoing recorded proceedings and
that the transcript is a true record to the best of my
ability.

Dated this 7th day of August, 2020.



Carmel Martinez,
TX CSR No. 8128
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