



ADMINISTRATIVE CONFERENCE OF THE UNITED STATES

**ARTIFICIAL INTELLIGENCE IN FEDERAL AGENCIES  
Government by Algorithm**

June 25, 2020

TRANSCRIPT  
(Not Reviewed for Errors)

**Panelists**

Justice Mariano-Florentino Cuéllar, Supreme Court of California and Stanford Law School

David Freeman Engstrom, Professor of Law and Associate Dean for Strategic Initiatives, Stanford Law School; Public Member, Administrative Conference of the United States

Daniel E. Ho, William Benjamin Scott and Luna M. Scott Professor of Law, Stanford Law School

Catherine M. Sharkey, Crystal Eastman Professor of Law, New York University School of Law; Senior Fellow, Administrative Conference of the United States

**Moderator**

Hillary Brill, Interim Executive Director, Institute for Technology Law and Policy

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Symposium on Artificial Intelligence in Federal  
Agencies

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1 (Beginning of audio recording.)

2 MR. WEINER: Good afternoon. I'm Matt Weiner,  
3 the vice chair and executive director of the  
4 Administrative Conference of the United States, ACUS,  
5 for short. We'll begin now -- we are waiting for two  
6 of our participants. We're not waiting so much as  
7 trying to connect them, and in particular, we're  
8 waiting for -- or we're trying to connect Justice  
9 Cuellar and Professor Engstrom at Stanford Law School.

10 I'll begin with just a few introductory remarks  
11 before I turn it over to our moderator. This is  
12 ACUS's and the Georgetown Law Center's Institute for  
13 Technology, Law, and Policies summer symposium on  
14 artificial intelligence in federal agencies.

15 Thank you for all -- thank you to all of you, to  
16 all of our attendees. We have a lot of people on the  
17 phone, many of you with real expertise on our subject.  
18 And so we're really happy to have you.

19 For those of you on the phone who are unfamiliar  
20 with ACUS, let me just say that ACUS is an independent  
21 federal agency within the executive branch that  
22 studies and makes recommendations to improve rule-  
23 making, adjudication, and other administrative  
24 processes.

25 Our symposium this summer will consist of four

1 virtual panels on four separate days. Each panel will  
2 be recorded and transcribed, and the recordings and  
3 transcriptions will be available at some point on  
4 ACUS's website.

5 For today's panel, we have the distinguished  
6 authors of a report, soon to be introduced, prepared  
7 for and commissioned by ACUS titled "Government by  
8 Algorithm: Artificial Intelligence in Federal  
9 Administrative Agencies".

10 And before turning it over to our panelists for  
11 our moderator, I just want to thank a few people.  
12 First and foremost, Hillary Brill -- first -- well,  
13 our panelists, but also Hillary Brill, the interim  
14 director of the institute at Georgetown. Two ACUS  
15 staff members who have done an extraordinary job in  
16 organizing this symposium, namely Todd Rogan  
17 (phonetic) and Todd Phillips (phonetic). And then the  
18 institute itself and in particular Hillary and Jeff  
19 Gary (phonetic), its project manager.

20 And with those brief introductory comments, let  
21 me turn it over to Hillary, our moderator. Hillary?

22 MS. BRILL: Hello, and thank you for that  
23 introduction. As you said, I'm Hillary Brill, and I  
24 lead Georgetown's Institute for Technology, Law, and  
25 Policy, and it is my privilege to be moderating

1 today's panel with our esteemed panelists and to be  
2 part of this symposium cohosted with ACUS.

3 And we are the pilot program of our four-part  
4 summer series. So I hope you enjoy it. There will be  
5 different series along the way, and as you just heard,  
6 you can binge watch the entire series at the end, as  
7 well, if you love it so much. So I hope you enjoy it.

8 We had planned at the institute -- had planned  
9 to host you on Georgetown Law's campus. As you can  
10 see because of current events, we are unfortunately  
11 unable to do that. But we are so glad that so many of  
12 you have joined us virtually, and as discussed, in so  
13 many areas that are important to this issue, you are  
14 experts. And we are pleased to have you as part of  
15 this conversation.

16 Thank you, ACUS. Thank you for working with the  
17 institute on this project to make this symposium  
18 possible. And thank you to everyone at the institute  
19 who worked on this, including my predecessor, who  
20 should be named, Alex Givens (phonetic), who is  
21 speaking, I hope, on one of these panels along the  
22 way. And she is the one who worked quite a bit on the  
23 organization with ACUS. So I want to thank Alex  
24 Givens and Jeff Gary for all the work that they put in  
25 to making this happen.

1           The institute, it's a think tank at Georgetown  
2 Law, where we do original policy work, and we also  
3 convene with collaborators, technologists, our  
4 faculty, students, and experts like yourselves in  
5 cross-disciplinary fields, bringing together  
6 technologists and policy makers, and government  
7 agencies like today.

8           At the institute, we spend a lot of time thinking  
9 about how to train lawyers and policy makers to better  
10 understand the way technology impacts our society.  
11 Today's collaboration with ACUS is part of that  
12 longstanding commitment to studying the impact of AI  
13 on society.

14           The institute has hosted in February a symposium  
15 on AI and disabilities, previous legislative  
16 workshops, and many panel series. But today -- today  
17 is about the report that these esteemed panelists have  
18 worked so hard in putting together, and it was no easy  
19 task. This report is going to highlight the many  
20 benefits that there are to using AI systems in  
21 government. And it will also explore how agencies  
22 truly use AI, a preliminary groundwork discussion that  
23 is necessary.

24           These benefits are benefits we want in our  
25 personal lives and benefits we want by our government

1 -- decreased costs, greater efficiency, improved  
2 quality, and the ability to harness vast amounts of  
3 data. These benefits are the reasons why, as the  
4 report notes, almost 50 percent of all agencies are  
5 using some sort of artificial intelligence.

6       However, today's report also addresses that  
7 increases AI adoption comes with increased concerns,  
8 especially if the systems are being used by government  
9 agencies in decision-making processes and used by our  
10 law enforcement.

11       Many AI systems have well-documented racial  
12 biases. The software itself is often not necessarily  
13 transparent or understandable, sometimes even to its  
14 own creators. And remedies, what happens if there is  
15 a bias in AI? There often (inaudible) after the fact,  
16 and they are erroneous determinations caused by AI,  
17 and what do you do after the fact? That may not be  
18 sufficient.

19       So this issue of bias inherently is tricky, as  
20 bias in AI itself isn't accidental. It's part of its  
21 function. The systems are there to make  
22 discriminatory decisions. But if we can't determine  
23 whether the program is discriminating in a permissible  
24 way rather than in an impermissible or frankly illegal  
25 way, well, then we need to deeply explore how our

1 government agencies should be using AI.

2 AI in government, as you will hear soon in more  
3 detail today, can provide tremendous benefits. But in  
4 some contexts, AI raises legal and moral concerns and  
5 may implicate due process rights or other civil  
6 liberties.

7 So thank you, panelists. We're going to explore  
8 these topics in context of their authorship and work  
9 on the report, Government by Algorithm: Artificial  
10 Intelligence in Federal Administrative Agencies.

11 We are first -- we are going to hear from Justice  
12 Cuellar, Supreme Court justice of California and  
13 professor at Standard Law, who is an expert in  
14 administrative law and legislation in cyber law, and  
15 has served in the Clinton and Obama administrations  
16 and has taught as a professor at Stanford since 2001.  
17 He received his B.A. from Harvard, J.D. from Yale, and  
18 Ph.D. from Stanford.

19 Then we will hear from Professional Engstrom from  
20 Stanford Law, who is an expert in administrative law,  
21 Constitutional law, and legal history.

22 I have to say there's so much more. You need to  
23 read their bios. It's just a short summary of the  
24 incredible panelists that we have.

25 His current scholarship focuses on the



1 intersection of law and artificial intelligence. He  
2 is a faculty affiliate at the Stanford Institute for  
3 Human-Centered Artificial Intelligence and the  
4 Stanford Center for Legal Informatics, and the  
5 Regulations and Evaluation and Governance Lab. He  
6 received a J.D. from Stanford, a Master's of Science  
7 from Oxford, and a Ph.D. from Yale, and has clerked  
8 for Chief Judge Wood on the Seventh Circuit.

