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1 would like to ask a question by Twitter, you can tweet  
2 your question using @FTC and #PrivacyCon20. Please  
3 understand that we may not be able to get to all of  
4 the questions.

5 Lastly, I wanted to thank all of the  
6 researchers and the panelists for their participation  
7 in today's event. We are very grateful for your work  
8 in this important area.

9 This program would not be possible without  
10 the great work done by many of our FTC colleagues. We  
11 would like to thank our colleagues that assisted us in  
12 reviewing all of the research submissions, including  
13 Monique Einhorn and Patrick McAlvanah. We would also  
14 like to thank those moderating panels today, including  
15 Ellen Connelly, Phoebe Rouge, Daniel Wood, and Lerone  
16 Banks.

17 Finally, this conference would not be  
18 possible without the help of Kristal Peters, Aryssa  
19 Henderson, James Murray, and Bruce Jennings;  
20 paralegals, Leah Singleton and Alex Iglesias; June  
21 Chang from our Division of Consumer and Business  
22 Education; Somethea Mam from the FTC media team;  
23 Juliana Henderson and Nicole Drayton in our Office of  
24 Public Affairs; and Shawn Whitaker at Open Exchange.  
25 Thank you all.

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1                   It is now my honor to welcome the Director  
2 of the Bureau of Consumer Protection at the Federal  
3

1                   OPENING REMARKS BY DIRECTOR ANDREW SMITH

2                   MR. SMITH: Thank you, Elisa.

3                   Welcome to PrivacyCon 2020 and thank you all  
4 for being here virtually. This is the fifth year that  
5 we've held PrivacyCon, which brings together  
6 researchers from around the country and around the  
7 world to discuss cutting-edge issues related to  
8 consumer privacy and security. I know that you will  
9 all miss the opportunity to see each other face to  
10 face, but the most important feature of PrivacyCon  
11 remains the same, the spotlight on topnotch research  
12 from a distinguished group of academics, physicians,  
13 economists, and other practitioners.

14                   Over the past few years, PrivacyCon has been  
15 critical in keeping the FTC and other stakeholders up  
16 to date on emerging technologies and related data and  
17 privacy security risks. PrivacyCon informs all of the  
18 work that we do here at the FTC, whether it be  
19 enforcement, business or consumer education or  
20 rulemaking and policy efforts.

21                   In light of that influence, I'll start with  
22 a few words about what the FTC has been doing to  
23 protect consumers' privacy since the last PrivacyCon.  
24 Vigorous enforcement is at the heart of what the FTC  
25 does. And in the past year, we've brought privacy and

1 security cases under the Fair Credit Reporting Act,  
2 the Children's Online Privacy Protection Act, the  
3 Gramm-Leach-Bliley Safeguards Rule, and our own FTC  
4 Act.

5           Shortly after last year's PrivacyCon, we  
6 announced settlements with Facebook, Equifax, and  
7 YouTube last year that shattered prior records for  
8 civil penalties or consumer redress for privacy and  
9 security violations. These settlements also required  
10 important structural changes with respect to how these  
11

1 financial information and emails, away from prying  
2 eyes.

3 We have also focused on educating business  
4 and consumers about data-related risks. For example,  
5 in recent months, we've issued guidance to businesses  
6 on how to develop coronavirus-related technologies  
7 that take privacy into account. We've offered advice  
8 on secure cloud computing and tips for using  
9 artificial intelligence and algorithms.

10 For consumers, we've put out guidance on how  
11 to safely use videoconferencing services and how to  
12 protect children's privacy while doing remote  
13 learning.

14 Rather than talking about past  
15 accomplishments, today's conversation needs to be  
16 focused on what the FTC should be doing going forward.  
17 Panelists today will discuss technologies ranging from  
18 mobile health and disaster apps to interconnected  
19 devices, such as smart speakers and cameras, to online  
20 ad delivery systems. Economists will report on their  
21 studies abroad to gauge the effects of privacy  
22 legislation in Europe. And researchers will describe  
23 mechanisms for consumer choice and how consumers  
24 protect themselves from identity theft.

25 The papers presented today will highlight



1 technological developments that could be a boon to  
2 consumers, but that also present risks to privacy,  
3 security, and, in at least one instance, equal  
4 opportunity.

5           One final note before I turn the discussion  
6 over to our first panel: In our call for research  
7 papers, we specifically asked for research on mobile  
8 health apps, and the first panel of the day will be  
9 devoted to that important topic. Why health apps?  
10 Industry reports show that consumers are increasingly  
11 using a variety of health-related apps, including  
12 fitness trackers, mood journals, smoking cessation or  
13 addiction aids, heart rate or sleep monitors,  
14 fertility trackers, diet guides, and more. Use of  
15 contact-tracing apps during the COVID-19 pandemic  
16 could add a whole new dimension to that trend.

17           Earlier this year, the Department of Health  
18 and Human Services issued rules that will make it  
19 easier for consumers to access medical records through  
20 the app of their choice. This expanded access to  
21 health information could be an enormous benefit to  
22 consumers. But as we all know, wherever data flows  
23



## PrivacyCon

1 engage with the public on this important and cutting-  
2 edge research, and I hope that you enjoy the FTC's  
3 fifth PrivacyCon.

4 So our first panel begins at 9:20, and I'll  
5 turn it over to Ellen Connelly and Elisa Jillson for  
6 that panel. Thank you.

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1                                   SESSION 1: HEALTH APPS

2                                   MS. CONNELLY: Good morning, everyone.

3 Welcome to PrivacyCon 2020. I am Ellen Connelly, and  
4 my co-moderator today is Elisa Jillson. We are both  
5 attorneys in the Division of Privacy and Identity  
6 Protection at the FTC. We want to welcome you to our  
7 first panel of the day, which is entitled Health Apps.

8                                   We have five panelists here to present some  
9 very interesting research. First will be Quinn  
10 Grundy. Quinn is an assistant professor at the  
11 University of Toronto and will present her research on  
12 the data-sharing practices of medicines apps.

13                                  Next, we have Kenneth Mandl of Boston  
14 Children's Hospital and Harvard Medical School. He  
15 will present his paper on the privacy implications of  
16 moving health data, such as electronic health record  
17 information, to entities that are not covered by  
18 HIPAA.

19                                  Then we have Dena Mendelsohn of Elektra  
20 Labs, who will tell us about her work evaluating the  
21 privacy risks of connected sensor technologies in  
22 medicine.

23                                  We will conclude the presentation portion of  
24 our panel with John Torous and Sarah Lagan from Beth  
25 Israel Deaconess Medical Center and Harvard Medical

1 School, describing their effort to develop a practical  
2 framework to aid consumers in their evaluation of  
3 health apps.

4 We have more detailed bios for all of our  
5 panelists available on the PrivacyCon website at  
6 ftc.gov.

7 At the conclusion of the presentations,  
8 we'll have a question-and-answer period, during which  
9 we'll be able to have further discussion about the  
10 research presented. We'll be taking questions from  
11 the audience during the Q&A portion of the event, so  
12 please send your questions to [privacycon@ftc.gov](mailto:privacycon@ftc.gov) and  
13 we will try to include them.

14 With that, I will turn it over to Quinn to  
15 start us off. Quinn?

16 MS. GRUNDY: Thanks, Ellen, and thank you,  
17 again, for the opportunity to speak today.

18 I am very excited to share with you some  
19 work my colleagues and I did looking at the data-  
20 sharing practices of apps that have to do with  
21 medicines. And I'm hoping to spark some discussion  
22 this morning about how we think about data sharing  
23 within the context of the wider mobile ecosystem.

24 Could I have the disclosures slide, please?

25 I first just wanted to acknowledge that this

1 project was funded by the Sydney Policy Lab at the  
2 University of Sydney and that we have no conflicts of  
3 interest.

4 Next slide, please.

5 "Drug App Comes Free, Ads Included." So  
6 this was a headline that ran in The New York Times  
7 back in 2011. This app, which is really popular among  
8 health professionals, provides information about  
9 prescribing, drug information, and clinical  
10 conditions. This article reported, however, that  
11 Epocrates was generating the bulk of its revenue from  
12 pharmaceutical companies that purchased targeted,  
13 tailored advertising that was delivered to users on the  
14 basis of their personal characteristics and browsing  
15 history.

16

1 are aggregated across multiple sources.

2 But consumers are in a really difficult  
3 position and really have very little way of knowing  
4 whether their apps or websites that they use share  
5 this data and with whom. So we wanted to add to this  
6 ongoing discussion by specifically examining the data-  
7 sharing practices of a sample of apps that we thought  
8 were likely to share sensitive, specific health  
9 information that might be of high value to commercial  
10 stakeholders. So these are apps that provide  
11 information about medications, whether consumers  
12 taking medications or health professionals  
13 administering and prescribing.

14 We wanted to know exactly what data these  
15 apps collected and where they sent it and then to  
16 extrapolate from this data sharing to understand where  
17 that data might travel beyond third parties within the  
18 wider mobile ecosystem.

19 Next slide, please.

20 Our methods. So just quickly, and there is

21

1 to medicine, so looking at the most popular apps.

2 We chose 24 of these apps that had some  
3 degree of interactivity. We designed a fake user  
4 profile, and in a lab setting, we interacted with  
5 these apps to simulate use. My colleague, Andrea  
6 Continella, developed a tool, Agrigento, that  
7 performed a traffic analysis to eavesdrop on the data  
8 sharing that these apps performed between themselves  
9 and the network. We analyzed the types of data shared  
10 and the IP addresses where it was sent.

11 We were able to identify the entities that  
12 had these IP addresses, and then looked at their  
13 websites and these companies' privacy policies to  
14 understand what they might do with user data. And,  
15 frequently, we found that they reported further  
16 sharing through integrations or other commercial  
17 partners. And so we were then able to identify what  
18 we called fourth parties and to simulate a worst case  
19 scenario of all the possible data sharing within this  
20 wider mobile ecosystem.

21 Next slide, please.

22 So in a sample of just 24 apps, a tiny  
23 fraction of the health app market, we found that the  
24 majority did share user data outside the app with the  
25 network and that some apps reported additional sharing



1 within their privacy policies. We had pre-specified  
2 types of user data that might be shared, including  
3 names, time zones, medications, or email.

4 Next slide, please.

5 We found that, most commonly, apps were  
6 sharing technical data, which might seem very benign  
7 on the face of it, so things like the device name, the  
8 operating system. But we did find that just over a  
9 third of these apps shared unique identifiers, such as  
10 Android IDs or email addresses. And a quarter shared  
11 the user's medication list, which is something that  
12 people could use to infer information about other  
13 sensitive things, like health conditions.

14 Next slide, please.

15 We conducted a network analysis of the data-  
16 sharing relationships between the apps and these third  
17 parties. So we identified 55 unique entities that  
18 received or processed user data, which included app  
19 developers and their parent companies and these third  
20 parties. We found that third parties received a  
21 median of three different pieces, or unique  
22 transmissions of user data, and as many as 24  
23 different types of user data.

24 In this network, you'll see the orange nodes  
25 are the apps, and the size of the node is the volume

1 of user data sent or received. The blue nodes are  
2 third parties that we characterized as infrastructure  
3 and represented about a third of the recipients.  
4 These were providers such as data storage, cloud  
5 providers. And because of their business model, which  
6 often involves keeping information secure, we reasoned  
7 that risks to privacy were low from this type of  
8 sharing.

9           The gray nodes, however, are entities that  
10 were involved in the collection, collation, analysis,  
11 and then commercialization of user data, and this  
12 involved advertisers, social media, or analytics  
13 companies. And because of their business models and  
14 the way they described handling user data, we reasoned  
15 that there might be privacy risks associated with this  
16 type of data sharing.

17           Next slide, please.

18           So first parties. We're calling first  
19 parties developers and parent companies that were  
20 receiving user data in our traffic analysis. We found  
21 that they received both the greatest volume and the  
22 greatest variety. And that might be expected, as this  
23 data was likely used to enhance the service that  
24 developer provided to users.

2523

1 websites and privacy policies, that developers were  
2 using this data for their own marketing purposes for  
3 products and services, but also the ability to tailor  
4 sponsored content, to sell advertising space, beyond  
5 banner ads, for example, and even to sell  
6 de-identified and aggregated data or analyses to third  
7 parties, like pharmaceutical companies or health  
8 insurance.

9           So for example, one app said they  
10 commercialized what they called the patient insights,  
11 from how medicines are used in the real world to  
12 healthcare stakeholders, like pharmaceutical  
13 companies. And so the sense that because developers  
14 were collecting information, that that might be safe  
15 and secure and private, may not, in fact, be entirely  
16 true.

17           Next slide, please.

18           When we looked deeper into the third parties  
19 receiving user data, there were 21 entities that we  
20 characterized as analytics. We found, when we  
21 analyzed their privacy policies, that these entities  
22 typically reserved the right to collect de-identified  
23 and aggregated data from app users for their own  
24 commercial purposes and to share these data among  
25 their commercial partners, or to transfer data as a

1 business asset in the event of a sale.

2 What was interesting was that for third  
3 parties, their privacy policies defined a relationship  
4 with the app developer, not the app user. And so if  
5 app users were concerned about the collection or  
6 sharing of their data, even if it was de-identified or  
7 aggregated, they were referred back to the developer  
8 in the event of a privacy complaint and couldn't take  
9 it up with the third party directly.

10 Next slide, please.

11 So fourth parties. We found that the third-  
12 party entities reported this ability to share end-user  
13 data with 216 different fourth parties, so entities  
14 beyond what directly received user data. And we found  
15 that these entities could potentially create highly  
16 detailed profiles of users, even if they could not  
17 identify them by name. So while certain data sources  
18 are clearly sensitive and personal, or identifying,  
19 like your date of birth or a drug list, others may  
20 seem irrelevant from a privacy perspective.

21 However, when combined, all these little  
22 pieces of information from a variety of different  
23 sources can create a fairly detailed picture of a user  
24 or to associate them with certain groups. So we  
25 conducted a network analysis to understand, again, how

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1 data might be aggregated within larger companies and  
2 their commercial partners, and we simulated this  
3 hypothetical data sharing.

4 Next slide, please.

5

1 of both those that collect and control user data --  
2 right now, a great deal of onus is placed on  
3 developers -- but also that process it, these third  
4 and fourth parties that sit behind the scenes.

5 I think we increasingly understand that the  
6 sharing of app user data ultimately has real world  
7 consequences. And I think the panelists in later  
8 talks today will be sharing some of these things, like  
9 bias in algorithms. These consequences include highly  
10 targeted advertising or the commercialization of data  
11 into algorithms that ultimately make decisions about  
12 people's insurance premiums, employability, or  
13 financial services.

14 We're seeing increased scrutiny of  
15 collection and sharing of sensitive, personal, or  
16 health data, but I think understanding how data are  
17 aggregated suggests that in combination, a much wider  
18 array of data types might actually be considered  
19 health data and used to make inferences about people  
20 and groups. So for example, even the existence of a  
21 health app or a mental health app on one's phone could  
22 be used to make inferences and decisions about a  
23 person.

24 Our current regulation focuses on securing  
25 individual informed consent through improving privacy

1 policies or labels for apps and protecting harms to  
2 individuals, for example, by ensuring that data are  
3 de-identified. However, when we think about the  
4 mobile ecosystem, the aggregation and sharing of data  
5 within this wider space, I think we also need to  
6 consider the disproportionate harms that can occur to  
7 certain groups when inferences are made on the basis  
8 of characteristic.

9           Next slide, please.

10           So in conclusion, I wanted to share our  
11 dashboard, [healthprivacy.info](http://healthprivacy.info), where the full data  
12 from this study are available, and it includes  
13 additional information about the security analysis we  
14 also performed and the apps that we sampled.

15           I'd like to thank Ellen and Elisa, again,  
16 for this opportunity, and to acknowledge my  
17 collaborators on this project, and in particular  
18 Andrea Continella, for developing the tool we used in  
19 the traffic analysis. And I'd like to thank, again,  
20

1           We're going to move on now to our next  
2 presenter, and next we'll hear from Ken. Ken, you're  
3 up.

4           MR. MANDL: Terrific. I'd like to thank the  
5 FTC organizers of PrivacyCon for putting together this  
6 spectacular program, and I'm honored to be able to  
7 participate.

8           Let me set the context for my talk. At the  
9 beginning of the Obama Administration -- and I assume  
10 my slides are going up -- at the beginning of the  
11 Obama Administration, Congress passed the HITECH Act,  
12 and the Federal Government invested \$48 billion to  
13 promote the adoption of electronic health records.  
14 Because I had worked with electronic health records as  
15 a physician and a researcher, I knew that these older  
16 1980s and 1990s software stacks would not advance the  
17 goals of a learning health system, where the data  
18 collected are put to work to improve health, control  
19 costs, drive discovery, underpin public health, and  
20 empower patients to manage their care and participate  
21 in research.

22           So I wrote in The New England Journal of  
23 Medicine a piece proposing that if we're going to  
24 invest this \$48 billion of federal dollars -- which,  
25 by the way, was complemented by probably between a



1 half a trillion and a trillion dollars of private and  
2 public investment in installing these electronic  
3 medical record systems and purchasing them -- if we're  
4 going to do that, why don't we think about a public  
5 interface that essentially turns the electronic health  
6 record into a smartphone-like platform that can run  
7 apps that can be added or deleted the same way they  
8 could on the iPhone?

9           And when we wrote this, the iPhone was one  
10 year old, and we were just starting to see the power  
11 of an application programming interface that allowed  
12 third-party apps to connect to a platform. The type  
13 of business advances, the types of innovation, the  
14 competition that you see in an app store, the truly  
15 spectacular examples of apps that were emerging, could  
16 we have this for medicine, too, even though we were  
17 investing in older technology as the sort of backbone  
18 of our health IT infrastructure?

19           So we were funded for \$15 million by the  
20 Office of the National Coordinator. And what we  
21 proposed was an application programming interface that  
22 would enable EHRs to run these apps. This was a high  
23 risk play, because each EHR was different, had no  
24 standard for the storage of data, and was not designed  
25 to ever let data out of its walls. In fact, quite the

1 opposite.

2 Patients had some access to their electronic  
3 health record through portals. Many of you may have  
4 used them. But those data are essentially behind  
5 glass. You can look at them, but you can't get a  
6 computable copy. You can't feed them into a  
7 computable process, like an app or an algorithm.

8 Now, HIPAA, passed in 1996, guaranteed that  
9 consumers could get access to a copy of their data in  
10 an electronic format if it was feasible. And from  
11 1996 until, essentially, a year or two ago, it was  
12 determined by healthcare and healthcare IT vendors  
13 that, in fact, it was not feasible. Now, whether  
14 that's true, I think, is a subject of debate. But the  
15 good news is that now, 10 years after the \$48 billion  
16 investment began, we have actually new regulation that  
17 comes from the Office of the National Coordinator of  
18 Health Information Technology, an HHS agency that  
19 oversaw the \$48 billion investment and that funded us  
20 and that now has passed regulation based on the 21st  
21 Century Cures Act.

22 I don't do very much lobbying, but I managed  
23 to get this one sentence into the 21st Century Cures  
24 Act, requiring an API that provides access to all data  
25 elements of a patient's electronic health record, and

1 that those elements can be accessed without special  
2 effort. This underpins the potential for an extremely  
3 robust apps economy.

4 A second API was also developed in our group  
5 and managed to make it in under the wire into the  
6 regulation, which allows us to get data on populations  
7 out of electronic health records as well. The first  
8 API is called SMART on FHIR.

9 Next slide, please.

10 And these two APIs together allow us to  
11 potentially think about healthcare innovation in a  
12 parallel way to how Tim Berners-Lee thought about the  
13 Web. I think the slides might be a bit ahead. There  
14 should be a slide of Tim Berners-Lee showing now on  
15 the World Wide Web.

16 In a sense, what we're trying to do for  
17 healthcare is similar to what he tried to do. He  
18 wanted to share pre-prints of his articles, and he  
19 invented a way to show those articles in HTML. He  
20 invented a Web server so that you could serve up those  
21 documents. He invented HTTP so that you could link to  
22 them, and he invented a Web browser so you could  
23 display them. All of these documents -- what Tim  
24 Berners-Lee created parsimoniously, and then  
25 instantiated through the World Wide Web Consortium,

1 enabled a tremendous economy to be built on top of  
2 these parsimonious rules and specifications.

3 The APIs regulated by the Office of the  
4 National Coordinator, stemming from the 21st Century

5 5

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1 us data on whole populations.

2 The next slide has a picture of the USCDI.  
3 The data that we're talking about is regulated as the  
4 United States Core Dataset for Interoperability and  
5 defines which health system data will be available  
6 through these APIs. This data set will expand over  
7 time, but now includes things like medications,  
8 diagnoses, laboratories.

9 The next slide shows the data protected by  
10 HIPAA on the left and the SMART API in the middle,  
11 where the patient can request the data, for example,  
12

1 all the time, that they include statements of whether  
2 and how the data is accessed, used, or sold, that they  
3 share this with users before accessing the data, and  
4 that they require express consent. So it establishes  
5 some elements of what needs to go in a privacy policy,  
6 and that is a good start.

7           The next slide, Analysis of Current  
8 Approaches, shows us that, yes, there are a few  
9 community-based efforts to address this. There is a  
10 model privacy notice. There are questionnaires that  
11 some of the electronic health record companies have  
12 actually developed to ask app developers what their  
13 intentions are. There are external codes of conduct.  
14 An early one comes out of something called the CARIN  
15 Alliance, and it gives us an attestation that is  
16 enforceable later, by the FTC, as to what that company  
17 will do with data collected by the app.

18           The next slide shows that there was  
19 opposition to this rule on the basis of multiple  
20 special interests. I strongly supported the rule  
21 publicly, but I have to agree with one of the points  
22 that was made in the opposition to the rule. And the  
23 rule was passed over this opposition, and I'm going to  
24 talk about some approaches that we're taking to  
25 address the point.

1           The point is that when data traverses that  
2 API, it loses, potentially, a lot of protection. And  
3 the opportunity here is to enable the FTC to handle  
4 the proper stewardship of those data. I addressed  
5 some of these points about the privacy of data once it  
6 has traversed the API and lost the HIPAA protections,  
7 in The New England Journal, around what do we need to  
8 do to be data citizens in the 21st century?