9 Professor Ho from Stanford Law is an expert in  
10 administrative law, regulatory policy, and  
11 antidiscrimination law. He's an associate director  
12 for the Stanford's Institute for Human-Centered  
13 Artificial Intelligence, and directs the Regulations,  
14 Evaluation, and Governance Lab at Stanford. He  
15 received his J.D. from Yale, Ph.D. from Harvard, and  
16 clerked for Judge Williams on the Appeals Court.

17 And Professor Sharkey. Professor Sharkey from  
18 NYU is one of the nation's top authorities on many  
19 different issues, including economic laws rule,  
20 punitive damages, and federal preemption. She is an  
21 appointed public member of our very own ACUS,  
22 Administrative Conference of the United States, and an  
23 elected member of ALI. She received her Master's of  
24 Science from Oxford, J.D. from Yale. She clerked for  
25 Judge Calabresi of the U.S. Court of Appeals for the

1 Second Circuit and Justice Souter.

2 So we are very fortunate to have you here today.  
3 With that, we'll proceed with the presentation by each  
4 author of the report and the discussions of some of  
5 your process and findings, of course, within the  
6 short, limited time that we have. We will go into  
7 more detail as the panels -- as the series progresses.  
8 But today is a true table setting of these issues.

9 So if we can begin, I'd like to start with  
10 Justice Cuellar.

11 JUSTICE CUELLAR: Hello, can you hear me?

12 MS. BRILL: Yes.

13 JUSTICE CUELLAR: Oh terrific. Thank you. It's  
14 been a little bit more challenging to get my kids to  
15 stop using their cellphones. Thank you, Hillary, for  
16 that terrific introduction, and thank you to ACUS for  
17 supporting this project. You are going to hear more  
18 from my colleagues about what we learned. I want to  
19 give a little bit of context for why, in some ways,  
20 this report was 64 years in the making.

21 So yesterday Wayne County prosecutor Kim Worthy,  
22 probably many of you know, admitted that a faulty  
23 facial recognition identification was responsible for  
24 a suspect's erroneous 30-hour detention and  
25 interrogation.

1           And stories like this make it pretty easy to see  
2 why the public is getting interested in how government  
3 uses this mix of analytical techniques in computing  
4 systems capable of learning that go under the heading  
5 of AI.

6           But I want to just take four minutes to start  
7 earlier in 1956. It's a humid New Hampshire summer,  
8 and several scholars are organizing a workshop on a  
9 topic they just decided to call artificial  
10 intelligence. This motley crew is led by the quirky  
11 mathematician John McCarthy but also includes  
12 logicians, electrical engineers, cognitive scientists,  
13 shockingly enough, no lawyers. And they waste little  
14 time in sketching out an agenda that summer that is  
15 just striking to look at, the topics they were  
16 discussing, because some of the very words they used  
17 to describe their scope of discussion could be taken  
18 out of the report that we have just been working on  
19 and released 64 years later.

20           Building knowledge bases for digital computers,  
21 natural language processing, computer vision, and even  
22 neural networks. They're all men and confident enough  
23 to expect very rapid progress in the ensuing years.

24           Four years later, Senator John F. Kennedy loses  
25 New Hampshire but wins the presidency, and the

1     arrestable and brilliant James Landis, scholar of  
2     administrative law, probably known to many of you,  
3     writes a report emphasizing to the President Elect the  
4     crucial role of administrative agencies. So he was  
5     talking about the tricky balance between political  
6     responsiveness and agency insulation, the value of  
7     government-wide efforts to make them work better, and  
8     that effort eventually culminates in the establishment  
9     of ACUS, which began operations in 1968.

10           It's fair to say that in the ensuing decades, at  
11     least some of the projects that Landis sketched out in  
12     his transition report to John F. Kennedy got more  
13     traction and moved more quickly than the agenda that  
14     John McCarthy and his colleagues sketched out at  
15     Dartmouth, which tended to be much more technically  
16     daunting than they expected.

17           But things began to change in stages. On the  
18     national security front, research never abated on AI  
19     and produced important changes in areas like avionics  
20     and even RAND Corporation advised geopolitical  
21     strategy. And a few years later, of course, the  
22     internet plus cheaper computing power brought massive  
23     disruption, and the rest is history.

24           So this rising interest in AI in the private  
25     sector in its current incarnation naturally triggered

1 among a lot of us pretty intense questions about  
2 essentially the intersection of the legacy of this  
3 Dartmouth workshop and the concerns that Landis spent  
4 most of his life on like what can we delegate to AI.  
5 How can we comply with law in an AI-spiked world? How  
6 do we stress test AI technology to detect its hidden  
7 biases so we can avoid what just happened in Wayne  
8 County? How can society change its civic institutions  
9 to use algorithms in a more efficient way to write  
10 rules, to adjudicate? And how, given that change, can  
11 we define more stable goals against which to measure  
12 change?

13         And let's be clear. These questions are  
14 obviously relevant not only to the federal government,  
15 but speaking of Wayne County, to states and localities  
16 that spend more than 80 percent of all government  
17 dollars, leaving aside entitlements, debt service, and  
18 defense.

19         All this is heady stuff, but the four of us  
20 almost simultaneously ran into a problem that ACUS  
21 helped us turn into an opportunity. It was hard to  
22 engage with these questions thoughtfully when we  
23 didn't even have a basic working knowledge of how much  
24 AI was being used by agencies around the country.

25         So with the help of ACUS and with colleagues that

1 I just have delighted in working with at every turn,  
2 we set out to pursue a project focused on getting a  
3 baseline picture of how AI use was playing out in  
4 government agencies, beginning with the federal  
5 government. We recruited some superb students from  
6 Stanford and NYU to work with us. We did our best to  
7 survey available testimony, press coverage, agency  
8 disclosures. We put to one side national security  
9 agencies for others to work on in the future, and we  
10 delved more deeply into particular agencies and issues  
11 benefitting enormously from the wisdom of federal  
12 officials at a vast range of agencies, maybe some of  
13 you are on this webinar.

14 And since the goal wasn't just to chronicle what  
15 agencies told us but to analyze the composite picture  
16 that emerged, we have the beginnings of this -- in  
17 this report of a taxonomy of concepts and ideas, the  
18 structure and agenda of reform, and a research that  
19 will last for some time, maybe for another 64 years.

20 I think it's fair to say that AI use is already  
21 extensive and varied in federal agencies and will  
22 become more so, and as you're going to hear from David  
23 and then Dan and then Cathy, even the current picture  
24 offers its share of striking surprises.

25 But the bottom line that I want you to remember

1 is that this report was in some ways 64 years in the  
2 making. Thank you, Hillary.

3 MS. BRILL: You're welcome. You're welcome.  
4 Thank you. And that was a great history lesson and  
5 true table setting. And I appreciate it. It was a  
6 great story and narrative to set -- set the stage for  
7 the rest of you.

8 Professor Engstrom.

9 PROFESSOR ENGSTROM: Sure, thank you. So I'll  
10 start by echoing Tio's (phonetic) thanks to ACUS.  
11 ACUS was absolutely tremendous in supporting this  
12 project from the start, and that ran from Matt Weiner  
13 at the top all the way -- all the way down. So thank  
14 you. We couldn't have produced a report that we're as  
15 proud of without your support throughout.

16 (Inaudible) quite a few agency officials on  
17 staff, perhaps, in the audience today. So this may be  
18 my best chance to thank them and to say that, you  
19 know, many of you are unsung in the report. We don't  
20 cite you by name. Agencies didn't want us to. But we  
21 couldn't have produced a report that was quite as rich  
22 as it was without your help. So thank you.

23 All right, I'm going to talk about enforcement.  
24 That was the part of the report where I ran point, and  
25 I don't have to explain to you that enforcement is a

1 critical part of governance. If you have too little  
2 of it, then there's probably costly lawbreaking going  
3 on out in the world. But going after the wrong people  
4 is also costly, and it's unfair.

5 And so several agencies within the federal  
6 administered state have begun using machine learning  
7 to support enforcement decisions. And the report --  
8 part 2 of the report is where the really rich case  
9 studies are, and in that part of the report, we  
10 profiled two tools, in particular, at the SEC that the  
11 SEC has fully implemented and is using.

12 One of those tools examines transaction data. So  
13 how do we structure data, numbers, to catch insider  
14 trading? Another tool used at the SEC parses the  
15 narrative disclosures of investment advisors. So  
16 these are registrants. People have to register with  
17 the SEC in order to do what they do, and this is very  
18 unstructured data. These are just paragraphs of text,  
19 and the SEC is using a machine learning tool to  
20 predict which among those investment advisors might be  
21 the bad apples, might be violating the federal  
22 securities laws.

23 There are plenty of other agencies that are  
24 developing or deploying machine learning in the  
25 enforcement space. The SEC, by no means, exhausts the



1 set. The Centers for Medicare and Medicaid Services  
2 is using some machine learning to catch healthcare  
3 fraud. The EPA is developing some tools that will  
4 predict Clean Water Act violations. The IRS is  
5 applying some ML in the tax fraud context.

6 There's also interesting stuff at the state  
7 level, and we assume that lots more of this is going  
8 to come online as machine learning continues to  
9 proliferate throughout the federal government and is  
10 joined up to the mountains of data on which many  
11 agencies sit.

12 So going forward, I think there are three kinds  
13 of work to be done. I'm expanding on what we've  
14 already done in the report. One is to continue to  
15 surface use cases, to slice and dice them, to  
16 understand their different dimensions. And I've  
17 started in on some of this in some of the follow-on  
18 work that I've done.

19 Obviously, all of these enforcement tools are  
20 united by this common focus on shrinking the haystack  
21 of a pool of violators. So you can think of these  
22 systems as recommender systems. They're not fully  
23 automated. They don't fully displace agency  
24 discretion. Rather, they help agencies decide where  
25 to allocate their scarce enforcement resources.

1 But beyond this, if you look across the tools,  
2 they're very much a varied lot. They differ in their  
3 sophistication. They range from logical, rule-based  
4 AI to some fairly sophisticated forms of machine  
5 learning. They differ in the types of predictions  
6 that they make. They differ in their sourcing,  
7 whether they were developed in-house by agency  
8 technologists or whether they were acquired through  
9 the procurement process.

10 And we think that one of the great contributions  
11 of the report is to bring to light some of these  
12 technical and operational details because as we think  
13 about how we might want to regulate this, how we might  
14 want to try to build an accountability structure  
15 around these tools, those details are really going to  
16 matter.

17 I have a skinny five minutes. I don't even know  
18 how much I have left, but let me just say two more  
19 things by way of placeholder that might inject some  
20 ideas into the conversation that's going to follow  
21 these short little presentations.

22 So I think two fairly good things to think about  
23 as we think about enforcement tools and algorithmic  
24 enforcement tools, in particular, one is how these  
25 tools are going to reshape the internal agency

1 structure and operation. And then another important  
2 question is how these tools are going to press on  
3 doctrine and force us to think about agency  
4 accountability in new ways.

5       So on the first of those, I'm doing some writing  
6 here, and the way I like to think about it is that  
7 these tools are going to shift the citing of  
8 discretion within agencies. And one nice way of  
9 thinking about is that these tools, as they become  
10 more and more pervasive within administrative  
11 agencies, they're going to push discretion up, over,  
12 and out.

13       So up, they're going to increase the managerial  
14 control of the managers over the more dispersed line  
15 level enforcement staff. Over, they're going to shift  
16 discretion to technologists. One way of thinking  
17 about administrative laws, it's an effort to allocate  
18 power within different types of agency stakeholders,  
19 among different types of agency stakeholders. So  
20 think lawyers, scientists, the political appointees of  
21 the top of an agency. And I think these tools are  
22 going to add technologists to that mix and some  
23 discretion is, therefore, going to be lodged in the  
24 technologists who will have control over the coding of  
25 the algorithms.

1           Second really important thing to think about is  
2           how we can build an accountability structure around  
3           these. The lawyers in the audience know that for a  
4           long time, administered law has hived off enforcement  
5           decision making from judicial review. Part of that is  
6           that we don't trust generalist judges to second guess  
7           agencies, especially around budgetary matters. But  
8           part of it, too, is that we don't think we can really  
9           reconstruct individual enforcement decisions well  
10          enough to permit judicial review.

11          And so here's an example where the advent or the  
12          increasing uptake of these tools could really press on  
13          doctrine in significant ways. And we might want to  
14          rethink, for instance, that hiving off of enforcement  
15          decision making from judicial review.

16          So that's all I'll say. Those are mostly just  
17          placeholders. I'll assume we'll come to the question  
18          of judicial review and accountability later on. I'll  
19          assume we'll come back to thinking about how this is  
20          going to alter the internal operation of agencies  
21          across different types of governance tasks. But  
22          hopefully that's a helpful injection of at least a  
23          couple of ideas into our conversation.

24          MS. BRILL: Thank you, Professor Engstrom. Now,  
25          Professor Ho, would you please discuss some of your

1 issues from your part of the report?

2 PROFESSOR HO: Great. Thanks, Hillary. And I  
3 want to thank Georgetown and academic, Matt and Todd,  
4 in particular, for facilitating all this. David  
5 already thanked the many agency officials who  
6 participated in the research for this report.

7 The other really important element of all of this  
8 was the way in which we brought 30 law and computer  
9 scientists, students from Stanford and NYU together,  
10 to really wrap their heads around these issues and  
11 really peek underneath the hood of what kinds of ML  
12 techniques were being deployed. So a big thanks goes  
13 out to our students, as well.

14 I've been asked to just say a couple of opening  
15 remarks around how AI is being used in agency  
16 adjudication. Before I turn to two of those examples,  
17 I just want to highlight one of the first parts of the  
18 report, which is that with these students, we looked  
19 at the top 140 agencies by FTEs, really to get a  
20 rigorous sense of the extent to which agencies were  
21 deploying AI. And two basic findings from that canvas  
22 were that out of these 140 agencies, nearly half had  
23 really given serious consideration of the use of AI  
24 and machine learning.

25 That said, when the computer scientists started

1 to look underneath the hood to really ascertain the  
2 level of sophistication, I think it was quite varied,  
3 and there was only about 12 percent of the use cases  
4 that were rated particularly high. Many were simply  
5 providing insufficient detail to really come up with a  
6 rigorous understanding of the level of sophistication.  
7 So there is yet a fair amount of work to be done on  
8 that front.

9 Let me speak briefly about two examples of  
10 innovation for mass adjudication. The first is in the  
11 Social Security Administration. As ACUS knows better  
12 than most agencies, ensuring the accuracy and  
13 consistency of mass adjudication is a major challenge  
14 for the administrative state.

15 So we've known for decades and decades that there  
16 can be a disturbing amount of arbitrariness in the  
17 grant rates when judges within an office are randomly  
18 assigned to cases where grant rates, for instance, for  
19 Social Security Disability can vary from as low as 8  
20 percent for one judge to 98 percent to another judge,  
21 leading some to decry this as a form of disability  
22 roulette.

23 And due process, that is the kind of  
24 constitutional underpinning for mass adjudication, is  
25 resource-intensive. It can take years at the Board of

1 Veterans Appeals, upwards of seven years for an appeal  
2 to actually be resolved from the time that it is  
3 filed. So there is tremendous -- there are tremendous  
4 gains here, potentially, for using AI, and the story  
5 of innovation in this space really comes from the  
6 Social Security Administration's appeals council,  
7 where the head of the appeal council, Gerald Ray, was  
8 really creative in prototyping potential solutions to  
9 overcome IT hiring rules. Judge Ray started to  
10 identify lawyers who also could code and bring the  
11 kind of structured information in to develop tools  
12 like predictive tool of the kinds of cases that were  
13 likely to be easy grants, therefore allowing the  
14 agency to skip hearings and make early grant  
15 determinations.