9           We have to be very cognizant that there will  
10 be, as an exception to the rule, I'm sure, but  
11 nonetheless, predatory app companies. We may have  
12 multiple forces, partially driven by privacy concerns,  
13 where we don't get the market economy of apps  
14 competing with each other and adding value to the  
15 health system. If we're not careful about the  
16

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1 the slide that shows the SMART app privacy manifest,  
2 which is a couple of slides down.

3 And the opportunity here is the following:  
4 The API provisions were accompanied by very strong  
5 regulations against information blocking, so that a  
6 health system cannot prevent a patient from choosing  
7 an app that they wish to connect to their electronic  
8 health record. An electronic health record vendor  
9 cannot prevent a patient from connecting an app.  
10 Overall, that's very good, because it gives patients  
11 agency, and it gives app developers and innovators the  
12 opportunity to have a large market.

13 The problem is that it could be perceived of  
14 as information blocking, just to tell patients and  
15 warn them about bad apps because bad apps may be in  
16 the eye of the beholder. And so the Office of the  
17 National Coordinator, in the regulation, actually  
18 addressed this with a potentially innovative solution.  
19 And that is that in the OAuth process that enables the  
20 authorization and authentication of the user and the  
21 app to the electronic health record, there is an  
22 opportunity to present the manifest of privacy  
23 policies. And, in fact, some of the electronic  
24 medical record companies have begun to do this.

25 And so there is, specifically regulated, an



1 approach that this will not be information blocking if  
2 basic information is provided. What kind of  
3 information could we provide; the location of the  
4 privacy policy, the data storage policy, the data  
5 usage policy, the data-sharing policy; who made the  
6 app developers send data to and for what purpose; what  
7 relevant data; the apps method for approaching  
8 patients before sharing their data with other parties,  
9 as we heard about from Quinn; and we can also put in  
10 trust entities badges if the apps have actually  
11 attested to certain practices.

12           However, what we may also want to be sure  
13 that we do is to also -- and we can go to the last  
14 slide, which is this timeline -- is make sure that  
15 this decade of work that has gone into liberating  
16 information from electronic health records to empower  
17 consumers and provide them with computable copies of  
18 data actually results in a safe ecosystem. Part of  
19 this is defining what the privacy policies are and  
20 making sure, perhaps even from a regulatory  
21 perspective, that those elements are there.

22           Research is needed on how patients  
23 understand those privacy policies, and I believe the  
24 FTC could have a strengthened role in enforcement of  
25 those policies, as well, to make sure that when there

1 are breaches of what is promised, that there is a  
2 strong enforcement reaction. And it's very critical  
3 to protect consumers from harms related to health  
4 data. And if we can make consumers feel safe in this  
5 environment, I think the opportunity is almost  
6 unlimited.

7 Thank you very much.

8 MS. CONNELLY: Thank you so much, Ken.

9 Dena, you're up next.

10 MS. MENDELSON: Hi. My name is Dena  
11 Mendelsohn. I'm the Director of Health Policy and  
12 Data Governance at Elektra Labs. We offer services to  
13 better evaluate and dispense connected health-  
14 monitoring technology, many of which feed into the  
15 health apps that you're hearing about today.

16 Prior to joining Elektra earlier this year,  
17 I served as senior policy counsel at Consumer Reports,  
18 where one of my most recent projects was reviewing the  
19 data practices and security of a handful of 00s ent W8ear,18

1           In today's presentation, I'm shifting gears  
2 slightly from the preceding speakers and will pan out  
3 to consider the ecosystem that feeds into and works  
4 with health apps. I will give you a broad overview of  
5 why clinicians are increasingly using biometric  
6 monitoring technologies and what type of due diligence  
7 we recommend before adopting this remote monitoring  
8 technology. I will conclude with what we recommend to  
9 simplify the decision process. Sneak preview, it's a  
10 label, somewhat akin to a nutrition label that we're  
11 all familiar with.

12           Next slide, please.

13           But, first, let's talk about why. Why  
14 collect digital measurements in real time at home?  
15 Well, the simple answer is that in research and care,  
16 remote sensing offers a more holistic view of a  
17 person's lived experience, especially when we're  
18 looking at chronic conditions that impact a person's  
19 daily life. Do we want to just know how they're doing  
20 through a few status points throughout their day?  
21 Well, not really when there's a better alternative,  
22 where we know how they're doing continuously  
23 throughout the day and over a longer period of time.

24           So while it would be simple to just step  
25 away from health apps, for those who are concerned

1 about their data rights, that really takes away some  
2 very powerful tools for them, and so it's not what I  
3 think any of us would recommend.

4 Next slide, please.

5 We believed in the value of the remote  
6 health-monitoring technology before COVID-19 took  
7 over, but the value of these technologies is even more  
8 clear during this difficult time. Uptake of remote  
9 monitoring technology, like connected sensors, are  
10 likely to rapidly increase during this pandemic,  
11 especially following guidance from the FDA and CMS  
12 that encourage widespread use. I think we've all seen  
13 a lot of articles about this in the lay press. Yet,  
14 public discussions of the risk of these technologies  
15 has been limited.

16 Next slide, please.

17 We should be at the Due Diligence is  
18 Necessary slide. And this is where, in our paper, we  
19 provide a deep dive into the due diligence that is  
20 critical when selecting connected sensor technology,  
21 whether it feeds into a health app or not.

22 Next slide, please.

23 What you're seeing here is a broad overview  
24 of our five-point holistic framework for balancing the  
25 benefits and risks of adopting connected health

1 technology. Again, many of this technology feeds into  
2 the health apps that we're talking about in this  
3 panel. The first three dimensions evaluate the data  
4 and subsequent results generated by connected  
5 biometric monitoring products.

6 The fourth dimension, utility and usability,  
7 evaluates the ease of implementation and adoption of  
8 the product. And the last dimension, economic  
9 feasibility, has the reader consider the cost and the  
10 value of adoption. As explained in the paper,  
11 evaluations should be multidimensional and a single  
12 score should be avoided.

13 Next slide, please.

14 So on this slide, we're looking at step one  
15 of the evaluation framework. And this is less about  
16 health apps and more about ensuring that the  
17 technology that's being used will generate information  
18 about a user that is suitable, both in terms of what  
19 measurements are made, the accuracy, and the  
20 appropriateness in the situation where it will be  
21 implemented.

22 Next slide, please.

23 As discussed in the paper, suitable  
24 technology must be verified and validated. Simply  
25 put, the technology must be accurate, both in the

1 measurements it makes, as well as any algorithms that  
2 it applies to the collected data, and that the  
3 technology were for a specific use case in mind.  
4 After all, not all technology is appropriate in all  
5 contexts.

6 Next slide, please.

7 The second part of the evaluation framework  
8 in this paper considers security.

9 Next slide.

10 On the Cybersecurity Considerations slide,  
11 the u01

1 governance is pretty uncertain.

2 Next slide, please.

3 As it is, in our healthcare system, we have

4 strong protections for patient bio specimens, like

5 blood or genomic data, but protections are murkier for

6 digital specimens. The same can be said of data

7 created by health apps. Make no mistake, wearables,

8 health apps, and in-home sensors offer great promise

9 for affordable, accessible, equitable, high-quality





1 consider whether a product has features that users  
2 need and whether it's designed in a way that folks  
3 will actually want to use it. And, finally, no  
4 evaluation will be completed without the consideration  
5 of the cost and value of the technology.

6 Next slide, please.

7 We should be looking at the Nutrition Label  
8 slide. Now that I've considered the holistic  
9 evaluation framework, I'll remind you that excellence  
10 in one dimension does not necessarily imply excellence  
11 in another. Indeed, significant deficiencies in any  
12 one dimension may lead to problems when using  
13 connected sensor technologies in research or in  
14 practice. Thus, we propose a framework that  
15 simplifies the evaluation process of connected sensor  
16 technologies for the intended use, but it does not  
17 give an individual score that would make a decision  
18 for the reader.

19 As remote health-monitoring technologies  
20 become increasingly commonplace, more and more people  
21 need to decide the risk/benefit type of evaluation  
22 that we explained in the paper. But this analysis  
23 will need to be more straightforward. As the paper  
24 concludes, they propose that a connected sensor  
25 technology label could be a useful piece of

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1 its efforts in moving PrivacyCon online this year.

2 Thank you.

3 MS. CONNELLY: Thank you so much, Dena, for  
4 that really interesting presentation.

5 And now we'll move to our final presenters  
6 for this part of the panel. Our final presenters are  
7 John and Sarah.

8 So John and Sarah, I'll turn it over to you.

9 DR. TOROUS: Oh, thank you for having us,  
10 and as going forth, I think you'll hear some themes  
11 that are repeating and some parts that are new.

12 But we'll start with the first slide. We'll  
13 see if it gets pulled up, Actionable App Evaluation.  
14 And let's see, is it up? I think it's not up yet.

15 MS. CONNELLY: We're experiencing a little  
16 bit of a time delay with certain browsers on the  
17 slides. So if you could maybe just start off and,  
18 hopefully, they'll catch up pretty quickly.

19 DR. TOROUS: So as I said, we'll talk about  
20 actionable health app evaluations. And, first, we  
21 want to thank our donor, the Argosy Foundation, which  
22 made this work possible. We couldn't really have done  
23 any of this without their support. And I think what  
24 we're talking about today - and I think Sarah and I  
25 are coming from an interesting position, where we're

1 doing clinical research, but we're also delivering  
2 clinical care. So we're looking at how these apps  
3 work in real world settings and how policies really  
4 impact care decisions and patients today on the  
5 ground.

6           And we know from experience there's many  
7 good smartphone health apps and wearables that can  
8 improve care. As we've heard about from other  
9 speakers, there's also some pretty concerning  
10 dangerous ones that can directly harm care, threaten  
11 care, or harm the whole field. And we know, again,  
12 that a lot of these healthcare apps wearables are  
13 pretty clever in that they call themselves "health and  
14 wellness devices." They don't really go under the  
15 medical category, so they work hard to kind of avoid  
16 different types of regulation.

17           So looking at the slides of privacy  
18 concerns, again, we know that many of these things  
19 live outside of HIPAA and other kind of privacy laws.

1 physicians, therapists, psychologists, social work  
2 colleagues, as well, and nurse practitioner nurses,  
3 and, again, that kind of set a line between how is it  
4 regulated, where is the data going.

5

1 and Depression Apps are Selling Your Data," which was  
2 a little bit concerning.

3 And, certainly, these privacy concerns we've  
4 heard are still with us today. This is just a  
5 headline from February 2020, so not that long ago,  
6 about a popular therapy app that's disclosing  
7 different aspects of users' data. I think in mental  
8 health, we're in a unique position, that a lot of  
9 digital health actually focuses on mental health  
10 because we can both collect data from sensors and apps  
11 that informs care. And in mental health, we can also  
12 offer people treatments via videos and technology. So  
13 a lot of this is actually happening in the mental  
14 health space, and privacy concerns have actually shown  
15 up a lot in the mental health space, as well as other  
16 spaces as well.

17 So you can see on this slide that says,  
18 "Exaggerated Claims of Effectiveness," in a different  
19 study with a group led by the Black Dog Institute in  
20 Australia, we actually read the app stores to say what  
21 are these apps claiming. If I'm a patient, I'm a  
22 clinician, I'm a physician, I'm an NP and I'm looking  
23 at these apps, if you read the app store claims, that  
24 they really kind of -- over half of them make claims  
25 that could be seen as medical, implying effectiveness.

1                   We actually went back and tried to tie it  
2 down to what is actually claimed in the literature,  
3 what is actually proven. And really, it's less than 2  
4 percent. So there's a huge dichotomy between what a  
5 consumer is seeing and what is actually supported.  
6 And I think there's different consequences, we've  
7 heard different speakers, to this misinformation.

8                   On the Perils of Misinformation slide, one  
9 really concerning aspect we saw was that a lot of  
10

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1 has over 100,000 downloads. And that's not always the  
2 best approach to do it. If you type in schizophrenia,  
3 this app that's really a pawn game shows up. It's  
4 stigmatizing. It's incorrect. It actually doesn't  
5 work on a lot of phones, and that's probably a good  
6 thing. But, again, just because it shows up highly in  
7



1 slide that says, "Deriving a Practical App Evaluation  
2 Framework."

3 MS. LAGAN: So in light of these concerns,  
4 we're now going to briefly discuss our efforts with  
5 the American Psychiatric Association to develop a  
6 framework specifically for the assessment of mental  
7 health apps, but applicable to health apps broadly as  
8 well.

9 So on the next slide, you'll see how there  
10 are numerous app evaluation schemes. So there's a  
11 clear need for an evaluation system beyond app store  
12 metrics, as we saw with these many concerns. And to  
13 respond to this need, there have been numerous app  
14 evaluation frameworks that have emerged, including the  
15 NHS in England, Denmark's MindApps system, and over  
16 45, as of 2018, with far more emerging in the two  
17 years since then.

18 So if we go to the next slide, the Potential  
19 for Harm with Lists and Static Ratings, many of these  
20 frameworks rely on lists or static ratings, which may  
21 fail to account for nuance in diverse app needs. Just  
22 as there's no A-plus medication or talk therapy,  
23 people react to and use apps differently. Even the  
24 same app may be used in different ways, depending on  
25 individual variation and preference and needs.

1 Further, the app market is constantly changing and  
2 very dynamic, and it's hard to know if these lists  
3 respond to the most current version of the app.

4 So if we go to the next slide, what we did

5

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1 really well on privacy questions specifically. So  
2 this recent scoping review of different evaluation  
3 systems for apps featured the APA model. And you can  
4

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1           There was recently an article in STAT News  
2 last week kind of showing how we can help people make  
3 apps. But the real question is, is there something  
4 that can actually help change clinical  
5 decision-making, change impact? And one thing we can  
6 do is because we have this database, we can query it.  
7 So one question we can ask of the apps we've looked  
8 at, do apps support downloads, do they offer more  
9 privacy features? As it showed a code in that line,  
10 but the answer was no. In contrast to last year's  
11 PrivacyCon with the apps we've looked at so far, we  
12 said, do apps that cost more offer more privacy  
13 features? If you pay more, do you get better privacy?  
14 And, again, from the subset of apps we've looked at,  
15 the answer was no.

16           We can also use this to help patients make  
17 smarter decisions. We can do patients with training.  
18 This was an app we don't endorse or not endorse any  
19 app. But before, we asked a group of patients, would  
20 you be interested in downloading this app? And,  
21 basically, it was 50/50. And after we had patients  
22 use the tool and ask questions, you can see that their  
23 decision-making changed. People said no.

24           We can also do this with clinicians. Again,  
25 just an example. Blue was before and then orange was

1 after. You can see we took a lot of clinicians who  
2 were in that three middle range. Someone said, hey,  
3 I'm not as interested in this app now. So it's  
4 possible to quickly let people search for apps, learn,  
5 and change how they're making decisions. So we're  
6 expanding on those.

7 And I'd say that, certainly, I think  
8 clinicians and patients both are pretty excited to  
9 learn about this stuff, they just don't always  
10 consider it because they think that these protections  
11 are inherent.

12 So we'll close by, again, thanking our donor  
13 who made this work possible and the FTC for inviting  
14 us.

15 MS. CONNELLY: Thank you so much, John and  
16 Sarah, and thank you to all the other panelists as  
17 well.

18 We'd like to move on now to our Q&A portion  
19 of the panel and, hopefully, engage in some good  
20 discussion, expanding upon some of the ideas that  
21 you've mentioned and maybe touching on some new ideas.

22 So I'll start us off, and I'd like to start  
23 with a question or two that are probably at the top of  
24 everyone's mind these days, and these are questions  
25 related to the pandemic. So as you've probably seen,

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1 patients is we look at how much information the app  
2 may be wanting, if it wants GPS for different levels.  
3 And then what we do is say, what is the risk/benefit?  
4 Usually, by talking with patients, people, again, are  
5 usually shocked that the app is collecting this much  
6 data, but then sometimes, oftentimes, they say it's  
7 not worth the benefit, but it is. But I think as long  
8 as people are informed and aware, that's a very good  
9 first step and people kind of realize the risk/benefit  
10 and going through that.

11 Usually, as people bring apps to us, we're  
12 adding them to our database and then going over it  
13 with patients, and sometimes we use our database. If  
14 an app doesn't come up with a good match, patients  
15 will say, well, what if I was willing to compromise on  
16 this or if I wanted more privacy? So usually, we have  
17 a discussion around it and it turns out to be, I would  
18 almost say, therapeutic and informative for all  
19 parties.

20 MS. CONNELLY: Thank you. I'd like to see  
21 if anyone else has anything to add. Maybe Quinn, do  
22 you have anything to add? Or Dena?

23 MS. MENDELSON: Yeah, I'll just add in the  
24 first step is making sure that individuals understand  
25 that, in many cases, HIPAA doesn't apply. So as

1 speakers said a few times today, there seems to be  
2 some misunderstanding or assumption that when we're  
3 talking about health, that all health is protected the  
4 same, and it's just simply not.

5           And then going from there, just reminding  
6 consumers that health apps is a very large market. So  
7 there are choices. It's not that you always have to  
8 give up your data. You need to be careful about  
9 picking which one you're going to go with and just be  
10 intentional about your selection, rather than simply  
11 downloading the most popular app or the one that one  
12 person may have recommended.

13           MS. CONNELLY: Thank you, Dena.

14           Quinn or Ken, do you have anything to add?

15           DS. GRUNDY: Yeah, I might offer a slightly  
16 different perspective. I think the pandemic has laid  
17 bare, in many areas of our lives, preexisting problems  
18 and really exacerbated them. And so I think this is a  
19 great example where there's actually maybe greater  
20 awareness around privacy and security of data than  
21 ever before. And I think what that will hopefully  
22 lead to is some collective demand that there be better  
23 protections.

24           And I can't really think of another consumer  
25 sector or industry or product where the same amount of



1           And the other caveat, unfortunately --  
2     because I'm sure many of these apps are very useful --  
3     is that privacy policies and terms of use can change,  
4     including for the data that you've already  
5     contributed. And so I think we really do need  
6     stronger protections going forward so that consumers  
7     can take advantage of this emerging apps economy.

8           One advantage in these API-based apps, where  
9     we have the transition that I talked about from a  
10    HIPAA-covered entity to the FTC regulation, is there,  
11    we really know what the data going in are and we have  
12    the opportunity to regulate those data as they go into  
13    FTC jurisdiction. With a mental health app, where  
14    it's really health-related but not coming from the  
15    health system, I think the oversight of those is even  
16    more complex. As complex as it is to regulate the  
17    health API-based apps, regulating apps that provide a  
18    health benefit is, I think, even more complex, but  
19    comprehensive legislation is probably what we need.

20           MS. CONNELLY: Okay. Dena, I see a hand  
21    raised, and I saw that John and Sarah did a lot of  
22    head nodding, so I'll give you another chance after  
23    Dena.

24           MS. MENDELSON: All right, thank you.

25           Yeah, I just wanted to thank Quinn and Ken

1 for bringing that up. In the immediate short term, we  
2 are not getting any privacy laws passed in the next  
3 short term, couple months, and so individuals do need  
4 to be very savvy in the marketplace. But like  
5 everyone else is saying, it does seem quite  
6 inappropriate to shift the burden to consumers to do a  
7 lot of homework, and it really makes an assumption  
8 that consumers are in a position to always protect  
9 themselves, when really that is not the case.

10 Another concern that I also have is that  
11 when we tell people to rely fully on privacy policies,  
12 we're basically putting developers and manufacturers  
13 in the position of creating their own laws and then  
14 following them. And then we're expecting the FTC to  
15 be able to enforce on every individual law, which also  
16 does not seem reasonable at this point.

17 So looking forward, what we definitely need  
18 is for lawmakers to promulgate comprehensive data  
19 protection for individuals.

20 MS. CONNELLY: Thank you.

21 John and Sarah?

22 DR. TOROUS: We'll agree, even from the  
23 study we presented, where we showed that the apps  
24 aren't really even following their own privacy  
25 policies. But I wonder if, as laws and legislation

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1 eventually take effect, there needs to almost be a  
2 focus on educating people to be aware of it, too. I  
3 think there may not be the demand for it because I  
4 think all of us tuned in and listening are aware of  
5 these issues.

6           But I think a lot of times the shock, when  
7 you show someone what data an app is taking, again, a  
8 clinician, a patient, it doesn't matter who, people  
9 actually don't expect that this much is happening or  
10 this type of data movement is happening. And again, I  
11 think it's because they say, well, when I'm in a  
12 clinic visit, I expect kind of privacy. This app istiiis app is

1 question about the Cures Act.

2 Elisa, I think you're on mute.

3 MS. JILLSON: Hi, can you all hear me now?

4 MS. CONNELLY: Yes.

5 MS. JILLSON: Yes. Okay, great.

6 So as Ken mentioned, following passage of  
7 the 21st Century Cures Act, the Department of Health  
8 and Human Services issued new rules intended to  
9 support patients' access to their electronic health  
10 information. Some observers believe that these new  
11 rules will significantly increase consumers' adoption  
12 of health apps, use of health apps, that are not  
13 covered by the HIPAA detailed privacy and security  
14 safeguards.

15 What are the implications of your research  
16 for the projected shift in how consumers use health  
17 apps? From a privacy perspective, how ready is the  
18 health app universe for this shift? And I guess my  
19 last question -- I know many of you have touched on  
20 policy implications and where more regulation or  
21 different regulation may be needed -- but coming back  
22 to the research, where is more research needed so that  
23 we are in a position to prod the app universe into the  
24 right direction?

25 DR. MANDL: This is a fantastic question.

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1



1           So the good news, again, is that uptake is  
2 slow, and where there is uptake, right now we have a  
3 lot of safety. But the issues and the caveats that we  
4 have seen throughout these talks are what we are  
5 facing not too long from now. And in addition to data  
6 that is going to be equally concerning, certainly the  
7 data that patients and consumers enter into mental  
8 health apps, is no less concerning than anything  
9 coming across that API.

10           Nonetheless, the data coming across those  
11 APIs will include, actually, clinical notes and  
12 summaries, eventually, hopefully potentially, images,  
13 things that are very revealing of many aspects of the  
14 patient. And I think we need to reinforce what  
15 happens as the data traverse those APIs with real  
16 standards for privacy policies and real means to  
17 enforce them, and tremendous education and research  
18 into how patients actually understand those policies  
19 and whether they can follow them and what the real  
20 risks are.