16 And perhaps the most innovative tool here is one  
17 that uses natural language processing to catch errors  
18 in draft decisions. So for instance, it will parse  
19 the draft language by an administrative law judge and  
20 then look at the functional impairment that's  
21 identified in the set of facts and compare that  
22 against a kind of table of job classifications to flag  
23 potential internal inconsistencies in the decision so  
24 that judges can go and review those draft decisions.

25 That's an extraordinary story of innovation

1 within government. But there are also two kind of  
2 ways in which it connects to core tenets of  
3 administrative law, much in the way that Professor  
4 Engstrom sort of alluded to.

5 One is that for the better part of the modern due  
6 process jurisprudence, we focused on accuracy, at  
7 least since Matthews versus Eldridge. And one  
8 question there is if you're (inaudible) hearings  
9 whether that might lead us to at least reconsider the  
10 kind of dignity prong of due process. At least we  
11 have anecdotal evidence of litigants who come in and  
12 report really knowing they're going to lose the case  
13 but finding real value in simply being heard.

14 And it's possible that by easing the burden of  
15 processing these kinds of cases that AI could actually  
16 recover that kind of lost constitutional value.

17 And the other one alluded to also by Professor  
18 Engstrom is about the internal allocation of  
19 authority. ACUS has thought a lot about the  
20 decisional independence of administrative law judges,  
21 and the adoption of something like the inside tool  
22 tends to be higher amongst staff attorneys. And so  
23 there's a question there about the internal allocation  
24 of decisional authority within the agency.

25 Second use case I'll just highlight briefly is an



1 example of informal adjudication in the U.S. Patent  
2 and Trademark Office, which is also no stranger to  
3 backlogs with 9,000 patent examiners. And the PTO has  
4 been prototyping methods to improve the classification  
5 and search of trademarks and patents. So the idea is  
6 the most time-consuming part for any patent examiner  
7 is identifying relevant prior art. And if you can  
8 build better search methods to reduce that search  
9 cost, that could help cut down the backlog of the  
10 agency.

11 On the trademark side, one of the most innovative  
12 tools is actually a computer vision model that allows  
13 trademark examiners to take a trademark sort of  
14 application and see whether there are visually similar  
15 prior registered marks based on a kind of computer  
16 vision algorithm.

17 Two last points just on that example is that I do  
18 think there are really important governance questions  
19 as the prior speakers have alluded to. One point here  
20 is that we've learned from the computer vision  
21 literature in the past few years there are lots of  
22 opportunities for adversarial learning, meaning gaming  
23 of brittle computer algorithms. And so if trademark  
24 examiners no longer actually themselves inspect  
25 visually similar marks, it's possible for

1 sophisticated parties potentially to game the  
2 trademark registration process if they know what kind  
3 of computer vision algorithm is built out. And that  
4 raises some serious questions about accountability and  
5 fairness with sophisticated parties are better  
6 positioned to fool trademark examiners.

7         And then the last thing that our -- the last  
8 point I'll make here is that this PTO case study  
9 highlights one of the tricky dimensions in terms of  
10 the role of contractors in building out AI solutions.  
11 About a third of the use cases we uncovered were  
12 developed by outside contractors. And oftentimes  
13 those use cases can be locked behind proprietary  
14 source code. But in the PTO case, there was an even  
15 more sort of apparent potential conflict of interest  
16 where the very contractor that was -- had built out a  
17 natural language processing-based engine to classify  
18 patents for assignment to different art units was also  
19 advertising selling the ability for patent applicants  
20 to be able to write their patents in a way to gain  
21 particular arguments.

22         So I think there are real kind of governance  
23 issues that need to be tackled in this space to make  
24 sure that AI is not abused in particular ways.

25         MS. BRILL: Thank you. And Professor Sharkey.

1 PROFESSOR SHARKEY: Thank you. So I want to  
2 thank Georgetown and Hillary, as well, and also give a  
3 shout out to Alexandra Givens. A decade and a half  
4 ago, she was one of my very first students, law  
5 students, and teaching assistants, and was phenomenal  
6 in that role. It was wonderful to reconnect through  
7 this work.

8 The second is, again, to thank ACUS. Just to be  
9 clear, ACUS is sort of like a hallmark of ACUS that  
10 they engage with academics and have us serve as  
11 consultants but then also serve as kind of a calling  
12 card to get input from a variety of different federal  
13 agencies and officials. And it's enormously helpful  
14 and productive, these kind of partnerships that they  
15 enable.

16 My -- I have a history with ACUS. As Hillary, as  
17 you mentioned, I'm an elected member but also back in,  
18 I think, 2010 when Paul Verkuil resurrected ACUS as  
19 its first head, I started as a consultant on a  
20 different project in which I also enormously  
21 benefitted from interviewing federal official, agency  
22 folks, many of whom might be on the call, and then  
23 under Matt's leadership was really honored to  
24 participate in this endeavor.

25 Final prefatory remark is just in some ways, I

1 think our project was unique, drawing together not  
2 only, you know, academics from different institutions,  
3 Stanford and NYU, also drawing in expertise from  
4 Justice Cuellar from the California State Supreme  
5 Court, but the students that we gathered were both  
6 lawyers and technical, computer science folks. And in  
7 a way, I think our project is kind of like a microcosm  
8 of what's needed and what distinguishes this from the  
9 earlier Dartmouth project, you know, that you  
10 mentioned because it brings together both legal  
11 expertise, policy input, along with technical savvy  
12 kind of at the outset of thinking about some of these  
13 problems.

14 And just a smaller footnote, it includes women as  
15 well as men. Female students, we have some female  
16 collaboration. I've been in contact (inaudible)  
17 reporters who say, oh, are there women interested in  
18 machine learning and artificial intelligence, and the  
19 future is bright if we look at (inaudible) students in  
20 this project.

21 But a few remarks from my perspective, I want to  
22 think about some of the findings that surfaced in the  
23 report with respect to the Food and Drug  
24 Administration as a kind of window onto the future of  
25 AI in regulatory analysis. And by regulatory

1 analysis, we include standard setting, guidance  
2 documents, and ultimately, rule-making.

3 And interestingly, the FDA is a great exemplar or  
4 lens into some of these issues because most people  
5 know that the future of healthcare, in particular, is  
6 going to be increasingly mediated by machines, by  
7 machine learning, by AI technologies.

8 And the other thing is that AI tools are  
9 extremely data hungry. This is sort of a theme that  
10 emerges throughout our report. And it's important to  
11 note that the FDA, which is the world's leading drug  
12 regulator, sits on an extremely large repository of  
13 data from clinical trials. And so the potential of  
14 being able to harness enormous datasets using these  
15 kinds of AI tools is really mindboggling.

16 There's also not only this existing data reserve  
17 but lots of emerging sources of data with respect to  
18 electronic health records, with respect to wearable  
19 technologies, and the like.

20 And so there are two main points that I want to  
21 bring out into our discussion. The first relates to  
22 something that Professor Engstrom foreshadowed, which  
23 is the way in which AI and machine learning might be  
24 actually quite transformative with respect to an  
25 agency's mission.

1           So the FDA is a great example of this. And from  
2 my perspective, at least, what this does, the machine  
3 learning and AI kind of fuels a transformative shift  
4 in the regulatory paradigm from being primarily a pre-  
5 market and a clearance for drugs and medical devices,  
6 shifting much more into the post-market surveillance.  
7 And that's going to harness using machine learning and  
8 AI with respect to dramatically improved ways to  
9 collect real world data and analyzing it kind of an  
10 ongoing basis.

11           But our report kind of uncovered with respect to  
12 the FDA there is that the FDA is kind of at a  
13 crossroads. On the one hand, they can go down an  
14 avenue of further refining existing AI tools,  
15 including primarily natural language processing.  
16 They've been using some pilots that look remarkably  
17 similar to what David was mentioning with respect to  
18 the SEC, namely using natural language (inaudible)  
19 processing to kind of sift through adverse event  
20 reports and try to figure out which ones deserve the  
21 agency's priorities and the like.