21           The other aspect, I think, is comprehensive  
22 privacy legislation so that, on the other end of  
23 this, these data that are health-related and health-  
24 relevant, are, in fact, in some way that the consumers  
25 are protected from the use of these data. And that's

1 going to take some real creativity, to come up with  
2 legislation that both promotes innovation and also  
3 protects patients.

4 MS. JILLSON: Thanks, Ken.

5 Do others have anything to add? Are there  
6 other areas where additional research is needed to  
7 make this app universe ready for us?

8 DR. TOROUS: I'll just briefly add, I think  
9 we still need to understand what both consumers and  
10 patients value in the data, what they are --  
11 understanding kind of how people understand what their  
12 data is worth, what they're willing to trade,  
13 compromise. We're not telling people never share your  
14 data, but I think we still haven't, again, educated  
15 people on what it is, what they have, why it's  
16 valuable, when it matters, more than less.

17 I think, as Dr. Mandl says, the stakes kind  
18 of got higher. It's on us to make sure at least  
19 everyone is aware. We don't have to put the burden on  
20 them, but certainly they need to know what they have.

21 MS. CONNELLY: That mute button. Okay, I  
22 think we'll move on to another topic. And I'd like to  
23 make some linkages between at least one slide that  
24 John and Sarah had up at this conference and some  
25 research that was presented at PrivacyCon 2019. So

1 some observers of the app market have argued that you  
2 get what you pay for. Free apps sell your data to  
3 turn a profit. The paid apps are a bit more privacy-  
4 protective. Research that was presented at PrivacyCon  
5 2019 challenged that idea, that paid apps are  
6 necessarily more privacy-protective than their free  
7 counterparts.

8 And so as I mentioned, John and Sarah, you  
9 had a slide on this that suggested some similar  
10 results from your analysis. I'd like to get some  
11 thoughts from all of the panelists about how does the  
12 free versus paid distinction play out in the health  
13 app context? And also your thoughts on whether  
14 additional research is needed here, and if so, what  
15 kind of research.

16 I'd like to start with Quinn for this, and  
17 then maybe move on to John, Sarah, and the others.

18 DS. GRUNDY: Sure. So I think, yeah, the  
19 work that John and Sarah and others have done  
20 obviously debunks the assumption that if you've paid  
21 for an app, your data will necessarily be private. I  
22 think one area that our research highlighted that  
23 maybe needs some more attention is the relationship  
24 between developers and third parties. In particular,  
25 there are a number of third-party services that are

1 used to monetize apps or to enhance the features of an  
2 app, whether that's user analytics or error testing or  
3 social media integration that are offered to  
4 developers in a freemium model.

5           So developers can access these services  
6 without cost and, often, that's in exchange for access  
7 to de-identified or aggregate user data. Often,  
8 developers who pay for higher tiers of service,  
9 sometimes there are different data-sharing agreements.  
10 The problem is that consumers have no way of  
11 knowing what kind of agreement developers have with  
12 third parties, what kind of data-sharing protections  
13 are in place, and the relationship between the user  
14 and the third party is far from transparent, and they  
15 actually, in many cases, have no relationship at all.

16           And so I think greater scrutiny and  
17 transparency with these behind-the-scenes  
18 relationships needs to occur so that consumers can  
19 understand what is ultimately happening with their  
20 data, whether not it has their name attached.

21           MS. CONNELLY: Thank you, Quinn.

22           John, Sarah?

23           DR. TOROUS: I think what Dr. Grundy said is  
24 exactly correct. I think the business model of apps  
25 is a different topic for a different day. But a lot

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1 of these apps are moving towards subscription models,  
2 so it actually also becomes complex. So they'll have  
3 a free version that's kind of a limited trial or  
4 limited features, and then you kind of can pay to  
5 continue using it. So business models are evolving.  
6

1 than unpaid ones. This could create a major issue,  
2 where lower-income individuals are put in a position  
3 of picking between a free app that may not be as  
4 privacy-protective versus having to pay in order to  
5 get access to, perhaps, an essential service, like a  
6 mental health app.

7           And so this is yet another reason why we  
8 need comprehensive data rights set in law so that we  
9 have a baseline that everybody, regardless of income  
10 or ability to pay, can expect from their health apps.

11           MS. JILLSON: Thank you all for those  
12 thoughts. We have just a few moments left, so I'd  
13 like to ask if you all have any wrap-up thoughts. We  
14 had an audience question about what legislation is  
15 needed in this area. I think that's probably a  
16 question that would take more than one minute of  
17 wrap-up. But if you could briefly, in your closing  
18 remarks, address where you think research should be  
19 headed and, if you'd like to, where you think  
20 regulation or legislation should be headed as well.

21           And we can start -- Ken, why don't you start  
22 us off?

23

1 third-party app. There we have a controlled  
2 environment and a regulatable environment. And  
3 getting that piece right will help consumers  
4 enormously in protecting their privacy and their  
5 integrity in the face of using apps and also in  
6 helping to prevent misuses of their data.

7           The research needs to be done in what  
8 patients expect at that moment, what they can  
9 understand, how much external protection they need,  
10 and where regulation versus sort of community  
11 standards becomes the most effective focus. But I'll  
12 emphasize that because the FTC could potentially be  
13 overseeing the regulation of a very large amount of  
14 health data for the first time, data that HHS is used  
15 to regulating, and the FTC is not yet used to  
16 regulating. I think we have an opportunity to really  
17 think this through together, as a community and as a  
18 nation, on how to make the FTC most effective in  
19 taking on this new role.

20

1 and to an extent, app developers. And I think the  
2 focus of regulation or legislation needs to shift to  
3 some of these really big players with much more power,  
4 including app stores and distributors, data  
5 aggregators and digital advertisers, who currently are  
6 very much behind the scenes and engaged in a lot of  
7 these sometimes dangerous and harmful practices but  
8 aren't really the topic of discussion at the moment.

9 MS. JILLSON: Dena?

10 MS. MENDELSON: I think at the end of the  
11 day, it's on our lawmakers to enact legislation that  
12 sets a data rights framework that could serve as a  
13 baseline for health apps and other connected  
14 technology. And that way, health app developers can  
15 focus on creating the best technology that can win in  
16 the marketplace and consumers could trust that the  
17 technology that they've chosen to further their health  
18 and their lives will not be used against them.

19 MS. JILLSON: Thanks.

20 And John and Sarah?

21 DR. TOROUS: It's hard to follow all of that  
22 up. So I think we would say perhaps we do need to  
23 start using and investing these frameworks in real  
24 world settings and actually, again, educating people,  
25 giving them resources they can use today.



1                   On a more flippant note, if anyone has a  
2 name for the database that we've built, we'd love your  
3 help in naming it. Calling it the App Database is a  
4 little bit boring. So please send us any names you  
5 have. We're open to it.

6                   MS. CONNELLY: Okay. And with that, we are  
7 over time. So I want to thank - Elisa, and I really  
8 want to thank all of our panelists for this really  
9 interesting discussion and great presentations. We  
10 appreciate it. We'll have a short break, and our next  
11 panel, which is Bias in AI Algorithms, will start at  
12 10:50. Thank you all so much.

13                   MS. MENDELSON: Thank you.

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1                   SESSION 2:   BIAS IN AI ALGORITHMS  
2                   MR. ROSSEN:   Good morning, everyone.   My

1 Algorithm Used to Manage the Health of Populations."  
2 And you could find their full bios on the event  
3 website.

4 We're going to have two 12- to 15-minute  
5 presentations, after which there will be an  
6 opportunity for some Q&A.

7 And with no further ado, I'm going to turn  
8 it over to our first panelist. So, Ali, I'll let you  
9 take it from here.

10 MR. ALI: Thank you. Are my slides online  
11 right now? Okay, I hope they are.

12 Well, thank you so much for the introduction  
13 and thanks to everyone who is watching this. So  
14 today, I wanted to talk a little bit about  
15 discrimination in online advertising. And if you've  
16 been following the news, you've probably read an  
17 article or two about it. But a lot of the focus in  
18 the past was focused on the targeting side of things,  
19 how these online platforms are built in a way where  
20 they provide this breadth of options to advertisers,  
21 in essence, enabling them to exclude certain users  
22 from seeing their ads.

23 But I'm not going to talk about that. What  
24 I wanted to focus on was the delivery side of things,  
25 where once an ad starts running, the algorithm is

1 making decisions on who to show the ad to. So that  
2 will be the focus of this talk.

3 But before I talk about my results, I wanted  
4 to give a brief climate on what the Facebook  
5 advertising system looks like. That's what we focus  
6 on in this study.

7 Next slide, please.

8 So here you can see sort of -- if you have a  
9 Facebook account, you can go to the Create Ad option  
10 in the top right, and in a couple of clicks, you'll  
11 end up on this section. You see you can target by  
12 location. There's a bunch of demographic variables  
13 here, age, gender, language. And at the bottom there,  
14 you can see that there's detailed targeting. These  
15 are interests that Facebook is constantly inferring  
16 about its users, whether you're interested in coffee  
17 or comics, and then they present all of these  
18 attributes to advertisers to target. And that has  
19 been the focus of a lot of the prior work.

20 Next slide.

21 For example, these are some of the examples.  
22 On the top here, you can see, back in 2016, ProPublica  
23 showed that they could target people looking for  
24 housing and exclude people by their ethnic affinity,  
25 as Facebook was indexing at the time. And, later, it

1 showed that even if Facebook goes ahead and blocks  
2 these features from being excluded, as they later did,  
3 a malicious advertiser can go ahead and find other  
4 proxies that correlate with race, and then go ahead  
5 and exclude that. So there's a lot that a malicious  
6 advertiser can do here, but that's not the focus here.

7 Next.

8 So we sort of look at the advertising system  
9 in these two tables. There's the advertiser, who is  
10 controlling the targeting part, where they design the  
11 target audience, what the ad looks like, how much  
12 money they want to pay. But then once the ad is  
13 created, it goes to review. The advertising platform  
14 is making decisions on which user they want to show  
15 these ads to. And they're running an auction.  
16 They're doing some estimates of relevance. We want to  
17 understand whether the differences -- any sort of  
18 discrimination can arise in this space. So can there  
19 be delivery skews on this second phase?

20 Next.

21 And we do that simply by actually buying ads  
22 from Facebook, because there's no clear way -- there's  
23 no data set where you have information about targeting  
24 and then the eventual information about delivery.  
25 What we had to do, we had to create our own ads, sign

1 up as an advertiser on Facebook, and then ask them how  
2 those ads are doing. Facebook is happy to report  
3 breakdowns by age, gender, location, multiple other  
4 things. So we used the APIs to collect all this  
5 information on the ads that we ran ourselves. We  
6 thought this was the best way to do this.

7 Next slide.

8 And one of the first set of ads we found  
9 were these two extremely stereotypical ads that we  
10 expected would skew a certain way. So one is  
11 advertising bodybuilding and the other one is  
12 advertising a makeup kit, pointing to Elle or  
13 bodybuilding.com, both websites that we don't own.  
14 And we targeted these two ads to the exact same set of  
15 random phone numbers in the US to see, given that the  
16 targeting is the same, how does the delivery affect?

17 Next slide.

18 And we see that there's these large  
19 differences, where one ad has, eventually, 85 percent  
20 of male audience and the other just has 5 percent. So  
21 it's clear that just the targeting, just the delivery  
22 phase, can cause these large differences, regardless  
23 of the targeting.

24 Next slide.

25 So that's the first question that I asked on

1 how these differences can arise in the delivery phase,  
2 yes. But we want to understand it better. Like how  
3 do these differences even get there? Like what  
4 elements of the ad is Facebook looking at? Are these  
5 differences because users are clicking on these ads  
6 more? Does this decide a priority? I'm going to try  
7 to go through all of these one by one and see.

8 Next.

9 So this is what a standard ad on Facebook  
10 would look like when you are advertising a link. You  
11 can see there's so many things you change here.  
12 There's the text on top. There's the image. There's  
13 the URL. These are just the user-facing attributes.  
14 And behind the scenes, there's other attributes as  
15 well, such as the daily budget, what audience you're  
16 selecting. And we wanted to tweak each of these to  
17 see what causes the most difference.

18 Next slide.

19 And we realized that even before we changed  
20 any of the interfacing attributes, as I mentioned,  
21 just changing the budget itself causes differences in  
22 how many women see the ad. So we ran this ad for  
23 Indeed, the job search website site, from one of our  
24 pages. And we noticed that the more money we were  
25 paying, the higher fraction of women in the eventual

1 audience we were reaching, arguably because women are  
2 more competitive on Facebook or because they're more  
3 expensive for some reason. But these are differences  
4 that the advertiser would not be able to realize  
5 what's happening because -- so we sort of stick to a  
6 \$20 budget for all of our experiments, so these  
7 baseline effects disappear.

8 Next slide.

9 And then we started to tweak the attributes  
10 of the ads themselves. So when we started running  
11 this, my expectation was they're running some sort of  
12 natural language processing and they look at the text  
13 that I put in the ad and that's how they decided who  
14 the ad is relevant to. Turns out I was wrong. We ran  
15 an ad with just a baseline, a white image, with a text  
16 on the white image. And we see that there's no  
17 differences between the bodybuilding and the cosmetic  
18 site. Adding the headline causes some differences,  
19 but not the sort that I mentioned earlier.

20 Next slide.

21 But adding the image immediately causes  
22 these large differences. We see that as soon as we  
23 add the image of the guy pumping iron and the  
24 bodybuilding, the initial skews that we saw just  
25 immediately replicate. So it seems like in these ads



1 we were running, the image is the strongest factor to  
2 the classification algorithm and its relevant  
3 estimate.

4 Next slide.

5 And one of those other things -- which this  
6 was also in our initial hypothesis -- it might be  
7 because people are clicking on these ads more or  
8 because people are interacting. But it turns out, we  
9 polled the API over the 24 hours multiple times, but  
10 it turns out that some sort of relevance estimate was  
11 made as soon as the ad started running and the  
12 platform sticks to a decision throughout the course of  
13 the ad. So there is clearly some initial decision  
14 being made.

15 Next slide.

16 And this was one of the harder things to  
17 measure, but we wanted to really be sure how much of  
18 this difference was because of any humans in the loop  
19 versus algorithms. By humans in the loop, I also mean  
20 users who might be giving telemetry data to Facebook,  
21 basically scrolling over my bodybuilding ads  
22 differently than cosmetics, or any sort of modulators  
23 just that might be in the loop.

24 So we wanted to create ads that would make  
25 no sense to people but would make sense to an image

1 computer vision algorithm. How we do that is we take  
2 images and we try to make them transparent. This is  
3 an example of that. You can see that this image looks  
4 slightly transparent. It's because -- you can see on

1 skewed towards women. And beyond both visible and  
2 invisible images, so that any sort of user interaction  
3 has gone away. It's just the image algorithm.

4 Next slide.

5 And you can see here, for example, the two  
6 blue-colored dots on the top. You can see the hollow  
7 ones are the ones where the male images were made  
8 invisible. Between the visible and invisible, there's  
9 barely any statistical significant difference. So the  
10 gender estimate, the gender skew remains the same,  
11 regardless of what it is. Because the user is seeing  
12 just a plain white square. It's not any sort of data  
13 that was being incorporated there. It's just that the  
14 image algorithm sees a certain image, it classifies  
15 it, and it sticks to its judgment.

16 Next.

17 So we went through all of these sort of to  
18 gain a better sense of how the algorithm is working.  
19 So we understand that it's mostly the image that's  
20 causing all of these differences. A lot of these  
21 differences are made as soon as the ad starts running,  
22 and humans are not as involved as we thought. And we  
23 say "at least" because we're not sure, because these  
24 ads aren't run for weeks or months. So we don't know  
25 what would happen if we got hundreds of clicks on

1     them.  But at least in the few days that we ran these  
2     ads, we see that a lot of these decisions are  
3     algorithmic.

4             Next slide.

5             But one of the other things we really wanted  
6     to measure was whether Facebook is capable of  
7     producing any sort of racial skews, and Facebook  
8     wouldn't report us breakdowns as it does with the  
9     gender, where we can ask the APA for information.  So  
10    to get at racial information, what we do is we take  
11    voter records from North Carolina.  So we build this  
12    methodology where we divide the state of North  
13    Carolina into regions, where we only take information  
14    of black voters from the voter records and upload that  
15    to Facebook to create an audience, and regions where  
16    we only take information about white users.

17            So from the voter records, we can get  
18    information like first name, last name, zip code, and  
19    a lot of other things, and we can target these people.  
20    So when Facebook reports the location back to us, we  
21    know that we only uploaded black users in this area,  
22    so we can infer their race.  And to test whether this  
23    works or not, we run yet another set of stereotypical  
24    ads.

25            Next slide, where we essentially take the

1 top 30 country albums, top 30 hip hop albums, all  
2 pointing to RollingStone.com, the same website, just  
3 different articles with images. And we see very, very  
4 strong skews, where the country music ad goes to 80  
5 percent white users in the audience and the hip hop ad  
6 is only 12 percent white users and the rest of the  
7 audience is black. So this sort of gives us  
8 confidence that this reverse inference methodology  
9 that we come up with for measuring race works, and we  
10 can use this to measure these effects in more  
11 important categories.

12 Next slide.

13 And by what I mean by more important  
14 categories are protected categories, employment, where  
15 it's illegal to discriminate. So a lot of the  
16 examples that I showed so far, they might be benign.  
17 Judging whether someone likes sneakers or not doesn't  
18 seem too problematic, but doing the same thing  
19 excluding someone from an employment opportunity would  
20 create some sort of liability.

21 So what we do is we create these job ads on  
22 multiple ads. For example, this is a job in the  
23 lumber industry, the cleaning industry. All of these  
24 ads point to Indeed.com, actually job searches. So if  
25 someone clicks on it, they actually go to an actual

1 job search. And we target the exact same set of  
2 people for all of these ads.

3 Next slide.

4 And we see the same differences exist, even  
5 for these jobs ads that we saw earlier. For example,  
6 on the left, you can see the gender distribution. You  
7 can see that the number of job ads are close to 90  
8 percent male, while the janitor ones are skewed  
9 towards women. And on the right, you can see the  
10 racial split, and you can see that the lumber jobs  
11 skew towards white people and the janitor actually  
12 skews slightly towards black users. Without the  
13 advertiser ever asking anyone to do so, this is the  
14 exact same set of people that both of these ads are  
15 targeting.

16 Next slide.

17 And we see not just in these two categories.  
18 We've done it for a variety of jobs, supermarket  
19 workers, secretaries, nurses. And you can see that  
20 across gender and race, there's so many differences  
21 that occur on the delivery side of things, even when  
22 the advertiser might not have intended to discriminate  
23 in any way.

24 Next slide.

25 So in essence to sort of summarize, what we

1 do is we provide these new methodologies to be able to  
2 measure Facebook's advertising system. And we show  
3 that regardless of how an advertiser decides to  
4 target, a lot of these differences can arise in the  
5 delivery phase. And not just in benign categories; it  
6 can also bring into protected categories, like  
7 employment.

8           So what are the real world implications for  
9 all of this? And I'd like to mention, last year, the  
10 Housing and Urban Development Department, they decided  
11 to sue Facebook because Facebook was enabling  
12 discrimination in housing opportunities. So our  
13 paper, we believe, sort of provides a way to  
14 investigate whether these differences -- how much of  
15 these differences arise from the delivery part versus  
16 how much of these differences are responsible by the  
17 algorithm itself, who's deciding who to show the ads  
18 to. So it's a methodology towards that.

19           We also think our paper sort of provides a  
20 unique nuance on the Communications Decency Act,  
21 Section 230. So this provides a lot of immunity to  
22 online publishers from all the content that they're  
23 hosting. So it's the responsibility of the people  
24 posting and not the publisher's. But what we show is  
25 that if so many of these decisions on which user

1 eventually ends up seeing something are contingent on  
2 the delivery algorithms, on the AI that's running in  
3 these systems, then it's not so clear then who's  
4 entirely responsible.

5           And, finally, I'd like to emphasize that  
6 we're still at the phase where we need more  
7 transparency into these systems. Whenever something  
8 goes wrong, online advertisers cannot continue to  
9 blame the advertisers for being discriminatory, when  
10 we clearly show that so many of these differences  
11 don't even depend on the advertising. A lot of these  
12 decisions are because these algorithms are optimizing  
13 so heavily for relevance that they might end up  
14 skewing these ads.

15           Next slide.

16           Yeah, that's all I have for today. I would  
17 like to profusely thank my collaborators, Piotr and  
18 Alan at Northeastern, Aleksandra at USC, and Aaron and  
19 Miranda at Upturn. And thank you, again, for  
20 listening.

21           MR. ROSSEN: Ali, thanks so much.

22           Next up, we have Professor Ziad Obermeyer.  
23 He's going to be presenting his paper, "Dissecting  
24 Racial Bias in an Algorithm Used to Manage the Health  
25 of Populations." Ziad, I'll turn it over to you.



1 DR. OBERMEYER: Thanks, Ben, and thank  
2 you so much, Ali.

3 I think that the work that Ali just  
4 presented was such an ingenious example of the kinds  
5 of ways that researchers have tried to essentially  
6 study algorithms in the wild. So if you think about  
7 all of the things that that research team had to do to  
8 kind of understand what exactly Facebook was doing,  
9 and in some ways, probably even better than Facebook  
10 understands what they're doing themselves, you know,  
11 it's this careful process of pinging the system,  
12 seeing what happens, reconstructing results. And all  
13 of this stuff is done, essentially, from the outside.  
14 Because in a lot of these settings, when we want to  
15 study algorithms that are operating at scale in our  
16 society, we can't get inside.

17 And we can't get inside for some reasons  
18 that are not so great, like the algorithm developers  
19 don't really want us to get inside. But also some  
20 reasons that are legitimate, that there are trade  
21 secrets and things that we legitimately don't want to  
22 make public.