22           The second avenue and maybe a very, very  
23 promising one that the FDA is really thinking about is  
24 collecting more structured or focused data and the  
25 ways in which they can go directly to sources, some of

1 which I mentioned at the outset with respect to this  
2 real world data.

3 Second, very briefly, a point that I want to  
4 bring out is the relationship to this idea of building  
5 internal capacity. I think the FDA, to me at least,  
6 provided some really interesting, surprising examples  
7 -- I'll mention one -- about the kinds of internal  
8 embedded expertise that's being developed.

9 And internal, what they call, incubator of  
10 machine learning, AI technology is called INFORMED at  
11 the FDA. It stands for Information Exchange and Data  
12 Transformation Initiative.

13 It was described to us, and we interviewed  
14 various federal officials who are involved with this  
15 as a regulatory sandbox. It's basically an internal  
16 incubator within the FDA of some of these machine  
17 learning AI tools.

18 And so to me what stood out is this is a way that  
19 an agency like the FDA can "fail cheaply". Right?  
20 The FDA is otherwise kind of an agency that would have  
21 a low-risk tolerance. Their decisions are life and  
22 death decisions. So you -- the margin for error there  
23 is pretty small. But having this internal incubator,  
24 they can try to kind of have exploration of some of  
25 these tools.

1           And the second and final point I'll make is that  
2   the FDA is an interesting agency because they not only  
3   are going to be using these technologies internally,  
4   they regulate AI out in the real world. So they have  
5   been approving medical devices, for example, that use  
6   machine learning/AI technologies. And so there's a  
7   way in which they have this internal incubator, and  
8   they are publishing their findings from the deployment  
9   of some of these technologies. They can search "e-  
10  risk" (phonetic) certain machine learning/AI tools  
11  that the private sector then can have more confidence  
12  as they go about using them. Thank you.

13           MS. BRILL: Thank you. Thank you so much to all  
14  of our panelists. And many of you mentioned all of  
15  the different people who participated in the report  
16  and the important collaboration between technologists  
17  and lawyers. And that has always been at the core,  
18  also, of what the institute is trying to do to bring  
19  technologists and lawyers together, and we are really  
20  pleased to see a report like this come from such  
21  collaboration.

22           You also mentioned a variety of things about  
23  accountability. You mentioned relationship building  
24  and internal capacity, Professor Sharkey. Surprising  
25  examples of AI in different government, a lot of



1 benefits in AI because we focus on concerns of AI, but  
2 there really are benefits to be recognized here, and  
3 discussion of gamesmanship and how do we handle third-  
4 party vendors.

5 We're going to discuss some of these in the time  
6 that we have and then have some questions from the  
7 audience. I want to first address bias, bias in AI,  
8 we know that that's a concern, and the report notes it  
9 as well. And racial bias, especially, is a concern  
10 with the problem of artificial intelligence and  
11 machine learning systems. This is true across the  
12 board, no matter what the systems are designed to do.

13 You note in your report that bias can come from a  
14 variety of different factors. It can come from  
15 whether the human coders -- themselves  
16 unintentionally, it could come from unrepresented  
17 data, linking datasets that might not otherwise be  
18 connected, or other sources.

19 But what I want to ask you on a preliminary basis  
20 is what are some of the use cases where the potential  
21 for bias that you guys learned about in your research  
22 that the potential for bias concerns you the most.  
23 And who wants to start?

24 JUSTICE CUELLAR: I'm happy to start. I will  
25 just tell you that obviously, bias is a huge problem.

1 But I will -- and then I'll give you one context where  
2 the team that I was working with, they certainly  
3 raised concerns about it, and then I'll just highlight  
4 one of the difficulties in talking about bias in the  
5 AI context.

6 So we looked at some published reports and  
7 testimony highlighting how agencies that do border-  
8 related enforcement use facial -- or beginning to use  
9 facial recognition. And this is an area, of course,  
10 where not surprisingly, the full extent of what is  
11 currently happening is sort of probably well beyond  
12 what we were able to wrap our minds around.

13 But there was enough that we could get a sense of  
14 that highlighted some of the very -- Professor  
15 Engstrom, for example, was talking about where the  
16 shift of discretion out includes the extent to which  
17 an agency purchases a set of software that reflects an  
18 architecture for thinking about visual data and  
19 working through visual data that may have  
20 probabilities of failure modes, even in the absence of  
21 any adversarial effort to make that happen.

22 So when the Wayne County stuff was reported, I  
23 was not surprised. I would say there's no question  
24 that there are probably some contexts where processing  
25 of visual data can be useful to an agency and probably

1 advance social welfare. But we have to be pretty  
2 careful.

3 Now, let me highlight one way in which the whole  
4 discussion of bias gets really tricky. There are  
5 going to be a lot of situations, and facial  
6 recognition will be one example where you can look for  
7 bias around race and around gender, where the  
8 definition of bias is pretty clear.

9 But then there are other contexts where the  
10 trade-offs are really about values, and one person's  
11 bias is another person's legitimate decision to  
12 prioritize one outcome over another.

13 So if you think about the choices that state  
14 regulators and NHTSA and the private sector will have  
15 around self-driving vehicles and the trolley problem-  
16 like choices that have to be made about where you put  
17 the risk, I think that we have to acknowledge that  
18 there are some blurry areas where questions that are  
19 partly technical, partly policy responsiveness  
20 questions are also, in some sense, at risk of  
21 triggering concerns about bias, given questions of  
22 who's in the room when the decision making happens, so  
23 to speak.

24 PROFESSOR HO: Yeah, I'm happy to follow on that.  
25 I think Justice Cuellar is right to kind of point to

1 the use case around facial recognition technology. We  
2 have a kind of in-depth case study of the Customs and  
3 Border Patrol Agency, where there were significant  
4 errors, and it was really hard for the agency even to  
5 ascertain what the source of errors were because the  
6 system that had been built up was proprietary.

7 And we have a pretty substantial evidence base  
8 that documents the potential for bias in facial  
9 recognition technology. And the National Institute of  
10 Standards and Technology itself has done really  
11 terrific work on performance benchmarking of facial  
12 recognition technology that also corroborates the fact  
13 that across some 47 vendors, there are really  
14 significant performance differences in terms of the  
15 accuracy of FRT when applied to minority groups. So  
16 that is an area of real concern.

17 Let me say two other things. One is that the  
18 scope of the report focused more on the civil side of  
19 things, specifically carved out sort of national  
20 security and military applications, which are also  
21 some of the areas of greatest concern. And so,  
22 Hillary, when your question, what are the things  
23 things that concern you the most, in a sense, we have  
24 to be careful here about most -- you know, given that  
25 it was covered within the report, given we excluded

1 sort of military and national security things, just  
2 because we realized it was going to be very  
3 challenging to gain any sort of transparent insight  
4 into a number of those applications.

5 But the kind of thing generally that you worry  
6 about that I think also connects to the civil  
7 enforcement side is what we now have seen in terms of  
8 the performance of predictive policing algorithms. So  
9 there's a great paper by a set of machine learners  
10 that basically shows that if you target and allocate  
11 police officers based upon arrests and then feed  
12 arrest data back into the model and refine it in that  
13 particular way, you could send police over to the  
14 exact same zip code over and over and over again in a  
15 kind of runaway feedback loop, even if the underlying  
16 crime rates were random.

17 So that is a really important thing for agencies  
18 to get right. And there is actually some important  
19 work to be done in terms of how to properly build in  
20 information as it comes in so that enforcement  
21 algorithms don't result in that kind of a runaway  
22 feedback loop.

23 The second thing I'll just say is that as  
24 Professor Engstrom had alluded to, there are really  
25 important doctrinal implications here. On the one

1 hand, a lot of anti-discrimination law has shifted  
2 towards sort of anti-classification as an undergirding  
3 principle. And what we know from the past decade of  
4 work in fairness, accountability, and transparency in  
5 machine learning is that blinding yourself to features  
6 like race and gender are really imperfect ways to  
7 account for the potential disparate impact of  
8 algorithms.