23 And so I wanted to talk through one example  
24 from our work where we had an enormous luxury relative  
25 to most studies of algorithms, which is that because

1 we were working in collaboration with a health system  
2 that had actually purchased one of these algorithms,  
3 we could see everything about it. We could see all  
4 the variables going into it. We knew exactly what the  
5 algorithm was doing. And maybe, most importantly, for  
6 the purposes of making the case that there was racial  
7 bias, we could actually follow up what happened to  
8 patients and document the impact on health outcomes.

9           And so I think that this one example, or at  
10 least I hope, can teach us some general lessons about,  
11 essentially, how to be good users of algorithms. And  
12 that's on the consumer side, but also on the  
13 regulatory side as we try to make sure that bias  
14 doesn't get into these algorithms, and if it does, how  
15 to hold organizations accountable.

16           So our example that I'm going to tell you a  
17 little bit of background on up front is about our  
18 system's effort to help complex patients. So in  
19 general, our health system does a not-so-great job of  
20 helping people with complex health needs. They often  
21 end up in the emergency department or in the hospital,  
22 if they're on many medications that often conflict.

23           And so over the past few years, the health  
24 system has gotten very interested in trying to  
25 intervene early on these patients. And the idea is if



1 carefully. And that's where algorithms come into this  
2 story.

3           So it's fundamentally about resource  
4 allocation. We have this scarce resource of extra  
5 help programs and we want to target those resources to  
6 the people who need it most. And if you think about  
7 most health systems, they're managing tens, if not  
8 hundreds of thousands, of patients. That's not a  
9 gr hv/job for humans to do. And so a lot of health  
10 systems have started investing in algorithms to at  
11 least start that screening process for them.

12           And so if you take the industry estimates  
13 seriously, the scale of this is just enormous. So the  
14 industry itself estimates that around 150 to 200  
15 million people are screened by this family of  
16 algorithms every year. The particular software that  
17 we're using is one of the largest in that market, and  
18 so that's what we're studying.

19           And the way these algorithms are generally  
20 used is almost as a first step. So there's a primary  
21 care population. And the algorithm just runs in the  
22 background and generates a score for everyone in that  
23 population, and then the health system does something  
24 with that score. So in the particular decision that  
25 we're studying, the top few people were just

1 fast-tracked into this high-risk care management  
2 program, and about the top half, except that top 2  
3 percent, 3 percent, those people were shown to their  
4 primary care doctor and the primary care doctors were  
5 asked, should this person be in this high-risk care  
6 management program?

7           So a lot of variety in the institutional  
8 practices, but, ultimately, the algorithm does a  
9 screening step, and then that screening is used to  
10 decide lots of things about the patient, but in this  
11 case, should that patient be enrolled in one of these  
12 programs?

13           So on the next slide, there's a graph. And  
14 I'm just going to talk through it slowly because I'll  
15 show you a few graphs that look like this and I just  
16 want to make sure they're all clear. So on this  
17 graph, on the X axis on the bottom, is the algorithm.  
18 So this is what the algorithm thinks about people, and  
19 it's arranged from very low risk on the left at zero  
20 to very high risk on the right. And those top few  
21 percent, to the right of that vertical dotted line,  
22 those are the people they get fast-tracked or  
23 autoidentified for this program.

24           On the Y axis is a measure of health. So  
25 this is basically at a given level of what the

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1 algorithm thinks about you, how healthy do you end up  
2 being in the next year. Concretely, it's a count of  
3 how many chronic conditions you have that flare up  
4 over that year.

5           The two lines show two groups of patients.  
6 The top line, the purple line, is black patients, and  
7 the bottom line, in gold, is white patients. And as  
8 you can see at every point in this distribution, black  
9 patients, at the same score as white patients, have  
10 worse health, on average. And so I think that  
11 violates what you could think of as our working  
12 definition of bias.

13           So the algorithm is being used to guide a  
14 decision. And so two people who have the same  
15 algorithm score are treated the same by the algorithm  
16 and, thus, by the health system who uses the  
17 algorithm. So those patients should go on to have  
18 similar health needs, irrespective of the color of  
19 their skin.

20           And what we find is that if you just look at  
21 2120

1 algorithm had no bias based on need, that number would  
2 rise to almost half, to 47 percent black. So this is  
3 not a trivial amount of bias. And, again, the  
4 definition of bias that we're working with is at the  
5 same algorithm score, people should have the same  
6 needs, and that turns out not to be the case.

7           So on the next slide, what we're trying to  
8 illustrate is where we think this bias got in. As I  
9 mentioned, we knew exactly what this algorithm was  
10 doing, what it was predicting, how, what variables.  
11 And it turns out that if you step back -- this is a  
12 very complex question. Who has health needs? So in  
13 most data sets, we don't have a variable called  
14 "health needs." And so what we do instead is we pick  
15 a proxy variable that's measured in the data sets that  
16 we have access to.

17           And what the algorithm developers did in  
18 this case -- which is a very common choice; this is  
19 not just about this particular developer; this is a  
20 very common strategy -- is we used costs as proxy for  
21 health needs. Now, that's not unreasonable because,  
22 in general, when you're sick you go get care and you  
23 generate healthcare costs. The problem is that even  
24 though, on average, that relationship is true, that  
25 you generate costs when you need healthcare, that

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1 relationship is very different for black patients and  
2 for white patients. So when you need healthcare,  
3 you're less likely to get it when you're black, and  
4 that leads to lower costs.

5 So in this graph, we're showing you on the X  
6 axis, instead of the algorithm, a measure of health.  
7 So increasing health needs further to the right. And  
8 what you see is that white patients always have more  
9



1 the biases we already know about and differences in  
2 income by ability. So all of these things, because  
3 they're subtle questions about correlations with  
4 underlying truth with race, they can be subtle, and  
5 that's why this wasn't caught.

6 It wasn't caught by the people who developed  
7 the algorithm, even though they were very well-  
8 intentioned. It wasn't caught by any of the clients  
9 that purchased the algorithm, even though these were  
10 people who have a deep commitment to fixing  
11 disparities and improving population health. And it  
12 wasn't caught by the humans who were either using the  
13 algorithm or being affected by it. And so that, what  
14 you can think of as a market failure, is the reason  
15 that I think there's an important role here for  
16 regulation. And so the question is how?

17 And so I'll just leave some of this to the  
18 discussion, but I'll just say that where anything  
19 starts, making sure that the algorithm that you  
20 develop or buy isn't biased, regulating and holding  
21 organizations accountable. All of this starts by  
22 having a very clean definition of what we mean by  
23 bias.

24 So in our case, it was two patients with the  
25 same risk score should have the same health needs



1 slide, if you want to reach out.

2 Thanks so much.

3 MR. ROSSEN: Great. Thank you so much. So

4 we have an opportunity for some Q&A. And I know if

5

1 with a working empirical definition of what bias looks  
2 like. And I think that a lot of the ways that we tend  
3 to do this in practice so far are we look at, is there  
4 a race-based adjustment? That doesn't guarantee that  
5 there's bias. The absence of a race-based adjustment  
6 does not guarantee that there's no bias. So I think  
7 really delving into the substance of what the  
8 algorithm is doing, what it's being used to do, and  
9 then coming up with a context-dependent definition of  
10 bias there that we can test empirically is the first  
11 step.

12           And so when we're working with these  
13 organizations, the first thing we do is we go really  
14 in-depth to understand, okay, here's what the  
15 algorithm is being used for. Here's the real thing  
16 that we're trying to get at. Here's what the  
17 algorithm actually does. And is there a difference  
18 there? So setting up a very clean definition of what  
19 bias is is the basis for software developers to audit  
20 their own products before they go into the field.

21           If you are purchasing an algorithm, you can  
22 set up queries to actually answer those questions. If  
23 you are a regulator, you can set up a definition for a  
24 given application, and then you can hold people  
25 accountable to it. So I think that's really the core

1 of what we did, and I think the work that Ali  
2 presented as well. It's really trying to translate  
3 the somewhat abstract notion of what bias means into  
4 an empirical data-driven definition in a particular  
5 data set.

6 And that's hard because there is no  
7 automated process that you can do for that. You  
8 actually need to really understand how the algorithm  
9 is being used and what disparate treatment or  
10 disparate impact would look like in this particular  
11 situation, and then set up a set of empirical tests  
12 following that.

13 MR. ROSSEN: Thank you. That's really  
14 interesting. And to sort of follow up from that,  
15 given that there is no off-the-shelf way of doing  
16 this, with these types of algorithms that are  
17 purchased from third-party developers, which is still,  
18 I think, the most common way that a lot of companies  
19 are getting their AI tools, is there a market failure  
20 there, in terms of who has the incentives or the  
21 obligations to really examine these types of  
22 algorithms and both the resources to look at, is it  
23 somewhere where regulation needs to set in or are  
24 there steps that your sort of ordinary companies are  
25 able to take to evaluate these risks?

1 DR. OBERMEYER: Yeah. I think, you  
2 know, empirically, at least in the case that we've  
3 studied, and I think in many others, there was a  
4 market failure because there was this problem that  
5 wasn't caught by anyone. I think the first part of  
6 fixing that is actually to put a name on it and to  
7 make it transparent that this is a problem. In all of  
8 my conversations with industry, I don't think there's  
9 a single software developer who wants to put out a  
10 biased algorithm.

11 And so a lot of them are already taking  
12 steps to do that internally, but I think because all  
13 of us are just learning about what bias looks like in  
14 different contexts and what it means, I don't think  
15 that there's a consensus definition on how you even do  
16 that if you you're the one that's developing the  
17 algorithm or if you're the one that's purchasing it.  
18 And so I do think that this is an area where  
19 regulatory guidance would be incredibly valuable.  
20 Because now that there's a lot of attention, there's a  
21 spotlight on these issues, nobody wants to be the  
22 company that is putting out an algorithm that someone  
23 later audits and finds to be biased.

24 So I think having regulators just set out a  
25 definition of what this looks like would be incredibly









1 brought up, Ben, which echoes Ali's point, is that, in  
2 some ways, algorithms can actually serve as a very  
3 valuable role of exposing bias in humans. So what was  
4 the algorithm in that case doing? Well, it was  
5 predicting some variant of, is this person going to be  
6 invited back to be interviewed by us?

7 Now, as Ali mentioned, that's a proxy for  
8 the quality of the applicant. But when the algorithm  
9 spit out these predictions that were predominantly  
10 white and male, that actually was like holding up a  
11 mirror to the recruitment process, that was the bias.  
12 That was the source of bias to begin with.

13 So in a funny way, algorithms can actually  
14 work to expose these biases in the human processes  
15 that are used to train them, and I think that that's a  
16 kind of underrated contribution of algorithm.  
17 Everyone gets mad at the algorithm, but it's not the  
18 algorithm. It's us. It's just reflecting back what  
19 we're doing.

20 MR. ROSSEN: That actually leads me to a  
21 question that we received from the audience, which is  
22 for you, Ziad, which was about, what were the  
23 alternative proxies that you ended up looking at in  
24 your work, as opposed to costs? How did you choose  
25 them? And is that process of choosing unbiased

1 proxies something that is replicable?

2 DR. OBERMEYER: Yeah. It's a great  
3 question, and I think that it does go back to  
4 understanding exactly what we want the algorithm to be  
5 doing. So we want the algorithm to identify people in  
6 whom we can intervene early and make a difference. So  
7 from that point of view, it's actually not obvious  
8 that you want to be predicting total costs. Total  
9 cost brings together a bunch of things that you can  
10 think of as, like, good costs, like people taking  
11 insulin, which costs money, and bad costs, which are  
12 things like people getting their toe cut off because  
13 they didn't take their insulin, which also costs  
14 money.

15 So when you put those together into a  
16 total cost metric, you're conflating a bunch of  
17 things that are not the same. And so what we did is  
18 we came up with a metric of avoidable costs, so things  
19 like, you know, getting your toe cut off because you  
20 didn't take your insulin and not the insulin itself.  
21 We also have lots of different measures of health that  
22 are applicable to different populations, and some are  
23 not.

24 So it took a lot more work, kind of like  
25 just substance knowledge-intensive work to come up

1 with these. But I do think that in most of the data  
2 sets we use, there's a rich set of alternatives. Some  
3 are more work than others, but I think the message  
4 from our work is that that extra effort can be hugely  
5 valuable because it can make the difference between a  
6 biased algorithm and one that actually works against  
7 the structural biases in our society.

8 DR. ALI: I'd like to go back and talk about  
9 that because it's very interesting what Ziad said  
10 about how these algorithms sort of hold a mirror to us  
11 and tell us how we're being biased. I really like  
12 that argument, but I hate when computer scientists use  
13 that argument to just evade all sort of  
14 responsibility.

15 I think a very common thing that computer  
16 scientists do is that, oh, the algorithm isn't biased,  
17 it's the data that's biased. But I think it's that  
18 very point where -- as someone who's trained as a  
19 computer scientist, who's been in way too many  
20 machine-learning classes, it's important to understand  
21 that just because the data is biased doesn't mean you  
22 let the thing go through. It's that very opportunity  
23 where the algorithm's holding a mirror to you to  
24 understand that you're now automating this harm that  
25 was accumulated over years. And that's where you need

1 to start auditing these systems.

2 As Ziad said, you need to have clean  
3 definitions of bias and work with those until you  
4 reduce that harm.

5 DR. OBERMEYER: I think that's a great  
6 point. I think there is a tendency to throw up our  
7 hands and say, well, we can't have algorithms because  
8 the data are biased and the data are biased because  
9 our society is biased. And all of that is true. But  
10 with a lot of work to take into account structural  
11 biases and historical inequalities, we can actually  
12 make the difference between good algorithms and bad  
13 algorithms.

14 MR. ROSSEN: I know we're running out of  
15 time, and I think that's a great place to end the  
16 coln 0 hsaons .I know wer sonexplaanel picksp oj11.94 0 0 11.94

1                   SESSION 3: THE INTERNET OF THINGS

2                   MS. ROUGE: Hi. So this is Phoebe Rouge,  
3 and today, for our third panel, we're going to be  
4 talking about privacy and the internet of things. We  
5 have three presenters here.

6                   The first one we're going to have, Daniel,  
7 who did his research at Northeastern University, and  
8 he's going to be talking about his research to look at  
9 the network traffic from various internet of things  
10 devices.

11                  DR. DUBOIS: Thank you for the introduction.  
12 Yeah, so now I will talk about information exposure  
13 from consumer IoT devices. And I will also thank my  
14 collaborator, Northeastern University, Jingjing Ren  
15 and David Choffnes, and from Imperial College London,  
16 Anna Maria Mandalari, Roman Kolcun, and Hamed Haddadi.

17                  Next slide.

18                  Usually, I start the presentation by asking  
19 the audience if they have any IoT device. Typically,  
20 the majority says no, but, actually, most of them then  
21 realize that they bought a TV in the last 10 years.  
22 That TV is likely a smart TV and that can be connected  
23 to the internet and that's a full IoT device.

24                  So what motivates this work is that IoT  
25 devices have access to private information. They have

1 the sensors. For example, smart speakers can listen  
2 to you, like a smart camera, smart doorbells, and  
3 watch you because they have a camera. And smart TV  
4 knows what you do, for example, what TV programs you  
5 watch. So all this information is actually shared  
6 with their own companies, those IoT devices, and their  
7 main purpose is actually to be internet connected. So  
8 there is a potential of privacy exposure from that.

9 And we have seen that that actually happens.  
10 The press has actually wrote many articles where there  
11 are devices, for example, sharing audio with Amazon  
12 workers and other persons like that. And this problem  
13 is very important because there are around 10 billion  
14 IoT devices deployed currently. And we want really to  
15 understand what they are doing.

16 Next slide, please.

17 In this work, we focused on the devices that  
18 are typically deployed in a smart home. We call them  
19 smart home devices, like appliances, smart lights, and  
20 other devices like that. So what we are interested in  
21 is to understand what the devices are doing. What  
22 does this mean?

23 We want to understand what is the  
24 destination of the traffic of them. Are these devices  
25 talking to their parent companies or are they talking

1 to some other third party? And, also, is the traffic  
2 staying in the country where it is generated or is it  
3 crossing the geographical boundaries? That's  
4 important because having state regulations may be  
5 different in another country, and sometimes even  
6 within one country, it may be different if the traffic  
7 stays inside or travels.

8 And, also, we want to understand is the  
9 traffic protected by encryption or not? What  
10 information is being sent? This is important because  
11 if a company is sending private information, it's  
12 likely that the user maybe is not aware of that. So  
13 we want to understand where things like that are  
14 happening and, also, if any information has been sent  
15 unexpectedly. For example, if you have a smart  
16 speaker, most people know that they have a microphone,  
17 but that microphone should not be transferring the  
18 voice all the time, but only when it's used. So we  
19 want to understand if that's true or not.

20 Next slide.

21 Answering those questions is not easy. It's  
22 actually a hard problem to measure privacy from IoT  
23 devices. And the reason is that the devices are  
24 typically black boxes that are much harder to analyze



1 manufacturers don't provide specifications, and  
2 probably for intellectual property reasons, all their  
3 information of how they work is not disclosed.

4           To overcome this problem, we want to use  
5 some technology. For example, we want to employ  
6 destination analysis and information inference so that  
7

1           So the devices that we considered are home  
2 IoT devices, in particular, smart cameras, smart hubs,  
3 home automation devices, like [indiscernible], smart  
4 thermostats, smart TVs, smart speakers, and many types  
5 of appliances from smart freezers to smart vacuum  
6 cleaners, for a total of 81 devices. And we were able  
7 to run 34,000 controlled experiments with these  
8 devices that were partially automated with our  
9 software.

10           We also monitor how those devices behave  
11 when not being used. For each device, we monitored  
12 112 hours of inactivity to see what they are doing.  
13 And, finally, we also looked at what the devices do  
14 when they are actually used by a study participant,  
15 and we monitored them for six months.

16           Next slide, please.

17           So once we set up our environment and our  
18 analysis framework, now we want to answer the question  
19 that I said before. And the first one is, where is  
20 the IoT network traffic going? We have a lot of plots  
21 from a lot of studies seeing where it's going. But  
22 what is important to know about this is that the  
23 traffic is actually going to some entities that are  
24 not the main manufacturer or the parent company. Most  
25 of the traffic is going to other companies. Most of

1    them are cloud services and CDN providers.  This is  
2    not necessarily a problem, but still, the traffic is  
3    still going under control of another entity.

4                    What is probably more interesting is that  
5    some of this traffic -- like we have seen situations  
6    where the traffic is going really to a completely  
7    wrong company.  For example, imagine that you have  
8    some smart TVs, or at least most of the ones that we  
9    analyzed, and it's contacting Netflix.  Doesn't look  
10   strange, but imagine that you never installed Netflix,  
11   you never open it, and you never logged in, and that  
12   TV is still contacting them.  So that is a bit of a  
13   problem that we found from the devices under test.

14                   Also, we have seen that the majority of the  
15   devices send traffic to another country.  Fifty-six  
16   percent of US devices contact other countries and 84  
17   percent of UK devices contact other countries.  
18   Strangely, the UK devices contact a lot of US  
19   destinations.  So this looks strange, but probably not  
20   too much if you think that those devices are typically  
21   developed by some smaller companies that maybe don't  
22   have the means to create an infrastructure in every  
23   region.  But still, there are different regulations  
24   that apply in each of these regions, and we don't know  
25   how is this compliant like with the US and also

1 European regulations.

2 Next slide, please.

3 In addition to the destination, we were also  
4 interested to the traffic itself. Is this traffic  
5 encrypted or not? At the beginning of the  
6 presentation, I said that most of the traffic is  
7 encrypted, so it's really hard to understand how the  
8 devices are behaving. But we analyzed more in detail,  
9 and we have seen that a lot of traffic is encrypted, a  
10 lot of traffic is unknown. That means that we don't  
11 know if it's unencrypted or encrypted, but it's still  
12 encoded in a way that cannot be read. If you are  
13 optimistic, we can see that it is encrypted as well,  
14 but some investigation has to be done.

15 But still, there is some traffic that is red  
16 in the figure that is unencrypted, especially from  
17 cameras, that are some of the cheapest devices that  
18 you can buy. We looked at this unencrypted traffic  
19

1 turn off, firmware updates activity and also when the  
2 device was set up for the first time, which behaves  
3 differently from when it's used later.

4 Next slide, please.

5 In addition to unencrypted traffic, we  
6 wanted to see if the encrypted traffic is also  
7 carrying some information. And the answer is yes.  
8 How did we do this? Well, simply, we look at our  
9 experiments. We tried to see how the traffic looks  
10 like when a camera is used to produce a video, and  
11 then we infer some patterns from this traffic and use  
12 these patterns to recognize when the video was sent in  
13 our traffic.

14 And by applying this methodology, we have  
15 seen that more than 90 percent of the devices that we  
16 tested that are able to produce a video or voice  
17 actually leak this information from encrypted traffic  
18 by using our technique. So one problem of this is  
19 that this technique can also be applied by any other  
20 entity. For example, an internet service provider has  
21 access to all the traffic that is produced in a  
22 household where the IoT devices are deployed. So they  
23 can infer activities and they can see what is done and  
24 what is not by those devices, which is a violation of  
25 privacy.

1                   Next slide, please.

2                   The last question we wanted to answer is if  
3 the devices behave unexpectedly or not. We have seen  
4 some cases where the devices behave unexpectedly. One  
5 of them is from popular doorbells, from actually  
6 different manufacturers. This doorbell was actually  
7 sending a recording of the video when a person was  
8 moving in front of them. This feature was not  
9 documented at the time and was not even possible to  
10 disable. So just owning and using those devices means  
11 that the device is self-recording when users don't  
12 expect that to happen.

13                   We are also seeing cases of smart TVs, not  
14 just contacting Netflix, but also other companies,  
15 that are not related to the apps that have been used  
16 during our experiments, such as Google and Facebook.

17                   And last, but not least, we have seen some  
18 very popular smart speakers being activated when you  
19 actually don't use them. Typically, they have a  
20 record. For example, Alexa can activate as my  
21 speaker, but unless they activate it if you say  
22 something that is different. For example, you could  
23 say, I like something, and some smart speakers  
24 activate. So this might just be a limitation of the  
25 device or maybe the manufacturers really want to know

1 what you like. So when you say, I like something, the  
2 device activates and sends a recording.

3 We're seeing other cases of unexpected  
4 behavior. For example, like a motion sensor reporting  
5 motion when there was no motion or devices  
6 spontaneously restarting or reconnecting. Those are  
7 all problems because when the device reconnects, they  
8 send all the information again. So they get more  
9 chances for violating their user privacy.

10 Next slide, please.

11 So all our findings of this study have  
12 attracted the attention of the press. So they wrote  
13 some articles that actually became very famous and  
14 attracted the attention also of the manufacturer. I  
15 will say later how we engaged with them to improve  
16 their devices.

17 Next slide, please.

18 So in summary, all the devices that we  
19 analyzed had some sort of problems, and the most  
20 important is that 57 percent of the devices and 56  
21 percent, have non-manufacturer destinations or they  
22 send traffic to destinations abroad. This is  
23 something that is unexpected. And, also, the vast  
24 majority of the devices, 89 percent in case of the US,  
25 are vulnerable to activity, for instance, meaning that

1 a profile can actually be created for the users of the  
2 devices and how they use them by whoever has access to  
3 the network traffic, like the ISP.

4 This work had some impact. As I said  
5 before, the press covered some of our findings and the  
6 manufacturer contacted us to get more information  
7 about why the devices are contacting Netflix, for  
8 example. We provided them all our information, along  
9 with our experiment, so that they could double-check.  
10 We never got anything back, like yes, we've fixed this  
11 or we don't. But at least they are aware of the  
12 problem and will see that some of the latest versions  
13 of the devices actually have improved a lot, compared  
14 to when we performed this study.

15 Also, all the software we produced is  
16 publicly available on the website that you see. It  
17 can be used to create, for example, new testing labs,  
18 and we are aware that there is one in Italy that has  
19 been built. And all the software we collected from  
20 all the devices can be used to perform further studies  
21 by the companies to understand how the devices behave.  
22 And all this data is also available on this same  
23 website and has already been downloaded more than 100  
24 times.

25 So this concludes my presentation, and feel



1 free to ask questions during the panel session. Thank  
2 you.

3 MS. ROUGE: Yes. Thank you very much,  
4 Daniel, for your presentation. That's so very  
5 interesting and a little -- so there is a lot of  
6 information out there, clearly, from the previous  
7 talks today, and there's a lot for consumers to  
8 understand.

9 So Pardis is now going to talk about her  
10 work with Carnegie Mellon and trying to package that  
11 information in something like a label so that  
12 consumers might word these things better.

13 DR. EMAMI-NAEINI: Thank you so much,  
14 Phoebe.

15 Hi, everybody, and thank you for joining my  
16 talk. I'm Pardis Emami-Naeini, and, today, I'm going  
17 to talk about our project to specify the contents of  
18 an IoT privacy and security label. This is a joint  
19 project with my colleagues, Yuvraj Agarwal, Lorrie  
20 Cranor, and Hanan Hibshi at Carnegie Mellon  
21 University. This work has been recently published at  
22 IEEE's Symposium on Security and Privacy, or S&P 2020.

23 Next.

24 IoT devices are everywhere. Some of the  
25 most common ones, which you might also have at home,

1 are voice assistants, smart doorbells, smart security  
2 cameras, smart thermostats, smart toothbrushes, and  
3 smart light bulbs.

4 Next.

5 And some less common ones are smart salt  
6 shakers, smart forks, smart umbrellas, and the most  
7 controversial of all, the smart toilets. And the list  
8 goes on and on.

9 Next.

10 People are increasingly purchasing smart  
11 devices. However, despite the surge in purchasing  
12 them, consumers are concerned about the privacy and  
13 security of the smart devices they purchase.

14 Next.

15 And people should be really concerned about  
16 these devices. After all, there's been news on how  
17 easily security cameras are getting hacked. But  
18 sometimes risk could have been mitigated if users of  
19 these devices were more informed. For example, after  
20 Ring security cameras got hacked, the company emailed  
21 their millions of users to use multifactor  
22 authentication. So maybe these devices could have not  
23 been easily hacked if users knew about better and more  
24 secure authentication mechanisms.

25 Next.

1                   You may have also heard about Google putting  
2   its consumers at risk by forgetting to mention that  
3   its Nest secure hub had a microphone, or in other  
4   words, failing to inform consumers about the device  
5   sensors.

6                   Next.

1 consumers, such as access control, sensor type, data  
2 sharing, and data selling.

3 Next.

4 Several pieces of legislation have been  
5 proposed, both inside the US and in countries outside  
6 of the US, including the UK, Singapore, and Finland,  
7 that would require IoT labels.

8 So I'm going to mention a few factors that  
9 should be included in these labels, but they don't  
10 contain too many details about what the labels should  
11 look like. And as you can see from the headlines,  
12 these proposals are primarily focused on security  
13 attributes without much attention to privacy  
14 practices. So our question here was, what should be  
15 included on an IoT privacy and security label?

16 Next.

17 To capture a holistic view, we invited a  
18 diverse sample of experts from industry, academia,  
19 government, and NGOs. To elicit expert opinion on the  
20 privacy and security factors, we followed a  
21 three-round Delphi process. In the Delphi method, the  
22



1 randomly assigned to review one-third of the  
2 attributes and, once again, we asked them to specify  
3 whether they would like to include or exclude the  
4 factor now after looking at all the reasons from the  
5 previous stage. To analyze the interview responses,  
6 as well as the opening answers from these surveys, we  
7 conducted thematic analysis, which is a recommended  
8 qualitative analysis approach, but information is high  
9 in subjectivity. We followed a six-step procedure  
10 recommended by Braun & Clarke to create the code book,  
11 find the themes, and merge them.

12 Next.

13 Experts acknowledge the value of the label  
14 in informing consumers' purchase behavior. An expert  
15 said, "What's good about a label is that it empowers  
16 the consumer to make a more active decision about  
17 cybersecurity rather than just being completely  
18 helpless as to what the security of her device might  
19 be. The average consumer doesn't have a privacy,  
20 security, or a legal department to review this stuff  
21 before they buy it. Enterprises do, but consumers do  
22 not, so someone's got to be looking out for consumers  
23 and giving the consumers this information."

24 Next.

25 In addition to informing consumers' purchase

1 behavior, some experts reported that the label could  
2 be a forcing function for manufacturers to be more  
3 accountable and transparent about their privacy and  
4 security practices. Moreover, experts mentioned that  
5 if the labels get adopted, it could initiate a  
6 competition in the market for manufacturers to enhance  
7 their practices. And I should mention, "There is  
8 value in forcing the company to write a list down,  
9 even if the consumer doesn't understand it. If you  
10 said, 'list your open ports,' there would be an  
11 incentive to make them few."

12 Next.

13 As I previously mentioned, experts wanted us  
14 to include 47 attributes on the label, which is  
15 clearly too many to show on a typical product package.  
16 Therefore, we designed a layered label with two  
17 layers. The primary layer is the concise format of  
18 the label, which could be printed and attached to the  
19 package of the product. And then there is a QR code  
20 and a URL at the bottom that directs consumers to the  
21 secondary layer, which has more detailed information  
22 and is in an online-only format. Online formats means  
23 that it can be updated as the firmware changes, which  
24 is critical as devices get updated often.

25 Another important reason to have this online

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1 layer is to have a way to accommodate companies  
2 updating their privacy and security practices.

3 Next.

4 Some of the attributes included on the  
5 primary layer, their security update lifetime, type of  
6 collected data, availability of automatic security  
7 updates, and availability of default passwords.

8 Next.

9



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- 1 comparison shopping for a smart device from two
- 2 different companies. We asked participants to compare



1                   To make the content of the label accessible  
2 to consumers, we put the most critical information on  
3 the primary layer and additional information on the  
4 secondary layer. To ease the process of label  
5 adoption and generation, we prepared a specification  
6 document, as well as a tool, to generate the label.

7                   And, now, we're currently looking for  
8 manufacturers and retailers to participate in a pilot

1 York University.

2           So as the previous two panelists have talked  
3 about, we are constantly surrounded by smart IoT  
4 devices, like cameras, Alexas, smart TVs, whatnot.  
5 These devices could be constantly watching us or  
6 listening to us. But, today, I'm going to talk about  
7 a way for us to watch these devices instead.

8           So as you see in the next slide, here's a  
9 video of me watching Roku TV. On the top corner, on  
10 the top half of the screen is the Roku TV, running the  
11 CBS app. I'm just opening the CBS app and watching  
12 the live news streaming, without doing anything.

13           At the bottom is a screenshot of the network  
14 activities of the CBS app on Roku TV. I'll talk about  
15 how I obtained this screenshot a little bit later.  
16 But here's the big takeaway. On the Y axis, vertical  
17 axis, is the number of bits sent and received per  
18 second. On the X axis is the time, sped up at 10  
19 times the speed. And each colored bar corresponds to  
20 some third-party advertising and tracking services  
21 that the Roku TV is talking to at the moment.

22           So remember, here I'm just passively  
23 streaming the CBS News, without doing anything on my  
24 Roku TV, and the TV is talking to three or four  
25 different third-party advertising tracking companies.

1 And one of the biggest ones is actually showing in  
2 pink. That is actually the Adobe Marketing Cloud.  
3 It's a little creepy, right? I'm not doing anything,  
4 watching TV, and my TV is watching me and talking to a  
5 bunch of advertising and tracking companies.

6 So in general -- next slide, please -- there  
7 are lots of concerns about IoT security and privacy,  
8 not just smart TVs, but Alexa, smart light bulbs,  
9 cameras. And as the previous panelists have aptly  
10 summarized, we don't know what's going on. It's a  
11 black box. We don't know what data is being sent. We  
12 don't know to whom the data is being sent to, and we  
13 don't know even from which IoT devices this data is  
14 coming from.

15 In general, there are two main problems, one  
16 for consumers, one for researchers. For consumers,  
17 these smart devices are like black boxes. We have no  
18 idea what they're going on behind the scenes. And  
19 there aren't very many good tools. If you want to  
20 start a Wireshark, good luck. It takes some time to  
21 set up a Wireshark to analyze network traffic. So  
22 that's the first problem for consumers.

23 The other problem is for researchers. Many  
24 research projects on IoT security privacy are  
25 limited to lab settings. Like security researchers

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1 would buy a bunch of devices, like maybe dozens of  
2 devices in the lab, and connect them to the network,  
3 analyze the traffic over Wireshark, and analyze the  
4 traffic. The problem is that there are more than  
5 dozens of devices. There are literally thousands of  
6 smart devices in the world, and how to scale the  
7 analysis to thousands of different kinds of devices in  
8 the world remains an unknown problem.

9           So to solve these problems faced by  
10 consumers and researchers, our vision -- next slide,  
11 please -- is to develop a simple tool for consumers.  
12

1 parties. That's useful insight.

2 So to provide this vision, we developed a  
3 tool called IoT Inspector, which you can download  
4 right now at this particular website on the screen.  
5 It is Windows-only for now, but we're coming up with  
6 Mac in the next version soon.

7 Next slide, please.

8 And here's what IoT Inspector does. At a  
9 very high level, it is a tool and it provides a data  
10 set. We launched the tool in April 2019. We've  
11 81onymou0 11.rsthe scre4 Tm0 Tc(11)Tj12 0 0 12 2m0w tclease.

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1 users. You can try to download it, too. Just Google

2





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1           In the next slide, I'm going to show you  
2 examples of findings from real devices from real users  
3 by IoT Inspector. Basically, there are two areas of  
4 findings. One is security, one is privacy. And this  
5 is just the tip of the iceberg. I'm just going to  
6 explain a few examples. So security-wise, we found  
7 the lack of encryption on many smart devices,  
8 including devices made by big manufacturers, like  
9 Google and Amazon. Smart TVs on Amazon, some of the  
10 apps don't really use encryption. They use, in some  
11 cases, just plain HTTP. And in some cases, they use  
12 encryption, but they use -- surprise, surprise --  
13 SSL 3.0, which is basically outdated encryption.

14           We have seen many devices with open unused  
15 ports, like cameras that have ports open on port 22.  
16 Like SSH, they are never used. But having unused open  
17 ports opens up opportunities for exploits by  
18 attackers. So these are some examples of security  
19 insights.

20           In terms of privacy, we found evidence of  
21 advertising and tracking on many smart TVs, including  
22 Roku and Amazon. It also found cross-device traffic.  
23 In particular, your IoT devices did not only talk to  
24 the cloud, they talk to each other. So basically, one  
25 device can potentially gather private information from



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1 sending traffic to other like residential addresses.

2 We tried to understand why this was

3 happening. We don't know, but they mentioned that

4 your camera is contacting a bunch of addresses. At

5



1 internet and they still work. So those are only the  
2 possible ways that come to my mind where consumers can  
3 protect themselves from this situation.

4 DR. HUANG: And some of the  
5 surprising things that we found is actually from smart  
6 TVs. One example is that, say, for instance, the Roku  
7 -- I'm sorry, the Amazon smart TV screen, for  
8 instance, has a built-in feature that basically says  
9 you can actually opt out of interest-based  
10 advertising. If you think that turning this off,  
11 turning off the interest-based advertising would  
12 reduce tracking, you're wrong.

13 So in one experiment, we found that we  
14 turned off interest-based advertising on both Roku and  
15 Amazon. We still see these devices potentially  
16 sensitive information to some third-party advertising  
17 tracking services. So yeah, it's one example. Tip of  
18 the iceberg for some of the privacy issues we found in  
19 smart TVs.

20 MS. ROUGE: Okay. So I guess sort of  
21 following on, Daniel, you mentioned some things that  
22 you might want to do if you get one of these smart  
23 devices to address some of the concerns.

24 I guess I'll start with Pardis. If you are  
25 a consumer that wants to buy a smart device, and I'm

1 watching this PrivacyCon and I'm like, wow, there's a  
2 lot of things to be concerned about, what's the first  
3 thing that you would look for? Like if I bought a  
4 smart device, what's the first thing I should do if I  
5 unpack it? Is there any setting I should change? Is  
6 there anything I should look at to make sure it does  
7 or doesn't do, anything along those lines?

8 DR. EMAMI-NAEINI: That's a very good  
9 question. So I think, basically, privacy really  
10 depends on your own preferences, definitely. So you  
11 may be concerned about some type of data and you may  
12 not be concerned about other types of data. But apart  
13 from that, I think what is really important for  
14 consumers to know about is to know what types of  
15 controls they can have, if they want to change them or  
16 not.

17 So basically, when you purchase a smart  
18 device, I think the first thing that you should do is  
19 to understand the settings of the device, the privacy  
20 and security settings of the device, to basically know  
21 how you can change data sharing, how you can opt out  
22 from data sharing, data selling, for example. Do you  
23 have this option?

24 And another, I think, important thing is to  
25 understand the basics of privacy and security

1 information of the smart device. For example, whether  
2 the device is the default password or whether you  
3 would get security updates. So there are some  
4 critical information, privacy and security  
5 information, some basics that you should really know  
6 about. And then other than that, the types of  
7 controls that you can have. So I think that's the  
8 first things that I would recommend consumers to do.

9 MS. ROUGE: Is there a particular setting  
10 that if I bought a smart device I should make sure it  
11 has or that I would immediately change when I bought  
12 it home?

13 DR. EMAMI-NAEINI: Yeah. So one thing that  
14 I'm concerned about, for example, is data being shared  
15 with third parties or my data being sold to third  
16 parties. And something that I would look for is, can  
17 I opt out from data sharing? And so this is the first  
18 thing that I would look for. But as I said, privacy  
19 is very subjective, so it really depends on your own  
20 preferences.

21 MS. ROUGE: Got it. That makes sense.

22 I guess, Danny, I would ask you the same  
23 question. You're looking at all of this data coming  
24 out of the smart devices. Is there something specific  
25 that you would look for as a control or something you

1 would want to change when you brought it home?

2 DR. HUANG: The first thing I want to  
3 do when I buy a new device is to run it over IoT  
4 Inspector and see what's it doing, basically.

5 And just echoing what Pardis said earlier,  
6 maybe different people have different privacy  
7 preferences. For me, I don't have a lot of tolerance  
8 for weird behaviors, but for others, maybe they would  
9 be okay with it. So I think having a tool like IoT  
10 Inspector allows users to gain transparency into  
11 exactly what's going on with the whole network and  
12 make a decision themselves, whether to return the  
13 product or continue using the product.

14 MS. ROUGE: Daniel, I'll just ask you the  
15 same question.

16 DR. DUBOIS: So usually, the problem is  
17 that, depending on -- like a normal consumer, is not  
18 able to configure to the privacy settings in the  
19 correct way because usually they are complicated.  
20 Sometimes, like in my experience installing like 81  
21 IoT devices, I had trouble to configure some of them.  
22 So even if you have a PhD, it might not be enough to  
23 do that properly.

24 So what I do, and I cannot suggest other  
25 people do that unless they have the technical

1 capabilities, is to try to isolate the devices from  
2 the public network as much as possible.

3           There are some open source tools, like Home  
4 Assistant, that are difficult to use for most people,  
5 but maybe in the future, there will be easier versions  
6 of that. And those tools can actually isolate the IoT  
7 device from the internet and they can control what the  
8 devices are doing and what they are not. And those  
9 tools are open sources so they can be analyzed. The  
10 code is open for everyone. And if your IoT device is  
11 behind a tool like that, it's much safer for use than  
12 if they use like a black box solutions, that you don't  
13 know exactly who they are talking to, what they are  
14 doing, what they are saying, and everything is like a  
15 question mark.

16           MS. ROUGE: All right. I'll start with  
17 Pardis again on this question. So as people become  
18 more aware -- you know, we see lots of headlines. We  
19 have this whole event, we have your research and the  
20 others getting out there. There's a lot of marketing  
21 talk, as far as how much IoT is going to proliferate,  
22 and we definitely see a lot of devices being sold.

23           Do you think, either in the course of your  
24 research, as you were asking questions or when you  
25 explain your research to others, do you see any

1 changes in people's feelings about IoT, as far as  
2 these are devices, okay, these clearly require a lot  
3 of care and feeding? Do you see people changing their  
4 minds and thinking differently about how IoT devices  
5 should be used in their home?

6 DR. EMAMI-NAEINI: Great question. Yeah, so  
7 in the interviews that we've conducted over the years,  
8 we've found that participants are concerned about the  
9 privacy and security of smart devices. And they know  
10 -- for example, smart speakers are very famous. So  
11 they know that, for example, they are doing some weird  
12 stuff because they've seen that on news, for example.  
13 And so they're very concerned.

14 But at the same time, when you ask them  
15 whether they'd purchase the device or not, they would  
16 still purchase it. And this is not really about  
17 whether they're concerned or not. I think it's mostly  
18 about whether there are alternatives in the market,  
19 and if consumers know that these alternatives are  
20 better, in terms of privacy and security.

21 So I think there are basically two issues,  
22 that you don't really know which devices are better  
23 and you don't even know how to define better privacy  
24 and security, because at the time of purchase, you  
25 have no information about the privacy and security of

1 these devices. So I think if you can solve these two  
2 issues, in the market if you can have better products,  
3 and if you can convey this to consumers that these are  
4 really better products, then I think consumers would  
5 be better able to apply their concerns. Now they're  
6 concerned, but they don't do anything about their  
7 concerns.

8 MS. ROUGE: Thank you. So one question I  
9 wanted to make sure -- to circle back -- we got from  
10 the audience. Danny, you had mentioned that your app  
11 is not approved for the Mac app store. And I'm  
12 wondering, could you just quickly explain why that  
13 might be?

14 DR. HUANG: ARP spoofing. It is an  
15 attack, basically, but we are turning this attack for  
16 good. That's a short answer.

17 MS. ROUGE: That makes sense. So yeah,  
18 we're right up at time, but I guess I just wanted to  
19 give each of you a chance to sort of -- if there's  
20 kind of one thing that you would want consumers to  
21 come away with from this presentation and from  
22 PrivacyCon, what's one concept that you'd like them to  
23 come away with?

24 And I guess we can start with Daniel.

25 DR. DUBOIS: Yes. So one thing that is

1 important to know is that IoT is not going away. It's  
2 becoming more common in our lives. So we cannot think  
3 that we'll reduce that type of exposure by just not  
4 buying this stuff. You can already see that. Try to  
5 buy a TV that is not smart. You will not be able to  
6 find one. And this might become common with many  
7 other objects. Of course, you don't have to connect  
8 them to the internet.

9 In my house, I have a device, a cooking  
10 device, that doesn't have any interface on it. It  
11 needs at least Bluetooth to work, because it requires  
12 a phone. And even if it needs Bluetooth, then the  
13 companion app of the device connects to the internet  
14 in some way. So we have to learn how to use these  
15 devices properly, and we need to keep doing research  
16 on the privacy concerns on them, because regulators  
17 will notice when these things are happening.

18 And as it happened already from the apps,  
19 the privacy regulations will be updated and the  
20 devices will be safer to use, hopefully, and there  
21 will be more transparency.

22 MS. ROUGE: Great.

23 Pardis?

24 DR. EMAMI-NAEINI: So this is not directly  
25 related to my presentation, but it's related to the





1 for smart devices. Many home routers allow you to set  
2 up a guest network. Just connect your smart devices  
3 to a guest network. So increasingly, you are working  
4 from home, you probably don't want your regular  
5 computers to be talking to and from the smart devices,  
6 if they are ever hacked. So one, set up a separate  
7 network.

8 Two, for devices like smart TVs, they have  
9 capability of tracking you and following you around.  
10 So, say, for instance, you want to start looking at  
11 some shoes on your website and start seeing these  
12 shoes in a smart TV, so what do you do? Use a  
13 separate account, a separate email address for your  
14 smart TV account. For me, I use a -- create a  
15 completely new Gmail account, just for my smart TV,  
16 so that I don't have advertisements that follow me  
17 around.

18 MS. ROUGE: Those are good practical  
19 suggestions.

20 All right. Well, we went a little over  
21 into our lunchtime, but thank you very much for  
22 your presentations and the discussion. This was  
23 really interesting. And we'll be back after lunch  
24 with presentations about specific devices, like  
25 cameras and such. So we will see you back here

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1     then.

2                                     (Lunch recess.)

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1 today focus on privacy issues around apps during  
2 emergency circumstances. The paper we submitted  
3 focused specifically on hurricanes and natural  
4 disasters, but I'll also discuss some implications  
5 along the way for other crisis contexts, including the  
6 current public health emergency, as we're exploring  
7 these things in follow-up research.