9 And so I think we're on a kind of collision  
10 course between anti-classification and what is known  
11 in the fairness in machine learning literature, which  
12 is that the way in which we understand and address  
13 bias is by developing formal algorithms that really  
14 build in these kind of fairness constraints that rely  
15 on having measures for protected attributes to really  
16 build in the appropriate safeguards.

17 PROFESSOR SHARKEY: Just a quick word, too,  
18 because, Hillary, you know, as you alluded to in your  
19 question we could -- bias, typically, I think, people  
20 put in the front of their minds these issues about  
21 disparate impact on various races, genders, et cetera.  
22 There's an optimistic story about the infusion of  
23 machine learning and AI with respect to bias, too, and  
24 the FDA story kind of captures part of that, which is  
25 that this is all about data, data, data, and how

1 representative the data is.

2       And so for example, if we're worried that present  
3 clinical trial data is rather unrepresentative, so it  
4 doesn't include data on all groups in society, et  
5 cetera, to the extent that these machine learning/AI  
6 tools allows us to harness lots more real world  
7 evidence coming from all sorts of different groups, et  
8 cetera, and seeing how things play out, that could  
9 lead to, you know, a de-biasing in a way that people  
10 don't typically think about sometimes because they  
11 don't raise anti-discrimination type issues.

12       PROFESSOR ENGSTROM: So let me just -- let me say  
13 a couple of very brief things, and I'll loop back to  
14 some things that I talked about in my introductory  
15 remarks. I think here's one of the places where  
16 really taking apart these tools and understanding  
17 their technical and operational details can matter.  
18 So think about the two SEC tools that I told you about  
19 in my -- in my five minutes.

20       One of those looks at conduct that's already been  
21 engaged in. If you think of that as like a reactive  
22 tool, this is the insider trading tool. You're  
23 looking at transactions already completed.

24       The other tool, though, is more of a -- you can  
25 call it a preemptive tool. You're trying to build a

1 profile of a likely violator of the law, and that's  
2 like a really important distinction if you think about  
3 it when we think about age discrimination and bias  
4 type concerns. A reactive approach where we have  
5 perfect transparency over the equities markets holds  
6 the promise of perfect enforcement and perfectly  
7 nondiscriminatory enforcement, if we can capture every  
8 instance of wrongdoing.

9 But the preemptive approach, where we're building  
10 a profile, is essentially a kind of profile. And so  
11 there's much potential there for discrimination. So  
12 that's the first plug I'll make as to the usefulness  
13 of our report in really trying to get under the hood  
14 of some of these tools.

15 The other thing -- and I'll go back to from my  
16 introductory remarks -- is this is another place where  
17 algorithms really press on doctrine when you think  
18 about these enforcement tools. They are mostly hived  
19 off from judicial review. Prosecutorial discretion is  
20 really important. The Armstrong case -- this is an  
21 equal protection case -- says that we don't permit  
22 selective prosecution claims unless there's a really  
23 strong evidentiary showing of both discriminatory  
24 intent and effect, and that's a really hard case to  
25 make out to even get review of these things.



1           So what you worry about in the enforcement  
2 context is that because (inaudible) in such  
3 substantial ways that there's a slow burn of  
4 discrimination that can go on.

5           Now, the use of algorithmic tools like criminal  
6 risk assessment at the state level, those have already  
7 been the subject of litigation. It's likely we're  
8 going to get a Supreme Court case on that. There will  
9 be guardrails built around those. You might not agree  
10 with what those guardrails are, but there will be  
11 guardrails built around those particular tools.

12           But I guess I worry more about that slow burn of  
13 bias, then, that can make its way into some of the  
14 data analytics that a lot of similar regulatory  
15 agencies are using, and they won't be reachable under  
16 current doctrine.

17           MS. BRILL: Thank you, all, for -- oh wait, did  
18 you have something else you wanted to say, Professor  
19 Ho? I didn't want to interrupt you.

20           There are a variety of different themes that came  
21 up with how to -- how should we potentially deal with  
22 the issue of bias. In addition to just finding bias,  
23 but how do we deal with the issue of bias. And one  
24 discussion that you mentioned was, you know, we have  
25 to first define what bias is, Justice Cuellar, and

1 that's -- that also brings up a whole variety of  
2 issues of what are standard settings on trying to stop  
3 bias, and who makes those decisions, and is it the  
4 government, or is it the person creating the actual  
5 software, and is that a private entity?

6 I'm not asking you answer that question, although  
7 I would love it, but we don't have enough time. I  
8 want to move on to -- because they were getting ready  
9 to answer, and I wanted to move on, actually, to the  
10 question of transparency, frankly, as a possible  
11 mechanism for some oversight because oversight was  
12 mentioned by several of you, as well, as something  
13 that should be taken into account in artificial  
14 intelligence.

15 In fact, in the report, one recommendation was  
16 setting up an AI oversight board, for example. But  
17 many agencies, as you know, are using AI, frankly,  
18 built by the private sector. And I believe it was  
19 you, Professor Ho, who was talking about this concern  
20 of accountability and transparency with actual third-  
21 party vendors. Some people are calling it Black Box  
22 AI. Or whatever way you want to describe it, which  
23 can significantly limit the way that we can see how  
24 those systems are being used due to trade secrets, if  
25 it's a third party, or other types of IP protections.

1           So what -- it's so complex now. It's not easy to  
2 explain how these artificial intelligence systems  
3 work, particularly when there's someone outside of the  
4 government who is making it. So if we can't have  
5 transparency, what do we do? What do we do for  
6 accountability? Should we not have third-party  
7 vendors? Should we ban these "Black Box AI"? What  
8 paths do you see, in general, to increase transparency  
9 and the challenges with increasing transparency?

10           JUSTICE CUELLAR: I know you're trying to  
11 deliberately be proactive when you say if we can't  
12 have transparency do we ban all contractors. Like, I  
13 would say, no, we don't ban all contracting, and I  
14 wouldn't give up entirely on transparency. I know my  
15 colleagues have a lot to say about this.

16           But let me just frame it by saying one thing  
17 about why we ought not to expect too much for  
18 transparency. I think a fair read of our report is  
19 that you don't really get an insight into how AI is  
20 going to perform in government if you just look at the  
21 algorithm or the math behind the algorithm. It's at  
22 least a function of what is the algorithm, what data  
23 will the algorithm use, what is the reliability of the  
24 computing system and network that the algorithm and  
25 the data are being processed in, how does the user

1 interface work to present data and recommendations to  
2 the user, and how does the organization perform.

3 So all that is to say that really this discussion  
4 has to be about benchmarking at least as much as it is  
5 about transparency. And there are going to be some  
6 situations where an agency can and will make a  
7 compelling argument, certainly one that could present  
8 a court, I would imagine under the appropriate  
9 statutes, that it has a good reason not to share every  
10 single thing about how it's working with AI with the  
11 public for enforcement-related reasons. But do we  
12 need more transparency? For sure. We just can't  
13 expect that will solve every problem.

14 PROFESSOR HO: Yeah, one thing that the report  
15 highlights that became really clear to us in talking  
16 to a range of the agency officials is how important  
17 what we refer to in the report as internal due process  
18 is in terms of at least the agency having enough of an  
19 understanding as to how a tool is really performing.

20 So that, to go back to the SSA example, was the  
21 brilliance of actually having a person like Kirk Lays  
22 (phonetic) who was both a lawyer and someone who can  
23 do forms of natural language processing really build  
24 the system out, and it was that internal capacity that  
25 really enabled him to scope out what is a problem

1 worth solving. And I think a quote from him -- "I  
2 developed the flags I wanted to have available as an  
3 adjudicator". And that is one of the kind of  
4 challenges when delegating something out to a  
5 contractor.

6 And I think at least, as Justice Cuellar said, in  
7 the enforcement context, there may be reasons not to  
8 have the decision system be completely transparent.  
9 The IRS, for instance, in its audit selection system  
10 guards very carefully how it selects because you would  
11 really be worried about reverse engineering if  
12 everyone knew exactly how audits were selected by the  
13 IRS. But what's very important is that the agency  
14 itself, the domain experts, have a really clear  
15 understanding.

16 And Professor Engstrom may be able to give us a  
17 little bit more insight into that dynamic at the SEC,  
18 where it was very much the sort of lawyers who were  
19 demanding greater transparency and intelligibility of  
20 the risks for selecting cases.

21 PROFESSOR ENGSTROM: Yeah, I can speak to that  
22 briefly, which is as we talked to the SEC officials  
23 and staff who put into place some of the algorithmic  
24 enforcement tools being used within the agency, they  
25 noted -- so take that second tool that I profiled, the

1 one that tries to figure out which investment advisors  
2 might be the bad apples.

3 So these are predictions that are generated in  
4 some central part of the agency by technologists. And  
5 then those outputs are then handed off to line level  
6 enforcers. And what we heard from the officials and  
7 staff as we talked to them about the implementation of  
8 this tool is that those line level enforcers are not  
9 at all impressed by being told that, hey, this fancy  
10 machine learning system threw a flag as to this  
11 investment advisor but not this one, you know, but not  
12 that one.

13 They want to know why. They want to know, you  
14 know, why the flag was thrown. They want to know  
15 which part of the narrative disclosure threw the flag.  
16 And so this gave us at least some reason for optimism  
17 that the different -- that the splitting off of, say,  
18 the technologists and those line level enforcers in  
19 the agency actually creates its own internal form of  
20 due process and demands for explanation.

21 MS. BRILL: Would you like to add anything,  
22 Professor Sharkey? I also -- I also wanted to say to  
23 the audience that you can provide questions. We're  
24 open to a question-and-answer session, so please do  
25 provide your questions. But Professor Sharkey?

1 PROFESSOR SHARKEY: Yeah, just very briefly. So  
2 first, I'll defer, of course, to Justice Cuellar about  
3 what kind of arguments judges would find persuasive on  
4 judicial review with respect to transparency or not --

5 JUSTICE CUELLAR: I was talking about  
6 hypothetical judges.

7 PROFESSOR SHARKEY: Right, right.

8 JUSTICE CUELLAR: And hypothetical courts.

9 PROFESSOR SHARKEY: Mysterious point, though,  
10 comes back to what I said earlier about our project  
11 being in some sense this microcosm. I think that what  
12 it means in terms of having sufficient level of  
13 explainability, reasons given, is a question that is a  
14 merger of legal expertise, policy expertise, and  
15 scientific savvy.

16 So groups, for example, like NHSTA that were  
17 mentioned before who are coming up with standard  
18 settings in various areas, I think they are onto the  
19 idea that while they have these laboratories with  
20 scientists who are developing what's possible in terms  
21 of the scientific capability, it behooves them to  
22 reach out to legal policy analysts, not waiting --  
23 sort of like the idea like we'll develop the  
24 technology first, and then the law will give us a  
25 thumbs-up/thumbs-down. Getting the legal policy input

1 along with the generation of this emergent technology,  
2 I think, is really critical and key.

3 PROFESSOR HO: Yeah, I'll say one other thing,  
4 just in terms of where the case law is headed here.  
5 Many folks in the audience will know of the Wisconsin  
6 Supreme Court's case in the Loomis decision, where the  
7 criminal risk assessment score was challenged under  
8 due process.

9 And one of the claims by Eric Loomis in that case  
10 was that the risk assessment algorithm was closed  
11 source, and it was not possible to actually know how  
12 the risk score was calculated.

13 And the way the Wisconsin Supreme Court disposed  
14 of the case was to conclude that because the inputs  
15 into the algorithm in the presentencing report were  
16 all available and transparent, there was no due  
17 process violation in not being able to peek underneath  
18 the hood.

19 And I think if there's one thing a report really  
20 highlights is that it's going to be important for the  
21 future of algorithmic governance to actually  
22 understand how something really is engineered. It is  
23 not enough, given the complexity of models, to say the  
24 inputs are all transparent because there may be many  
25 things going on underneath the hood that are going to



1 be important as a policy and as a legal matter.

2 MS. BRILL: So I want to open questions up to the  
3 audience, if we hopefully still have some audience  
4 members with us because this panel was scheduled to go  
5 from 1:00 to 2:15 and to allow you to have some  
6 opportunity after you heard the panelists to ask some  
7 questions.

8 And one question that was brought up by the  
9 audience was specific -- oh, to submit a question,  
10 please type it in the chat box. So please open up  
11 your chat box. All of you have one. It is there.  
12 There is a part that says questions. Please go into  
13 the questions, and if you have one, please go ahead  
14 and submit it.

15 One question from the audience was what part of  
16 the APA do you think AI challenges the most.

17 JUSTICE CUELLAR: Oh, I love that question. I'm  
18 actually curious to hear what my colleagues say about  
19 that.

20 MS. BRILL: Great.

21 JUSTICE CUELLAR: I'll just throw out what counts  
22 as arbitrary and capriciousness has been zipped up  
23 kind of at the heart of administrative law for a  
24 while, a portion of it, and I think that this is a  
25 really great moment where the question is being culled

1 in a new way by the intersection of user interfaces,  
2 algorithms, data, and organizational performance. And  
3 I think we'll have to be a lot more specific about  
4 what that means.

5 PROFESSOR SHARKEY: Yeah, I would just echo -- I  
6 mean, a bunch of work that I've done outside of AI has  
7 focused on how courts increasingly try to scrutinize  
8 kind of the empirical basis for what makes something a  
9 reasonable decision on the part of the agency.

10 And so the focus, you know, this idea of what  
11 part of machine learning/AI that gets infused,  
12 particularly in the regulatory rule-making context, is  
13 going to, I think, require probably the most work.

14 MS. BRILL: There's a question -- oh I'm sorry,  
15 Professor Engstrom.

16 PROFESSOR ENGSTROM: I was going to say this is  
17 just a give a boy a hammer moment. Everything looks  
18 like a nail. But I think this (inaudible) enforcement  
19 has always been this tweener governance task. It's  
20 always existed in this kind of limbo. It's both a  
21 wholesale and a retail endeavor that has an  
22 adjudicative component. It has a rule-making  
23 component to it. And so I think that there is going  
24 to be some very interesting sort of near to midterm  
25 thinking that needs to be done about whether we might

1 want to reshape ex-post review, allow relatively more  
2 challenges to enforcement decision-making that would  
3 require some kind of an amendment to the Heckler V.  
4 Chaney line of cases.

5 It's also conceivable that we would want to  
6 declare algorithms and algorithmic systems of various  
7 types rules that are -- that must go through notice  
8 and comment. That doesn't mean every algorithmic  
9 system would have to do so, but some would, and we  
10 could try to think about smart line drawings to  
11 determine which types of algorithmic systems do have  
12 to be pushed through that process. But -- and I think  
13 it could be done.

14 But I think that -- I do think there'll be some  
15 very interesting thinking there, and it does present  
16 all the usual trade-offs between ex-post review of  
17 enforcement decision-making or other types of  
18 decision-making or in a notice-and-comment context, we  
19 could kind of call that ex-ante review.

20 MS. BRILL: Thank you. There is a question  
21 specifically for Professor Ho. I'm going to put you  
22 on the spot. Professor Ho, can you speak more on the  
23 potential for reverse engineering of systems and  
24 overly transparent systems? Are there any policy  
25 remedies to mitigate them?

1 PROFESSOR HO: As a law professor, it's nice to  
2 have the tables turned on me to be cold-called  
3 (inaudible) like this. So just so I understand the  
4 question, what are the potential remedies for kind of  
5 reserve engineering, I take it?

6 Yeah, I think it's going to be one of those  
7 fairly domain-specific inquiries. So for instance, in  
8 the trademark context or the patent context, are there  
9 kind of good faith obligations. And so if there is  
10 someone who has used a reverse-engineered kind of mark  
11 to evade the computer vision algorithm, it's an open  
12 question whether that would potentially violate sort  
13 of the practice rules in front of the PTO.