8           Moving on to the next slide, this is  
9 pertinent given that many factors shaping social norms  
10 and emergencies, such as individuals' inclination to  
11 share more personal information under disaster  
12 situations, as documented in many previous research  
13 studies, extends to other crises. During a hurricane  
14 or a fire, people think it's appropriate to share  
15 their location with first responders, for example,  
16 just as during a pandemic, many people are willing to  
17 share information for the purposes of contact tracing  
18 with public-health officials, although not necessarily  
19 with other actors.

20           As we see on the next slide, there are a  
21 variety of digital platforms to structure information  
22 flows during emergency circumstances, with government  
23 agencies both providing their own platforms and  
24 channels, as well as recommending others, in addition  
25 to the prevalent use of tools, like Facebook Safety

1 Check.

2           In this study, we focused on those apps that  
3 were recommended to users during hurricane season, as  
4 can be seen on the next slide. These apps can be  
5 divided into five distinct categories: Those apps  
6 developed by government agencies, such as FEMA; those  
7 apps developed by trusted organizations that partner  
8 with the public sector to provide relief, such as the Red  
9 Cross. There are also apps that are general weather  
10 apps recommended during these times.

11           Additionally, there are hurricane-specific  
12 apps from private sector developers that can be  
13 divided into two additional categories: Those that  
14 are transparent about their development, in contrast  
15 with those that appear, either by name or branding, to  
16 belong to government agencies, despite private  
17 development. This latter category is problematic from  
18 a consumer protection and deception standpoint. And  
19 many frequently change their names, though not  
20 necessarily their code or behaviors. As Apple or  
21 Google take them down from the marketplace, they  
22 simply reenter the market with superficial changes.

23           Moving on to the next slide, we framed our  
24 analysis of these apps in terms of privacy as  
25 contextual integrity. This is to say we conceive of

1 privacy as the appropriate flow of personal information  
2 in a context, in contrast with the privacy harm.  
3 That can be understood as inappropriate information  
4 flows. In this sense, information flows themselves can  
5 be deconstructed in terms of information subjects,  
6 senders, recipients, and types, as well as transmission  
7 principles, in order to compare them and understand where  
8 violations of users' expectations might occur.

9           We use this framework to make comparisons  
10 throughout our overall research framework, as seen on  
11 the next slide. We compare the context of privacy  
12 policies as endogenous governance and regulations as  
13 exogenous governance of information flows with actual  
14 information flows and practice, which we identified  
15 from a combination of static analysis of permissions;  
16 dynamic app analysis of flow traces, including the  
17 recipients and decryption of traffic to identify  
18 information types; as well as user experiences,  
19 described anecdotally in reviews and simulated through  
20 our own controlled experiments within virtual mobile  
21 machines.

22           As we can see on the next slide, the

1 significant say, in addition to federal regulation and  
2 distinctions between Personally Identifiable  
3 Information as PII and Sensitive Personally  
4 Identifiable Information as SPII. The key points for  
5 our purposes today are highlighted on the next slide.

6 Specifically, I would like to note both the  
7 ambiguities of routine uses, which is likely a source  
8 of discontinuity between government and partner  
9 organizations, whose routine uses vary significantly;  
10 and the nuance of trusted partners, including other  
11 government agencies at various levels; utility  
12 companies; hospitals; and relief organizations, from  
13 the Red Cross to religious groups, and things like  
14 Team Rubicon. These partners are subject to  
15 restrictions, which are actually similar to those on  
16 federal agencies under the Privacy Act, including  
17 limiting redissemination and to need-to-know  
18 circumstances.

19 Some of you may remember that this came to  
20



1 are sharing location information, for a variety of  
2 different reasons, with many third parties. Some of  
3 these flows violate not only regulations, such as the  
4 Red Cross sharing location of victims with Flickr and  
5 social media companies via an installed third-party  
6 library, but many are not disclosed in their privacy  
7 policies.

8 I will differentiate between these types of  
9 violations in a minute. But, first, I'd like to  
10 briefly revisit some additional concerns raised by  
11 users on the next slide.

12 In addition to requirements from governance,  
13 user expectations should also theoretically be met  
14 under conditions of contextual integrity. Some users  
15 noted that user permissions or options to control  
16 personal information did not work on the very apps  
17 being promoted as the best to use during a hurricane.  
18 Concerns about persistent tracking were particularly  
19 significant in these complaints.

20 Further, others noted, in relationship to  
21 the Red Cross apps, which are depicted on the next  
22 slide, that some of the persistent tracking  
23 information was too accessible to anyone who requested  
24 it, tracking individuals in real time and  
25 indefinitely, though both of those problems have now



1     comply either with their own privacy policy or  
2     regulation, but not both, and those that are compliant  
3     with neither.

4             Looking more specifically on the next slide  
5     at those that are compliant, as highlighted in green,  
6     there were three apps that behaved appropriately,  
7     transmitting no personal information to any third  
8     parties, complying with all expected regulation and  
9     behaving in practice as was disclosed in the user  
10    agreement.

11            On the next slide, as highlighted in yellow,  
12    we see apps that did not act in ways consistent with  
13    information flows described in their own privacy  
14    policies, but that did not actually violate any laws  
15    or requirements under contractual obligations with the  
16    government. These apps simply violate user  
17    expectations.

18            On the next slide, as highlighted in orange,  
19    we see apps that comply with their privacy policy but  
20    that are otherwise problematic. Some of these, such  
21    as Dark Sky and Global Storms, inappropriately share  
22    data with trusted partners, though they themselves are  
23    not trusted partners. The others violate user  
24    expectations and are problematic from a deception  
25    standpoint, rather than privacy violations, as they



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1 the first question is, how much analysis have you done  
2 with contact-tracing apps? And what has been the  
3 outcome?

4 DR. SANFILIPPO: So this is, I think, a  
5 really logical direction to take the previous study,  
6 the paper that we shared is sort of a pilot study,  
7 exploring how we could bring all of these different  
8 types of data analysis together in order to understand  
9 relative levels of compliance and violation of user  
10 expectations. What we have done thus far with  
11 contact-tracing apps is to collect, obviously, all of  
12 the apps and begin testing some of the user concerns  
13 that have been articulated.

14 However, the dynamic app analysis following  
15 traffic has not necessarily happened in every case  
16 because some of the apps we're considering haven't  
17 actually been deployed, and so we're sort of doing  
18 preliminary analysis on some of these based on user  
19 concerns. But we're able to categorize them according  
20 to the same parameters about who has developed  
21 them, how transparently they've been developed, and  
22 what types of exogenous regulations or policies might  
23 apply to them.

24 DR. BANKS: I see. And so based on some of  
25 that preliminary analysis, you are seeing at least

1 some early signs that suggest some of the issues  
2 identified in some of the other apps that you've  
3 looked at in your paper are also starting to crop up  
4 in these contact-tracing apps. Is that right?

5 DR. SANFILIPPO: Yeah, yeah.

6 DR. BANKS: Yeah. Given that, do you have  
7 some recommendations for the approach that regulators  
8 should take towards analyzing these apps? And,  
9 particularly, given the fact that, unlike maybe other  
10 disasters, like hurricanes, where there is somewhat of  
11 a definitive beginning and end, the pandemic,  
12 unfortunately, does not necessarily have that  
13 clear-cut delineation.

14 So the question is really, do you have some  
15 suggestions for how regulators should approach it?  
16 And are those suggestions different based on the  
17 nature of a pandemic, which, I think, is different  
18 from other disasters?

19 DR. SANFILIPPO: I think that's a really  
20 good point. However, I think that duration and sort  
21 of a time element of this particular emergency context  
22 could still be addressed. So it would be my  
23 recommendation not that we think about when the  
24 pandemic context is done definitively as a whole, but,  
25 rather, when individual harms that could be associated



1 with exposure to someone with COVID actually  
2 terminate.

3           There is an end to a period in which someone  
4 may have been infected through this. And so it's not  
5 necessarily a matter of maintaining all of that data  
6 set from beginning to end of pandemic, but, rather,  
7 maintaining it only as long as is necessary in order  
8 to trace particular harms and to protect public  
9 health.

10           Further, I think making guarantees that this  
11 data won't be used for other purposes would be much  
12 more consistent with individuals' concerns. For  
13 example, the level of trust between a public health  
14 department and trust in particular commercial  
15 platforms is not necessarily equivalent. And so I  
16 imagine that much more compelling arguments and  
17 impetus to use some of these things could be made if  
18 the actor responsible for this data and making  
19 assurances that it will not be used for other purposes  
20 or after a period of time would be much more  
21 trustworthy from the perspective of users, at least in  
22 terms of the complaints that we're investigating, or  
23 concerns we're investigating at this point.

24           DR. BANKS: I understand. Let me ask you  
25 one more question from the consumer side.

1                   So I assume that you've probably analyzed  
2 more privacy policies than a typical consumer has ever  
3 actually read, right? Do you have some advice on how  
4 consumers can read them more effectively to address  
5 those concerns, some tips that you may have, given  
6 your comprehensive analysis, that you can advise  
7

1 flagging particular issues that you might be concerned  
2 about or third-party advertisers, for example, and  
3 looking specifically for those things amongst the text  
4 is, perhaps, one of the most useful ways you can sort  
5 of skim these policies without necessarily reading  
6 through all of the legal jargon yourself. You can  
7 sort of flag particular concepts, or third parties, or  
8 uses that you're uncomfortable with, and read to see  
9 if they are covered within a policy.

10 DR. BANKS: That makes total sense.  
11 Hopefully, the consumers that are listening today will  
12 take some of that advice. Thank you very much for  
13 your great work.

14 DR. SANFILIPPO: Thank you.

15 DR. BANKS: Next, we'll have Christin  
16 Wilson, who will present the team from Clemson's work  
17 on getting malicious skills into Amazon's Alexa Skill  
18 Store.

19 Welcome, Christin.

20 MR. WILSON: Thank you. So good afternoon,  
21 everyone. Before I begin, I would like to thank FTC  
22 for providing me this opportunity. I would also like  
23 to thank my research team at Clemson University,  
24 especially Dr. Long Cheng, Dr. Hongxin Hu, Song,  
25 Jeffrey and Daniel.

1                   So we are excited to present our paper,  
2 "Dangerous Skills Got Certified: Measuring the  
3 Trustworthiness of the Amazon Alexa Platform." So a  
4 brief introduction, the user base of Amazon Alexa has  
5 been rising rapidly over the last couple of years, and  
6 this actually encourages third-party developers to  
7 build new skills. So here, "skill" refers to a voice  
8 app, so that's what the Amazon Alexa platform calls  
9 it.

10                   So a skill has to be certified by the team  
11 before it's published to the end-users. And a weak  
12 rating system will result in malicious skills entering  
13 the store. So these can be privacy-invasive, this can  
14 disseminate inappropriate information to users, et  
15 cetera. So we are especially concerned about children  
16 and the skills meant for them.

17                   So on the next slide, we have our three  
18 research questions. Number one, we want to evaluate  
19 whether the certification system is efficient and  
20 trustworthy. Number two, do policy-violating skills  
21 exist in the skill score currently? Third, how do  
22 Google Assistant's certification systems compare?

23                   Next slide.

24                   So before we move further, let's just  
25 discuss how can third-party skills collect data. So

1 there are two methods. The first method is to  
2 configure permissions in the skill. So when a  
3 developer develops a skill, he can just configure some  
4 permissions. So what happens is when a user enables  
5 the skill, a prompt will be sent to his phone -- the  
6 Amazon Alexa app on his phone, and you have to provide  
7 permission. And this data is actually taken from the  
8 developer account, so you're not providing it. It's  
9 just taken from the account.

10 The second method is to collect the  
11 information through voice. So this is directly done  
12 during an interaction. So Alexa will just ask you,  
13 what is your name, and you can speak it back to them.  
14 So in this case, no prior consent or permission is  
15 taken while this skill is enabled.

16 So now, we come to the next slide.

17 This is the first research question.  
18 Evaluate the certification system. So we developed  
19 skills that violate 7 privacy and 14 content policy  
20 guidelines. So this is actually provided by the  
21 Amazon team to the developers in the developer  
22 documentation. We do have some ethical disclosures.  
23 We have obtained approval from our university's IRB.  
24 We do not use or share any of the information  
25 collected, if any. And we remove the skill as soon as

1 we see that it is certified. And for high-risk  
2 violations, we do try to provide a disclosure.

3 So the next slide discusses the first  
4 subsection. It's violation of children-specific  
5 policies. So these policies mainly focus on the  
6 collection of data from children and the content  
7 provided to children. So like in the image, you can  
8 see that you do not want a skill asking a child for  
9 personal information or encouraging him to drink or  
10 smoke, or do something illegal without telling his or  
11 her parents.

12 So in the next slide, you can see that we  
13 were able to get 119 skills certified in this  
14 category. So there are two types of skills, one that  
15 could collect data and one that would provide some  
16 inappropriate content. For the ones that could  
17 collect data, it had the following features. So it  
18 could collect personal information -- and remember  
19 that the users are actually children and it's  
20 completely restricted by Amazon to collect personal  
21 information from children.

22 The second one was it could save the  
23 collected information in the developer's database. So  
24 we could save it in our DynamoDB. The third one is  
25 they didn't provide a privacy policy. The fourth one

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1 is no prior consent is taken from parent or guardian  
2 before the collection of data. So when the skill is  
3 enabled, nothing is told to the parents, and when the  
4 child uses it, personal information will be taken from  
5 them.

6 And then no access is provided to view,  
7 delete, or modify the collected information from our  
8

1 example of a skill that we submitted. You can see  
2 that the skill "moral stories" was live on the -- it  
3 asked for the user's name. It got the full name and  
4 generated a story with their name. But you can see  
5 that no privacy policy was provided. It's a  
6 kids-category skill, and you can see that the name was  
7 actually saved in the DynamoDB database. So we made  
8 this just for illustration purposes, and we ourselves  
9 provided that name and it's not actual user data.

10 And next slide.

11 So the experiment results, we've been able  
12 to certify 234 skills in total. So it's not 234  
13 unique skills, but it's like 234 different  
14 certifications, I would say. So it was conducted over  
15 about a year. And we did have to resubmit some of  
16 these skills. So initially, some of these skills were  
17 actually rejected, so what did we do? We just had to  
18 use a simple counter to delay the session in which our  
19 privacy-policy violating response is delivered.

20 So if we set the counter as four, the first  
21 four responses from a fact app will be perfectly fine,  
22 and the team would actually certify the skill based on  
23 that. And after that, since the counter was fourth  
24 starting from the fifth, the policy-violating response  
25 will be very good.





1 us asking for the personal information without  
2 providing a privacy policy, and that, too, from kids.  
3 So this shows a negligence from their part, I would  
4 say.

5 Next slide.

6 So our second research question was to look  
7 for existing policy-violating skills in the store. We  
8 only tested 825 skills. There are about 100,000  
9 skills, which we can't actually check. So we just get  
10 skills that either had a negative review or had a  
11 privacy policy provided.

12 So by looking for skills that had a privacy  
13 policy provided, what we wanted to do was, like, Alexa  
14 only requires skills that collect personal information  
15 to include a privacy policy. So this was our  
16 assumption that they might be collecting personal  
17 information. Made us look through them. And we  
18 identified 52 skills with possible privacy violations.  
19 Again, we use the word "possible" because we can't  
20 really ensure whether some policy violations actually  
21 existed, because we can't access the code. There was  
22 also 51 broken skills that didn't work. So there is  
23 no constant check being done to see if the skills are  
24 working perfect.

25 So the next slide, we have a few examples

1 about some privacy-policy problems we saw during the  
2 manual testing. So the image on the right is actually  
3 a skill developed by Amazon, and it's actually a  
4 weather app, and it's available by default on all  
5 Alexa devices. So it mentioned in the description  
6 that it collects the user's device location, like any  
7 other weather app would do, but it does not provide a  
8 privacy policy in the usually allotted space.

9           So since this is an Amazon-developed skill,  
10 it's okay because you can actually find one in the  
11 bottom of the page. But there are other skills that  
12 are not developed by Amazon and mention about  
13 collection of data in their description, but don't  
14 really provide a privacy policy.

15           The other image is an example of a badly  
16 written privacy policy. We don't really know what the  
17 developer actually meant by that line. There are also  
18 examples of privacy policy URLs leading to the Google  
19 search webpage, other developers' privacy policy, et  
20 cetera. So these were links provided before  
21 certification. So during certification, the team  
22 could actually see the URL, and they just might not  
23 have gone through it or just neglected it.

24           Next slide.

25           We also did a preliminary comparative

1 measurement on the Google Assistant platform. So we  
2 got 15 out of the 85 kids actions certified. And for  
3 general actions, we got 101 out of 185 certified. So  
4 actions is the Google equivalent of skills. This data  
5 just suggests that Google's vetting is better, but,  
6 again, this is a preliminary study, so we can't really  
7 state that.

8 We did see some inconsistency in feedback  
9 here, too. And the post-certification vulnerability  
10 exists here as well. So this vulnerability means that  
11 once a skill is certified, you can make changes, and  
12 then it will be deployed to the live audience without  
13 requiring a recertification. So yeah, this still  
14 exists in both Amazon and Google, and I think this has  
15 been discussed in some other papers as well. We did  
16 manual testing on the 76 kids sections as well -- or  
17 17staonostroblemon.ctions, So this vulgoes thesayat14

1 yet.

2           The Google team, on the other hand -- the  
3 counter-abuse systems actually issued us an award as  
4 part of the Vulnerability Reward Program for our work.

5           And coming on to our final slide, you can  
6 see that we have provided a website link. More  
7 details and video demos are actually provided in the  
8 website. You guys can take a look at that. If you  
9 have any questions, I can take them now.

10           DR. BANKS: Great. Thank you very much,  
11 Christin.

12           So first, for the audience, if you do have  
13 any questions for Christin, please do email us at  
14 [privacycon@ftc.gov](mailto:privacycon@ftc.gov) right now if you have some  
15 questions. He presented a lot of information and,  
16 hopefully, you have lots of good questions.

17           So while we're waiting for a few audience  
18 questions to come in, I'll ask you a question that  
19 kind of starts at the end of your presentation. You  
20 mentioned that you reported these results to Amazon  
21 and Google. First, congratulations on the award from  
22 Google. That's an accomplishment in and of itself.

23           So my question is about Amazon's response.  
24 So how receptive were they initially, I guess, to your  
25 findings? And what was their feedback and,

1 particularly, your claim about the ease with which it  
2 is to circumvent their process? And how did they  
3 address the issues that you raised?

4 MR. WILSON: So I would say they were very  
5 eager in our results. They got into a call with us as  
6 soon as they got the email. We did have a lengthy  
7 meeting discussing about what work we actually did,  
8 how we see it was. Even they asked, like, did you  
9 guys try some other method? And we were like, no,  
10 this was collectively very easy to do this, so we  
11 didn't have to go for harder techniques and stuff.

12 But, yeah, they're were really eager to know  
13 about our work. They are still investigating. They  
14 have tried to get as much information from us, so  
15 they're actually looking at the certification log of  
16 every skill that we actually published. So I think  
17 they are doing a good job, but it's still being done,  
18 so we don't know the final result yet.

19 DR. BANKS: I see. Well, at least it sounds  
20 like it's a pretty collaborative process --

21 MR. WILSON: Yes.

22 DR. BANKS: -- which is not always the case  
23 in these types of instances. So I think it's good to  
24 see that.

25 MR. WILSON: Mm-hmm.

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1 it from being made. The developers can change it any  
2 time right now, and it will be deployed to the live  
3 audience. So this is not something that should be  
4 done. It should be blocked is what we are saying.

5 Many other researchers also said this in  
6 other papers, that developers should not be allowed to  
7 change the code. But until recently, the developers  
8 could only change the back-end code. The front-end  
9 code could not be changed. But, recently, they have  
10 changed that, too. So now, you can update both the  
11 front-end code and back-end code without requiring a  
12 recertification.

13 DR. BANKS: Okay. I kind of want to make  
14 that point clear. So it sounds like what you're  
15 saying is that there's a pretty significant blind spot  
16 that Amazon has for third-party code, in that the  
17 certifiers within Amazon cannot actually see the code.  
18 And if the developers make modifications to that code,  
19 that does not have to get recertified.

20 Can you really make clear the significance  
21 of that blind spot in terms of what the potential  
22 vulnerabilities that can arise from that are?

23 MR. WILSON: So with the blind spot, what  
24 the problem is -- like even if you create a chat bot  
25 that can go test the skill for 1,000 times, the



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1 malicious thing can happen on the 1,001st session. So  
2 you can't actually find it. So unless you have the  
3 back-end code, you can't actually find out all the  
4 policy violations.

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1                   We usually used to name their variables as  
2 first name, last name. And if they just look at the  
3 code once, they can see we are collecting the full  
4 name of the user. So if they actually looked at the  
5 code, we would say that they would have definitely  
6 found this. But, yeah, still, this is an assumption.

7                   DR. BANKS: Okay, I understand. O.and. O.Ts aresj11.

1 and the skill [indiscernible] with it. But we do not  
2 really know if the skill was actually collecting the  
3 full name because, I think, personal information is  
4 going to be the full name, according to COPPA, and not  
5 just the first name. So like I said, since we don't  
6 have access to the code, we don't really know what  
7 they are collecting. Are they keeping both the first  
8 name and the last name or are they just taking the  
9 first name, all those kind of things.

10 DR. BANKS: I understand. So it sounds like  
11 that's an area for some closer analysis.

12 MR. WILSON: Yes.

13 DR. BANKS: So thank you very much,  
14 Christin, for your work.

15 Next, we'll have Aerin Zhang. She's here to  
16 present CMU's research into consumer attitudes about  
17 video surveillance and facial recognition.

18 Welcome, Aerin.

19 MS. ZHANG: Thank you, Lerone. I appreciate  
20 this opportunity to present our research at  
21 PrivacyCon.

22 So today, I will present our work on  
23 understanding people's privacy attitudes towards video  
24 analytics technologies. This work is part of the  
25 Personalized Privacy Assistant project. There were 17

1 million surveillance cameras in the US in 2018, and if  
2 that number is not impressive enough, 1 billion  
3 cameras are expected to be deployed globally by the  
4 year 2021.

5           The massive amount of video data captured by  
6 these cameras motivates video analytics technologies,  
7 which use computer software to automatically process  
8 and understand videos. Such technologies have been  
9 greatly improved due to recent events in deep learning  
10 and computer vision, and they are becoming  
11 increasingly sophisticated. Such software can be  
12 easily applied to real-time IP cameras or store  
13 footage from any cameras. Those analyses often happen  
14 without subject's awareness or consent.

15           Important information about the data  
16 collection, like how long the footage is retained,  
17 whether the information could be shared with other  
18 entities or the purpose of analysis, is often not  
19 available to data subjects. Privacy regulations, like  
20 GDPR, include stricter laws to govern the use of video  
21 analytics. The regulations require entities that use  
22 video analytics notify data subjects and enable them  
23 to opt in or out of some practices at or before the  
24 point of collection.

25           But there are several different types of

1 video analytics technologies today. Facial  
2 recognition is the most prominent type and also has  
3 several variations. It can identify an individual by  
4 matching an image of a person to a database of known  
5 people. There's also anonymous face detection that  
6 can be used to estimate demographics of the person.

7 Another type is facial expression  
8 recognition that detects individuals emotions. Other  
9 than facial recognition, scene detection is also one  
10 type of video analytics. This image shows how the  
11 software is analyzing the video feed to count the  
12 number of passengers in the subway compartment.

13 Next slide, please.

14 The gap between the current disclosure  
15 practices and the requirements of the regulation draw  
16 our attention to the lack of guidance on how to do a  
17 better job at communicating these data practices and  
18 what choices to expose to data subjects. In order to  
19 facilitate appropriate notice and choice about these  
20 different types of data analytics deployments, we  
21 first want to understand people's privacy expectations  
22 and preferences with regard to these deployments.

23 We asked the following research question.  
24 Do people know about these deployments? And how do  
25 people feel about them? Especially, we are interested



1                   Next slide, please.

2                   So we first did an extensive survey of news  
3 articles about real-world deployments of video  
4 analytics technologies. We identified four major  
5 categories in a variety of contexts. The first  
6 category is for security, which includes automatically  
7 detecting petty crime scenes, like pickpocketing,  
8 break-ins, or using facial recognition to identify  
9 known criminals and bad actors.

10                  The second important type is for commercial  
11 uses. It's been used to count the number of people in  
12 a facility in order to optimize operation, like staff  
13 management. Or it's used for targeted advertising  
14 based on demographics, individual profiles, or  
15 reactions when people are looking at items. Yes, you  
16 can be advertised based on what you look at and your  
17 facial expression. It has also been used to rate  
18 people's engagement at museums, movie theaters, and  
19 comedy clubs.

20                  The third key usage revolves around  
21 identification and authentication. Facial recognition  
22 can be used to replace work IDs, membership, and  
23 loyalty cards. It has been used to track attendance  
24 at gyms, schools, workplaces, and even churches.

25                  And the last category of uses is more

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1           On the days participants receive push  
2 notifications through the app, they also got an email  
3 in the evening to complete a daily summary. The  
4 summary asked participants to revisit notifications  
5 they received during the day and to provide additional  
6 responses. The process will happen for 10 days, and  
7 participants finish the study with a post-study  
8 survey.

9           Now, I'm moving on to some of the results we  
10 found in our study. Due to the length of the  
11 presentation today, I'm only showing some of the  
12 results and more can be found in our paper. So this  
13 slide shows a summary of participants' comfort levels  
14 organized around 16 different purposes we previously  
15 identified. It was clear to us there is no scenario  
16 where everybody feels uniformly about. People's  
17 responses vary greatly for each purpose. For  
18 instance, scenarios related to security appear to  
19 surprise participants the least. Close to 72 percent  
20 would feel somewhat or very comfortable about these  
21 scenarios.

22           On the other end of the spectrum, we  
23 observed considerably less acceptance by event  
24 scenarios, like health and productivity predictions,  
25 where only 70 percent feel somewhat or very

1 uncomfortable.

2           Participants are least comfortable with  
3 employees making predictions about their work  
4 productivity. So after the 10-day study, 75 out of  
5 123 participants grew more concerned about these  
6 practices. Eighty percent of these 75 participants  
7 developed stronger awareness of the possible  
8 deployment of video analytics technologies as they  
9 received notifications on their phone every day. They  
10 were not aware that video analytics could be used for  
11 so many purposes at such a diverse set of venues and  
12 with this level of sophistication.

13           One participant commented, "Some of the  
14 scenarios and growth of the technology you mentioned,  
15 I had never considered. Freaked me out."

16           Twenty-seven percent emphasized the privacy  
17 issues of these technologies, like the lack of notice  
18 or consent. Twenty-five percent expressed concerns  
19 about specific usage of these technologies. One said,  
20 "I didn't realize I could be marketed to based on what  
21 I'm looking at in a store....I found this whole  
22 practice disconcerting." Four percent were worried  
23 about implications like how the data is shared, what  
24 could be inferred from the data, and the potential  
25 abuse.

1           Next slide, please.

2           So just to give a complete picture, I'm  
3 going to show some opinions of participants who stayed  
4 equally concerned or actually grew less concerned over  
5 the course of the study, even though they are  
6 minorities. So 27 percent of them claim they are  
7 already familiar with these technologies. Twenty-  
8 three were not bothered by the practices. They said  
9 something like, if you're not a criminal, you  
10 shouldn't be worried about facial recognition. And 21  
11 percent expressed some level of resignation,  
12 describing the technology as ubiquitous and out of  
13 their control. Fifteen percent did not believe that  
14 the scenarios showed to them were real. And 13  
15 percent who learned the benefits of these technologies  
16 become more accepting.

17           Now we move on to the next slide, showing  
18 results on those notification preferences. We asked  
19 participants, how would you want to be notified? The  
20 choices range from notify me every time to do not  
21 notify me. Again, we observed that people show  
22 diverse notification preferences.

23           This graph shows how their preferences  
24 changed before and after the study. More than half  
25 ended up with different preferences, and the majority

1 are looking for some type of selective notification  
2 solution instead of being notified every time.

3 Next slide, please.

4 So interestingly, we observed that people  
5 grew more concerned in general, but opted for less  
6 frequent notifications as time passes. This change in  
7 preferences is attributed to some level of privacy  
8 fatigue as people got a better appreciation of the  
9 number of times they are likely to be notified. So  
10 one participant described their fear for privacy  
11 fatigue as they received many notifications.

12 Next slide, please.

13 Even with our 10-day study, we already  
14 observed privacy fatigue. So remember the regulations  
15 which expect people to manually opt in or out of video  
16 analytics each time they encounter such functionality,  
17 but because of the increasingly widespread deployment  
18 of those softwares, this could result in an  
19 unrealistically high number of privacy decisions.

20 So the natural question to ask is, how could  
21 we reduce user burden and assist users in making  
22 privacy decisions? So I want to first provide some  
23 context of how obtaining consent works with video  
24 analytics data collections. But there are some recent  
25 technical advances that made it possible to obfuscate

1 people's faces in real time, allowing people to opt  
2 out of video analytics.

3           There are also academic efforts to build a  
4 privacy infrastructure and a privacy assistant app for  
5 Internet of Things. Such an app running on people's  
6 smartphones would alert users of nearby IoT sensors,  
7 for example, cameras with video analytics software  
8 enabled, and present them with potential choices, like  
9 opt in or opt out.

10           However, with all the efforts, the high user  
11 burden remains a problem. So with the data collected  
12 from our study, we're able to use clustering  
13 techniques to reduce user burden. We first grouped  
14 like-minded users to generate privacy profiles and  
15 then leverage clustered profiles to make predictions  
16 of people's allow or deny decisions. So using this  
17 method, we're able to predict 94 percent of the  
18 allow/deny decisions with 89 percent accuracy.

19           Next slide, please.

20           So it is worth taking a closer look at the  
21 clusters of the like-minded subjects identified by our  
22 clustering algorithms. This graph shows privacy  
23 profiles of six clusters. Each cell represents  
24 whether people in this cluster allow or deny data  
25 practices for a specific purpose. The color blue

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1           So this concludes the presentation.

2           DR. BANKS: Thank you very much, Aerin.

3           Again, for the audience, if you have any  
4 questions for Aerin about what consumers have to say  
5 about video surveillance, please send your questions  
6 to [privacycon@ftc.gov](mailto:privacycon@ftc.gov) right now. We have a few  
7 minutes left.

8           All right, so thank you, again, Aerin, for  
9 that work, and thank you for spending time talking to  
10 consumers. I'd like to spend some more time doing  
11 that, too.

12           Let me ask you one question as we wait for  
13 some audience questions to come in. In other contexts  
14 and other privacy research, we often hear the term  
15 "privacy paradox" thrown around, and other people use  
16 it, too. In your interactions with consumers, did you  
17 observe any privacy paradoxes or any counterintuitive  
18 behavior or responses?

19           MS. ZHANG: I think the privacy fatigue that  
20 we described had something to do with the privacy  
21 paradox, but the privacy paradox deals with actual  
22 behaviors that we, in the study, did not really  
23 measure. So we are basically asking their opinions.  
24 So the privacy paradox describes the discrepancies  
25 between the actual behaviors and their saying that

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1 MS. ZHANG: Yes.

2 DR. BANKS: So thank you, again, Aerin.

3 And I'd like to thank all of our researchers  
4 today. You're doing great work, and it's informed me  
5 a lot today. And I hope our audience got as much out  
6 of it as I did. So thank you very much. And I think  
7 we have another panel coming in immediately after us.  
8 Thank you, again, and thank you to the audience for  
9 your attention.

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1                   SESSION 5: INTERNATIONAL PRIVACY

2                   MR. WOOD: Okay. Welcome to the fifth panel  
3 of this year's PrivacyCon. The topic of this panel is  
4 international privacy.

5                   I'm Dan Wood. I'm an economist in the  
6 Bureau of Economics at the Federal Trade Commission  
7 and the Division of Consumer Protection.

8                   With me are four panelists. The first is  
9 Guy Aridor. He's an economics PhD candidate at  
10 Columbia University. And the research he's going to  
11 be talking about today is about how the European  
12 Union's General Data Protection Regulation, or GDPR,  
13 how its opt-in requirement affected the mix of  
14 consumer data observed by intermediary web services.

15                  The second panelist is Garrett Johnson.  
16 He's an Assistant Professor of Marketing at Questrom  
17 from School of Business at Boston University, and he's  
18 going to be talking about how GDPR affected market  
19 concentration among web-technology vendors.

20                  Our third panelist is Jeff Prince. Jeff is  
21 a Professor of Business Economics and Public Policy at  
22 the Kelley School of Business at Indiana University.  
23 He's also the Harold A. Poling Chair of Strategic  
24 Management and Co-Director of the Institute for  
25 Business Analytics at the Business School. And his

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1 research he'll be presenting is about measuring  
2 individual's valuation of online privacy across  
3 countries and also across privacy domains.

4 Christine Utz is our last panelist. And

5

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1 increasingly reliant on this consumer-generated data.

2 There's a worry that such privacy regulation might

3 impact their function.

4               There's two main uses of data in the digital

5 economy. The first is that this data is the fuel

6 behind a lot of the machine-learning technologies

7

1                   Next slide.

2                   So the empirical setting for this paper is  
3 the data is provided to us from a third-party  
4 intermediary in the online travel industry, which  
5 spans the majority of this industry across the globe.  
6 This intermediary's sort of an ideal setting to  
7 study the consequences of the GDPR on data-reliant  
8 firms for several reasons. The first is that the data  
9 that this firm collects is directly at the heart of  
10 the consent portion of GDPR, such that properly  
11 implemented consent should allow consumers to opt out  
12 of data collection from this intermediary.

13                   Second, the primary business of this  
14 intermediary is to collect user search and purchase  
15 histories and to predict whether or not consumers are  
16 going to purchase a flight or hotel, and then  
17 conditional on this prediction, show some advertising,  
18 which is how most of their revenue is derived from advertising,

1                   So what do we do in this paper in terms of  
2   our empirical strategies? So we used a relatively  
3   standard tool from economics, known as difference-in-  
4   differences, which allows us to get at the causal  
5   impact of the policy. And, in particular, our  
6   treatment group here are the travel agencies in major  
7   European countries and the control group here are  
8   travel agencies in non-EU countries. And our analysis  
9   revolves around the GDPR implementation date, which was  
10  Friday, May 25, 2018.

11                  And it's important to point out that our  
12  specification will allow us to look at the causal  
13  impact of the policy overall and not necessarily on  
14  particular manifestations of the policy.

15                  And so we look at the period from beginning  
16  of April 2018 until the end of July 2018. And I'm  
17  going to report two specifications here. One is just  
18  going to give the overall causal effect over this time  
19  period and the second is going to give a time-varying one.

20                  Okay, so next slide.

21                  The first thing we do is try to use our  
22  specification to indirectly measure consumer opt-out.  
23  So it's important to understand how GDPR opt-out  
24  manifests itself in the data that we see from the  
25  intermediary. In particular, when a consumer opts out

1 of data collection, their data is not showing up in  
2 the database at all. And so what we do is we measure  
3 opt-out indirectly by estimating the difference  
4 between the observed users and the number of users  
5 that would have been observed had GDPR not been  
6 around.

7 And so to measure this, we're going to  
8 consider the following outcome variables. One is the  
9 total number of unique cookies and the second is the  
10 total number of recorded searches. And so, again,  
11 this will allow us to indirectly have an estimate for  
12 how many consumers opt out, but it's also going to  
13 tell us about how the overall scale of the data that  
14 the firm sees changes.

15 Next slide.

16 So this is the time-variant specification.  
17 So you can see a sharp drop at week 22, which is  
18 exactly the week of GDPR implementation. And you see  
19 a steady decline of roughly 10 percent to 12 percent,  
20 and this is consistent across the different outcome  
21 variables.

22 Next slide.

23 Okay. So now what do we turn to? So we've  
24 established that there is a 10 percent to 12 percent  
25 drop in the total number of users that firms observe.

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1 eliminated completely. And so a substitution between  
2 these may lead to a different data-generating process  
3 and longer consumer search histories.

4 Next slide.

5 So this figure sort of illustrates exactly  
6 what I'm talking about. So in the far left, you can  
7 see the identifier column is the identifier that the  
8 intermediary is observing for a particular user. And  
9 then in the other three columns, you're going to see  
10 consumer histories.

11 So if you focus on the first panel, the  
12 full-visibility panel, that gives the true data,  
13 that if the firm perfectly observed everything is  
14 what they would see. And so what you see is four  
15 distinct consumers with distinct search and purchase  
16 histories.

17 In the middle panel is the obfuscation  
18 regime, which is the pre-GDPR. And so let's suppose  
19 the first three consumers, they don't change their  
20 behaviors at all. But suppose the fourth is privacy  
21 conscious, so periodically deletes cookies or uses  
22 private browsing. So now what happens with this guy is  
23 his identifier is now partitioned into two users. So  
24 the intermediary thinks that it's saved two people,  
25 but it's actually one person. And as you can see,

1 consumer 4 and consumer 1 now have identical  
2 histories, and consumer 5 consumer 2 have identical  
3 histories.

4 Now, what happens under GDPR? So this  
5 privacy conscious consumer can now opt out of the  
6 data. So you see that the firm only observes three  
7 users now, but they arguably have cleaner identifiers.

8 So there's sort of two takeaways here. One  
9 is moving from the second panel to the third panel is  
10 going to mechanically increase persistence. And the  
11 second is that it might actually help the firm predict  
12 consumer behavior because they have clear user  
13 histories. And we have an extended discussion of this  
14 in the paper.

15 Next slide.

16 So now, what we want to do is we want to  
17 look at what happens to advertising revenues? And so  
18 all we're going to report here is just the results of  
19 our specifications without many more details, but it's  
20 important to contextualize the advertising setting  
21 here. So we're not thinking about behaviorally  
22 targeted advertising where advertisers are bidding  
23 directly on consumer histories. We're thinking here  
24 of keyword search advertising, so similar to  
25 Google-sponsored search. So an example is advertisers

1 are bidding on consumers who search from a flight from  
2 New York City to L.A. So any changes to bidder  
3 behavior are reflecting the average value of a  
4 consumer.

5 Next slide.

6 Okay. So these are results using the same  
7 specification as before. So first, what we find is  
8 the total number of advertisements that get clicked on  
9 has a similar effect size drop as we saw before, which  
10 is roughly 13 percent.

11 Next slide.

12 So we look at revenue. And so revenue is a  
13 bit interesting. So I don't report the time-varying  
14 graph here, but what we see is there is a sharp  
15 decline at the onset of GDPR and a slight increase  
16 afterwards. So we find a negative-point estimate, but  
17 it's relatively imprecise and statistically insignificant.  
18 And the reason why, we think, is because -- if we go  
19 to the next slide -- the average bid for a consumer --  
20 and this is for GDPR -- actually increases, which  
21 points to the fact that advertisers had a higher  
22 average value of consumers after GDPR. And so this  
23 partially offsets the loss from opt-out but not  
24 completely.

25 Okay. So that was in advertising. Then,



1 diagram I showed you before, it might actually be  
2 possible that the substitution from cookie obfuscation  
3 to opt-out actually leads to cleaner identifiers than  
4 exerts an externality to consumers by making them more  
5 predictable.

6           And so in our setting, we can use the same  
7 special specification as before precisely because the  
8 firm trains their prediction model for each site on  
9 whatever data they accrue from that site, which means  
10 that changes in data from one website don't affect the  
11 firm's ability to predict on another website.

12           And so what do we find?

13           Next slide.

14           So we do a short-run exercise, which we  
15 just put it through the same specification as before.  
16 And we find that there is slight improvements in  
17 prediction, but the big takeaway, I think, for us, the  
18 prediction didn't get substantially worse, according  
19 to the measure utilized by the intermediary.

20           Now, we were a bit worried that the  
21 short-run effects might not give enough time for the  
22 intermediary to adjust its prediction rhythm. And so  
23 what we do is we do a back-of-the-envelope logarithmic  
24 exercise where we sort of take the changes we saw from  
25 our earlier difference-in-difference estimate in the

1 change in the overall scale and longer consumer search  
2 histories and we asked how should those affect  
3 prediction. And what we find is a roughly similar  
4 result.

5 Okay, next slide.

6 Well, what did we do today? So we looked at  
7 the impact of GDPR on a number of different outcome  
8 variables. I think there's two high-level takeaways  
9 that are very closely related. The first is I think  
10 we highlight how government-mandated privacy  
11 protections do interact with other privacy needs. And  
12 this can be important for understanding the value of  
13 such regulation.

14 And second is that we highlight that  
15 consumer privacy decisions have externalities on other  
16 consumers, which is not something that legislation  
17 such as the GDPR really thinks about. And, finally,  
18 just in terms of welfare, going back to the tension we  
19 talked about before, do consumers benefit? Privacy  
20 conscious consumers clearly do. For the others, it  
21 depends on the alignment of the preferences of firms  
22 and consumers. Do firms suffer? Firms lose a  
23 significant number of consumers from opt-out, but  
24 remaining consumers are higher value, so it's not  
25 wholly negative. And, finally, the ability to predict

1 is not substantially worse.

2 Okay, thanks.

3 MR. WOOD: Okay, great. Thank you, Guy.

4 Next up is Garrett Johnson.

5 DR. JOHNSON: Thanks, Dan.

6 I'm honored to be back this year to present  
7 our second GDPR paper with the same set of coauthors.  
8 It's with Scott Shriver at Boulder and Sam Goldberg at  
9 Northwestern.

10 Next slide, please.

11 Our main research question is, can privacy  
12 policy hurt competition? Now, there's a theoretical  
13 tension between privacy and competition policy, but  
14 this claim lacks empirical evidence. One reason for  
15 this tension is economies of scale, that larger firms  
16 may have more resources to comply with regulation. We  
17

1 its enforcement deadline of May 25, 2018, as an event  
2 study.

3 Now, the GDPR is very complex, but its many  
4 elements contribute to increasing both the logistical  
5 cost and legal risk associated with processing  
6 personal data. And this is going to have important  
7 consequences for the web. We study the technology  
8 vendor industry that provides an ecosystem for the  
9 web to thrive. Specifically, these vendors help  
10 websites to monetize themselves with ads, to load and  
11 share content, as well as measure and optimize site  
12 traffic.

13 Now, in order to provide many of these  
14 services, vendors often have to share what the GDPR  
15 considers to be personal data. And as a result of  
16 this, the industry has faced intense regulatory  
17 scrutiny with at least three EU countries releasing  
18 major reports or statements criticizing the industry.  
19 But, so far, the regulators have not issued any fines.

20 Next slide.

21 So today, I'm going to briefly discuss our  
22 data and then discuss our results in three stages,  
23 talk about the GDPR's impact on vendors, its impact on  
24 concentration, and then differences by website.

25 Next slide, please.



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1

So we begin with our data.

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1 France. Second, we use a specialized piece of  
2 software, called webxray, developed by a researcher at  
3 CMU named Tim Libert. And that allows us to record  
4 all the third-party domain interactions when we visit  
5 a website. And, finally, we repeat this for 28,000  
6 top sites regularly throughout 2018, and these sites  
7 in our data sample are the top 2,000 websites in each  
8 of the 28 EU countries, as well as the US, Canada, and  
9 globally.

10 Next slide.

11 So for our results, we begin by looking at  
12 the GDPR's effect on vendor use.

13 Next slide.

14 So this figure shows the average number of  
15 vendors per site over 2018. And immediately prior to  
16 the GDPR, sites used 14.4 vendors on average. One  
17 week later, this falls to 12.4 vendors, which is its  
18 lowest level. And this is a 15 percent reduction in  
19 vendor use, which we refer to as the short-run effect  
20 of the GDPR. Now, obviously, we would have preferred  
21 to collect a longer pre-period, but we know from  
22 auxiliary data and related research that the pre-trend  
23 here is flat.

24 Furthermore, websites appear to have waited  
25 to the last minute to make changes to their website,

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1    which is why three-quarters of the drop in vendors  
2    happens within just a few days of the enforcement  
3    deadline.