14 But my other colleagues may also have other  
15 insights here as to the kinds of concerns that arise.  
16 There are, of course, other instances where  
17 transparency and like reverse engineering, if you've  
18 got the incentives set up right, may actually be the  
19 desirable thing.

20 So for instance, I think this is the interesting  
21 contrast between sort of benefits algorithms and  
22 enforcement algorithms. In the benefits context, if  
23 part of what happens is you're making much more  
24 transparent the conditions under which you're entitled  
25 to a disability benefit, that may not be reverse

1 engineering. You may actually be more crisply  
2 communicating what the eligibility criteria are, and  
3 that may actually be something that is desirable,  
4 given the documented amount of discretion that we do  
5 see in making disability determinations.

6 PROFESSOR ENGSTROM: So can I tack on just a  
7 little bit there? Which is if you really look into  
8 the emerging, quite excellent literature on  
9 transparency around AI, both in the private sector and  
10 in the public sector, there's lots of interesting  
11 conversation about what transparency means, what types  
12 of explanations would satisfy it.

13 So a distinction you'll often see is between  
14 decision-level transparency and system-level  
15 transparency. Decision-level transparency is where a  
16 person might be entitled to some very thorough  
17 explanation as to the provenance of the particular  
18 decision. But it could be that transparency is hashed  
19 out quite nicely by more system-level explanation.  
20 Like what are the -- you know, what are the basics of  
21 the model, what are the basics of the data inputs,  
22 things like that.

23 And so I think here, it's important to note that  
24 the logics and the imperatives of different governance  
25 tasks are really different. The logics and

1 imperatives of enforcement are very different from,  
2 say, the social welfare benefits context.

3 And so we might want decision-level transparency  
4 in the welfare context. But we can't provide that in  
5 the enforcement context because it kills the tool. If  
6 you open source the tool, you kill its usefulness.

7 MS. BRILL: So in a sense, you're saying it  
8 should be context-specific for potentially what level  
9 of transparency we have. And it's quite interesting -  
10 - we don't have enough time for everyone's questions,  
11 but many of the questions revolve around transparency  
12 and what can be done to -- to solve the issues with  
13 that.

14 And I can't say what's in the minds of the people  
15 that are writing it, but I think it comes from the not  
16 understanding and the concern and then everything  
17 around the fear. And maybe if we understood what  
18 these types of systems were doing, then we would feel  
19 a lot more comfortable.

20 And I think as -- for those of you who have  
21 questions that weren't answered, there are there more  
22 panels on this report, and there will be more  
23 discussions about these issues.

24 So I want to end on this question. As you're all  
25 lawyers, and you're all technologists, and you all

1 have put together this great work, will Congress now  
2 need to enact new statutes to govern how agencies use  
3 new AI tools, or will existing statutes be adequate to  
4 the task? And let it be known, this is an audience  
5 question. I'm not cold calling you. Any professor  
6 can jump in whenever they feel comfortable. But what  
7 do you think about what Congress needs to do?

8 PROFESSOR SHARKEY: So I'll jump in with -- I'll  
9 take it on small bore in the following way. There was  
10 a dispute that surfaced that's actually not reported  
11 in our report because we didn't focus -- we didn't do  
12 a use case study for NHSTA, but we did review various  
13 officials for NHSTA, et cetera, and there was a  
14 disagreement as to whether or not their current  
15 regulatory status allowed them to mandate that car  
16 manufacturers give them direct data or not and what  
17 this meant for the future of their use of machine  
18 learning and AI.

19 And so I guess before -- what I would want to do  
20 is before answering that question about Congress does  
21 or doesn't have to do, it would be worth studying  
22 existing regulatory mandates, agency by agency, and  
23 engaging in these debates about what -- you know, how  
24 you can push the limits in terms of saying that the  
25 agency already has the authority.

1           And I would center many of these questions around  
2 gathering of data, at least for agencies like NHSTA  
3 and FDA that are going to be these regulators of  
4 health and safety out in the real world.

5           PROFESSOR HO: Yeah, I also am reluctant to  
6 speculate as to what exactly Congress should do. But  
7 I do want to kind of answer this broader theme,  
8 Hillary, that you're pointing out as to concerns about  
9 transparency because I really do think it goes back to  
10 the point about internal capacity. That is the most  
11 complicated machine learning models right now could be  
12 sledgehammers to kill a fly. That is, there are --  
13 there's a kind of complexity/accuracy trade-off. But  
14 it may not always require a sledgehammer to solve  
15 particular problems. And the people who are going to  
16 be best situated to really understand that are going  
17 to be agency staff who have an insight into these  
18 tools and understand the domain. And that's really  
19 where we think some of the biggest gains are likely to  
20 be made.

21           There is also some real fruitful models here, for  
22 instance, in terms of academic agency collaborations  
23 to start to bring in some of that insight in-house  
24 into the agency. So I'm not sure about any specific  
25 recommendations, but I think it is important to think



1 about the internal capacity within agencies to  
2 navigate that transparency, complexity, accuracy  
3 trade-off in choosing which tools are suitable for the  
4 problem at hand.

5 JUSTICE CUELLAR: I really like Professor Ho's  
6 answer, and I'll just build on it by making the  
7 following observation: there are two considerations  
8 that are normative and one that's descriptive,  
9 practical, that might inform any discussion of this  
10 topic.

11 The first normative consideration is how much we  
12 can realistically imagine a trans substantive approach  
13 to AI that is going to make sense at a high level of  
14 generality like APA style for NHSTA and for FDA and  
15 for the SEC and for SSA and so on. And I have my  
16 doubts.

17 I think part of what is helpful about this report  
18 is to highlight how there are definitely cross-cutting  
19 themes, but there's a lot of context-specific, subtle  
20 work that really is right at the intersection of some  
21 fairly bespoke technical issues and some very bespoke  
22 legal and factual and politically common issues that  
23 should live at the more specific level.

24 The other normative consideration is how much we  
25 want to preempt the kind of experimentation happening

1 not only in the private sector but in the states.  
2 Laboratories of democracy with one or another  
3 crosscutting solution.

4 The descriptive, practical observation is  
5 Congress has had real trouble passing even basic  
6 cybersecurity legislation. It's not exactly in a  
7 particularly productive period of its history for any  
8 number of reasons. So query whether we can expect a  
9 lot of action.

10 MS. BRILL: We didn't ask if Congress would.  
11 Well, I guess -- if they should.

12 JUSTICE CUELLAR: Just throwing it in as an added  
13 bonus for what it's worth.

14 MS. BRILL: I don't want to cut you off, but we  
15 have just a moment in closing, and I wanted to thank  
16 all of you for the great insight and hard work that  
17 you put into this report and the table setting.

18 I mean, you brought up all the issues. You  
19 brought up all of the themes. You did most of my  
20 work. You just summarized the fact that a lot of this  
21 is context-specific, and a lot of the themes are  
22 across the board discussions that other people seem to  
23 want to hear about are about transparency, are about  
24 what is bias, what does that mean, and who decides it,  
25 and what are the actual agencies that are going to be

1 determining that and setting those standards, and what  
2 is the public/private connection with that  
3 relationship.

4 And you said this is 64 years in the making. I  
5 don't think we have 64 more years to answer those  
6 questions, although -- you know, it could happen that  
7 someone else could be talking about remember that  
8 webinar back 64 years ago. But we do need good  
9 discussions, and the rest of this symposium will  
10 hopefully bring it to the experts that joined us. So  
11 thank you all today for -- plenty of thank you to the  
12 audience, and thank you again to ACUS and everyone who  
13 helped make this possible.

14 MULTIPLE VOICES: Thank you.

15 (End of audio recording.)

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CERTIFICATE

I, Wendy Sawyer, do hereby certify that I was authorized to and transcribed the foregoing recorded proceedings and that the transcript is a true record, to the best of my ability.

DATED this 9th day of July, 2020.



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WENDY SAWYER, CDLT

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