4                    The reduction in vendor use is short-lived,

5

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1 just the number of websites that use a vendor. So in  
2 the sidebar example, you can see that Google Analytics  
3 has a reach of two sites and Adobe Analytics has a  
4 reach of one site. And then to calculate relative  
5 market shares, we just take the vendor's reach divided  
6 by the total reach so that in the sidebar example,  
7 Google Analytics has two-thirds market share and Adobe  
8 analytics has one-third market share.

9 Now, note, we are not observing any revenue  
10 or costs cost that's changing hands between vendors  
11 and publishers. We're only observing these vendor  
12 links. Our measure of concentration then, which is  
13 the Herfindahl-Hirschman Index, or HHI, is just the  
14 sum of the squared market shares. And this index is  
15 going to be increasing and the level of concentration,  
16 so zero is a perfectly competitive market and 10,000  
17 points is a monopoly. Because as a relative  
18 definition of HHI, if all vendors fall by the same  
19 percentage, then the relative HHI is going to be  
20 invariant.

21 Next slide, please.

22 Now, we plot relative HHI over time, and we  
23 see the evolution of concentration is the mirror image  
24 of the average number of vendors. In particular,  
25 concentration rises 17 percent post-GDPR in the short



1 audience measurement and social media, we see  
2 concentration is still increasing between 2 and 6  
3 percent.

4 Next slide.

5 Now, I want to quickly examine one of our  
6 three extensions that illuminate the mechanism for the  
7 concentration result. We consider the role of the big  
8 two companies -- Google and Facebook -- and there are  
9 many associated vendors. As before, with all vendors,  
10 we see that HHI rises 17.3 percent. However, when we  
11 exclude the vendors associated with the big two,  
12 concentration actually falls 6.2 percent. So maybe we  
13 need to update the old adage that nobody gets fired  
14 for hiring IBM to also include Google and Facebook.

15 Next slide, please.

16 Now, I want to quickly illuminate some  
17 differences by website that tell us something about  
18 the economics of how websites are making decisions

1 the share of traffic they get from EU users. We can  
2 see that sites with between 90 percent and 100 percent  
3 of EU users, on the right-hand side of the figure,  
4 drop a little over two vendors on average in the short  
5 run, where sites with between zero and 10 percent, the  
6 lowest estimate on the left-hand side drop a little  
7 over five vendors on average in the short run.

8 We think that this reflects the incentives  
9 in the GDPR that place a 4 percent penalty on global  
10 revenue. This means that sites with few EU users have  
11 relatively little to gain, in terms of revenue from  
12 the EU, but relatively more to lose from a penalty on  
13 their global revenue. The GDPR incentive then has the  
14 perverse effect that sites with the greatest share of  
15 EU users do the least to cut vendors.

16 Finally, notice the discontinuity for sites  
17 with zero percent EU on the far left-hand side  
18 illuminated in orange. Many of these sites are  
19

1 is that the average number of vendors grew slowly in  
2 countries like Denmark and the Netherlands, but grew  
3 rapidly in countries like Bulgaria and Poland. Now,  
4 the GDPR is meant to harmonize regulation within the  
5 EU, but it's still enforced, in part, at the country  
6 level. So we found a survey measure from the EU that  
7 measures regulatory strictness specific to data  
8 protection. We found that regulatory strictness is  
9 negatively correlated with the post-GDPR growth in  
10 vendor use. This suggests that site beliefs about the  
11 probability of GDPR enforcement help to explain the  
12 2018 evolution in vendor use.

13 Next slide, my last slide.

14 We started out with a theorized tension  
15 between privacy and competition policy and, today,  
16 we're able to show you the first empirical evidence of  
17 this tension. The GDPR had its intended consequence  
18 of decreasing web-technology vendor use and its  
19 associated data sharing. But it had two unintended  
20 consequences. First, we saw an increase in vendor  
21 concentration and, second, we saw that sites with the  
22 most EU visitors reduced vendors the least, an  
23 apparent side effect of the GDPR's penalty design.

24 Thank you.

25 MR. WOOD: Well, thank you, Garrett.



1                   Our third presenter is going to be Jeff  
2 Prince.

3                   Jeff, you have to unmute.

4                   DR. PRINCE: Thank you. There. I'm unmuted  
5 now. Perfect. Even better.

6                   So thank you again to the FTC organizers for  
7 the opportunity to speak and for Dan for moderating  
8 this session.

9                   This is joint work with Scott Wallsten at  
10 the Technology Policy Institute. And we received  
11 financial support from the Inter-American Development  
12 Bank for this work. So we're looking at how much is  
13 privacy worth around the world and across platforms.

14                   Next slide, please.

15                   So prior speakers have already kind of  
16 highlighted this with the GDPR. But this is across  
17 many countries around the globe. Governments around  
18 the world are grappling with data privacy policy. And  
19 as economists, we're always thinking about the  
20 tradeoffs of policy. So at a very rough level, we can  
21 think about balancing privacy preferences for the  
22 citizens with the benefits from use of the data.

23                   And one thing that has been emphasized in  
24 many places is that it's particularly difficult to  
25 measure the privacy preferences. And that's something



1 that someone would make with regard to their privacy.  
2 And the design of these surveys is well suited for  
3 measuring tradeoffs, which is what we're interested  
4 in.

5 Next slide, please.

6 And so here we have an example for Facebook,  
7 just to give you a sense of what we're talking about.  
8 So here a respondent is presented with four different  
9 options. And each option has different information  
10 that's being shared and then monthly payments  
11 associated with it.

12 And so to give you a very clear example of a  
13 tradeoff, if you look at option two versus option  
14 four, the information that's being shared is the same  
15 except for option two, you're not going to be sharing  
16 your texts. Option four, you will, but with option  
17 four, you get paid more. And so it allows people to  
18 make the tradeoff with, you know, is that additional  
19 money worth it to me to give up that information or  
20 not? And so then that choice helps us to pin down how  
21 people value different types of privacy.

22 Next slide, please.

23 And so we used the firm called Dynata. Back  
24 when we used it, they were referred to as Research  
25 Now. They administered these surveys online for us.

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1 We had 325 surveys for each type, and a type being a  
2 country, platform, and then we also included a  
3 randomized prompt, where you either got it or you  
4

1           So the next few slides present some of our  
2 results and tables. This one is a very aggregated  
3 result. So what we have here is, averaged across  
4 platforms and countries, what is the willingness to  
5 accept in dollars per month, using a purchase price  
6 parity index to compare across countries for the  
7 different types of data privacy.

8           And a summary of what we find here is that,  
9 A, there is a lot of variation, as you can see. The  
10 financial information is particularly well guarded, so  
11 those are on the higher end. Also, fingerprint  
12 information had high WTA, along with text information  
13 and contacts.

14           Next slide, please.

15           This one here has a lot more information. I  
16 know it's a lot to process all those bars, but let me  
17 just highlight a couple main points from those. One  
18 is, if you notice, the orange bar is Germany. That  
19 one is almost always the highest one for each of them.  
20 I think for 8 out of 10 it's the highest.

21           Another, I think, broad point to take away  
22 from this is that for the rest of the countries,  
23 there's a lot of similarity and there's not a fixed  
24 ordering. So it's not as clear that one country  
25 generally has higher willingness to accept than

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1 others, with the exception of Germany.

2 Next slide, please.

3 And then here's virtually everything we have  
4 in terms of averages broken down across all the  
5 dimensions, so across platform and country for the  
6 different types of online information. Again, I know  
7 it's a lot to try and swim through, but let me just  
8 highlight a couple high-level observations.

9 One is, if you look at the bars across the  
10 different countries for the different data types,  
11 again, you see a lot of similarities in even the  
12 absolute values but even more so the relative values.  
13 So if you look at the wireless, upper left quadrant  
14 there, the red bars are always the highest, the orange  
15 bars are almost always the second highest, followed by  
16 the brown. And so there's a lot of consistency in the  
17 relative preferences for different types of privacy  
18 across the different countries.

19 Next slide, please.

20 So some key takeaways. Overall, what we  
21 find is relative values are quite similar across our  
22 six countries. And then another set of results that  
23 were harder to present in tables but are also in the  
24 paper is that, at a rough level, the within-country  
25 variation -- so if you think about the distribution of

1 preferences for a particular type of online  
2 information with regard to privacy within a country,  
3 it is quite similar across countries. So how spread  
4 the preferences are, the WTA measures are, across  
5 citizens within a given country is similar across  
6 countries.

7           And so some key takeaways from those results  
8 is that public and private policies may want to offer  
9 similar relative protections, at least to the extent  
10 that these countries are representative. If you think  
11 about tiered protections, where you think about  
12 private firms could offer different levels of  
13 protection for different prices, those would likely  
14 have comparable appeal across countries. And then the  
15 distribution of support for public policies is likely  
16 to be similar across countries.

17           Next slide, please.

18           And then as I highlighted, Germany is  
19 different, at least within the set of countries we  
20 looked at. They're different overall and with  
21 financial information in particular. So a key driver  
22

1 regard to the distribution of preferences within  
2 Germany, they appear to be the most homogeneous. So  
3 the spread of WTAs for different types of privacy is  
4 notably smaller for Germany than for the other  
5 countries we looked at.

6 Next slide, please.

7 And then a few other results that I think  
8 are worth highlighting that we found. When we break  
9 it down across sex, women versus men, the willingness  
10 to accept for women was notably higher than that of  
11 men for different types of online privacy, often by  
12 about an order of two times. If you go across age,  
13 for the older cohort versus the younger, the  
14 willingness to accept was substantially higher, often  
15 by two, three, or even four times as much. Income,  
16 though, does not predict the willingness to accept  
17 very well.

18 And then last but not least, with regards to  
19 that leading statement I mentioned earlier, the  
20 preferences did not seem to be impacted by that, which  
21 suggests that they're not easily swayed by prompts  
22 that one might put out with regard to the value of  
23 data and giving up privacy, or its potential value.  
24 People's preferences seem to be unimpacted by that.  
25 And with that, I will conclude. Thank you very much.



1 MR. WOOD: Okay. Thank you, Jeff.

2 Our last speaker is going to be Christine  
3 Utz. Christine.

4 MS. UTZ: Thanks, Dan, and everyone at the  
5 FTC, for having me back here at PrivacyCon.

6 What I'm going to present today is a direct  
7 follow-up to our GDPR paper from last year's  
8 PrivacyCon. This is joint work with my colleagues  
9 Martin, Sascha, Florian, and Thorsten and was  
10 previously published at ACM CCS 2019.

11 So I'm sure you've all -- next slide,  
12 please.

13 I'm sure if you've seen all of these before.  
14 These are consent notices, colloquially known as  
15 cookie banners. And these are little popup boxes that  
16 show up on lots of websites these days. And they  
17 inform you of the website's data collection practices  
18 and ask you for your consent.

19 The legal foundation of these notices is the19

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1 date.

2           Recently, there have been some vendors of  
3 third-party consent libraries that have started to  
4 also implement the new CCPA Do Not Sell requirement in  
5 these consent notices. So maybe we'll be seeing more  
6 and more of these also with the CCPA as a legal  
7 foundation.

8           Consent notices can be arbitrarily complex.  
9 So you can have just the basic one with just an allow  
10 button, like the dark one. Or you can have a more  
11 fine-grained selection, where you can select different  
12 categories of cookies, like in the one on the top  
13 right corner.

14           Next slide, please.

15           So we saw all of these notices become more  
16 and more complex. And we can come up with a couple of  
17 research questions. So how often do people interact  
18 with these notices? Do different changes in the  
19 parameters of the user interface of these notices  
20 influence what decisions users make? And why do they  
21 choose to interact and not interact with these  
22 notices? And what do people expect to happen when  
23 they allow or deny cookies?

24           Next slide.

25           So we decided just to find answers to all of

1 these questions in the field. So we had the  
2 opportunity to team up with a German e-commerce  
3 website. And that site has about 20K unique visitors  
4 per month. Most of them just google something, and  
5 then find an article on the website, read it, and then  
6 leave the site. It runs on WordPress and uses common  
7 third-party services, like Google Analytics or  
8 embedded YouTube videos or a design framework called  
9 Ionic.

10 And we modified a WordPress plugin to  
11 display arbitrary consent notices on that website.  
12 And with this plugin, we conducted three iterative  
13 experiments between November 2018 and March 2019 in a  
14 between-subject study.

15 Before we could get started, we had to  
16 evaluate the available design space for the UI of  
17 consent notices. So we luckily still had a couple of  
18 consent notices laying around from our paper from last  
19 year. So we just sampled 1,000 of those and inspected  
20 them and identified the design space for consent  
21 notices.

22 Next slide, please.

23 So we identified eight different UI  
24 parameters of consent notices. Three of them are  
25



1                   Next slide, please.

2                   Our study setup looked as follows. So the  
3 user visited the website, and then they were shown one  
4 of n consent notices, with n being the number of  
5 notices in the current experiment. Our plugin then  
6 would log all interactions between the user and the  
7 notice, such as clicking an okay button or ticking a  
8 checkbox or clicking the privacy policy link.

9                   If the user chose to interact with the  
10 notice, we replaced the content of the notice with  
11 another notice that mentioned that this is a  
12 university study and gave them the choice to either  
13 participate or close the notice for once and for all.  
14 And if they chose to participate, we just redirected  
15 them to our survey. But we were also interested in  
16 people who chose not to interact with the notice. And  
17 for that, after 30 seconds without any interaction, we  
18 automatically replaced the notice with the study  
19 invitation. And then, again, if they chose to  
20 participate, they were sent to another version of the  
21 survey.

22                   Next slide, please.

23                   So these are the results of our first  
24 experiment, location. In this experiment, we  
25 displayed a binary notice to encourage user

1 interaction, and we displayed it at six different  
2 positions.

3 Here and in the following, I'll only report  
4 interaction rates. In the paper, we have a more  
5 fine-grained analysis that shows what people actually  
6 clicked. And here we found that the position that  
7 yielded the highest interaction rate was in the lower  
8 left corner of the screen.

9 We had some theories where this might be the  
10 case. So the theory for top versus bottom was that on  
11 top, usually the banner is more likely to cover some  
12 less important parts of the website, like some header  
13 or a menu, while on the bottom you usually have some  
14 content and text. And the same argument applies for  
15 left versus right, because if you have text written in  
16 the Latin alphabet, everything is skewed to the left,  
17 so more important information can be -- so there's  
18 more information on the left versus on the right.

19 Next slide, please.

20 In our second experiment, we looked at the  
21 different options offered by the website and the  
22 influence of nudging. And here we had five different  
23 banners in terms of option. So we have one banner  
24 that doesn't offer you any type of option at all. The  
25 one on the very left, you just have a little x to make

1 the notes go away. Then the next banner is one that  
2 just has an accept button. And here you can see the  
3 non-nudging variant of all the banners. So this exit  
4 button is not highlighted. The next banner in the  
5 middle is the binary banner you've already seen. And  
6 here this is the non-nudging where each button looks  
7 like the other.

8           And then we had some more fine-grained  
9 options, one that allows you to check or uncheck  
10 different categories and one that has the same for  
11 different third-party vendors. And here the  
12 non-nudging variants don't have pre-ticked checkboxes,  
13 while the nudging variant would have pre-ticked  
14 checkboxes.

15           And here we saw a big influence of nudging.  
16 Because in almost all cases, the nudging variants  
17 yielded higher interaction rates. And the binary  
18 banner had the highest interaction rates. But  
19 combined with the qualitative data from our survey, we  
20 also saw that the category-based banner was also  
21 popular with users.

22           Next slide, please.

23           We then took a brief look at what people  
24 actually clicked. And here's just a quick example.  
25 So these are the selections people made on the

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1 window-based banner. And you can see if you do not  
2 pre-tick the checkboxes, then there were only about  
3 1 percent of visitors that actively opted in for one  
4 of the vendors, while in the case where you have  
5 pre-ticked checkboxes, we had about 10 percent who  
6 agreed to data collection by these third parties.

7 As for the results of experiment three, I  
8 don't have them on slides here because we didn't see  
9 any significant influence of either the presence of a  
10 privacy policy link and technical versus nontechnical  
11 language.

12 Next slide.

13 So then we took a brief look at what  
14 people wrote as answers into our survey. And we asked  
15 them why they chose to click or not click the banner.  
16 And among the reasons for not clicking -- for  
17 clicking, excuse me, we saw that one prominent reason  
18 was the expectation that the website would not work  
19 otherwise.

20 And this misconception was also present in  
21 other questions, like -- next slide -- when we asked  
22 what users expected to happen if they clicked decline  
23 or accept. The top reason or the top statement, what  
24 would happen if they hit decline, was that the website  
25 cannot be accessed. And this was named more often



1 than just mere functionality limitations, which would  
2 be much more likely than the website not working at  
3 all.

4 So what did we learn from all of this? We  
5 saw that the interaction rate is mainly influenced by  
6 position of the banner on the website and not the  
7 effects of nudging and preselections. We saw that  
8 users appeared to favor a binary or category-based  
9 approach versus more fine-grained ones, like  
10 vendor-based approaches. And there are widespread  
11 misconceptions about how consent notices work.

12 So one of them was that the site cannot be  
13 accessed without consent. So one recommendation here  
14 would be to inform users about the functionality  
15 limitations they can expect when they do not allow the  
16 use of cookies. And then from the survey, we also saw  
17 that people have some privacy by default expectations.  
18 So they expect no data being collected before they  
19 actively make a decision. And this is really not the  
20 case in reality. So this would be an issue that could  
21 be addressed by regulators because currently there are  
22 no incentives for companies to actively protect their  
23 visitors' privacy.

24 Thanks.

25 MR. WOOD: Thank you. I'd like to thank all

1 the panelists for excellent papers and really  
2 interesting research that they've contributed to this  
3 panel.

4 Now [audio malfunction] the way you would  
5 through email. And, hopefully, the slide that's  
6 available now is showing you where you'd send them.

7 But before that, I have a couple of  
8 questions for the panelists myself. And I'll start  
9 with Christine. So, Christine, your research found  
10 that the position of dialogues, the set of choices  
11 offered and other nudges significantly may influence  
12 consumer consent choices. How pessimistic should  
13 these findings make us about the possibility of  
14 mandating that firms obtain informed consent  
15 in other online contexts? Are those mandates going to  
16 be hard to make workable?

17 MS. UTZ: I would say that this depends on  
18 what this mandate looks like. Because in the case of  
19 the EU and GDPR, there was a lot of confusion about  
20 what informed consent actually means, because  
21 initially there was a big lack of guidelines how  
22 consent should be collected and what's actually free  
23 and informed consent. And only recently the EU has  
24 put out some documents that give a little more insight  
25 in that. But there are still lots of questions to be

1 answered.

2                   And I think, yeah, if you want to introduce  
3 new mandates for firms to collect online consent, then  
4 there really should be some guidelines, along with a  
5 mandate that would help companies and anyone else  
6 who's collecting personal data to comply with the new  
7 regulations.

8                   MR. WOOD: Okay, interesting.

9                   I guess I'll rotate through the panelists.  
10 And my next question is for Jeff. So the privacy  
11 paradox, roughly stated, is that people report  
12 stronger preferences for privacy in surveys than they  
13 demonstrate with their actual behavior.

14                   How well do the valuations for privacy you  
15

1 But again, you know, we're looking at major platforms  
2 rather than a single app. So people might look at  
3 that decision differently.

4 More broadly, I think, you know, with the  
5 privacy paradox, it's tough to say. I think, you  
6 know, this is one of the reasons why I think more  
7 quantification is valuable, because a lot of times, as  
8 people know, we ask people, do they value their  
9 privacy, and the answer is yes, maybe even a lot. But  
10 then that might not line up with what quantifiable  
11 metrics would be in terms of how much they value their  
12 privacy.

13 And, in fact, even with our numbers, we had  
14 outlets interpret our numbers as being large and we  
15 had outlets interpret our numbers as being small. So  
16 in some ways, it's a lot about perspective. So it's  
17 hard to align our figures with what people and  
18 people's qualitative analyses have revealed. But I  
19 think, you know, our hope is to contribute more to the  
20 quantifiable version of people's value for privacy.

21 MR. WOOD: Right. Well, so it seems to me  
22 like your numbers are going to become a standard for  
23 future research in the privacy space. So I  
24 thought they were really interesting.

25 DR. PRINCE: Thank you.

1           MR. WOOD: My next question -- like I said,  
2 I'm rotating -- is for Garrett, Garrett Johnson. So  
3 you talked a little bit about this, but it seemed like  
4 a lot of what you measured was the short-run  
5 adjustment to GDPR enforcement. Should we evaluate  
6 the effect of GDPR based on that? Or is the long-run  
7 adjustment what we should be interested in, or are  
8 both useful?

9           DR. JOHNSON: There we go.  
10           It's an important question. My answer is  
11 emphatically that the short-run provides the best  
12 available evidence. But I want to make the three big  
13 points here. The first is that the GDPR is really  
14 confusing to study in this industry, because  
15 regulators have been slow playing the industry. So  
16 even as of today, the EU has not fined any of these  
17 websites or technology vendors. But at least three EU  
18 countries have criticized the industry for practices  
19 that do not comply with the GDPR.

20           So again and again, the EU keeps delaying  
21 enforcement and giving the industry time to adjust its  
22 practices. So the big question is, how are you going  
23 to study a law that hasn't been enforced? So we try  
24 to argue that the best time to do so is when the firms  
25 are most afraid of enforcement and change their

1 behavior accordingly. And our evidence does suggest  
2 that beliefs play an important role, like the fact  
3 that countries that face stricter regulators seem to  
4 keep their vendor use lower than those that don't,  
5 and, also, some evidence that also we talk about in  
6 the paper.

7           And the last thing I'll say is that this is  
8 an industry that moves very quickly, that has -- it's  
9 a fast growing market. And we see in general that the  
10 number of vendors increases over time. So given this  
11 fact, I think the best evidence we have is this big  
12 trend break we see right around May 25, 2018, which is  
13 the month right after the GDPR deadline.

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1                   So when thinking about it, I think there's  
2 two things. So the first is that I think there's two  
3 dimensions to think about from the consumer  
4

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1 partner -- the intermediary we partner with sort of  
2 views itself as a competitor to Google.

3 And we think that our study sort of helps  
4 understand how a niche advertising intermediary gets  
5 impacted in terms of profitability in data observed by  
6 a smaller advertising intermediary. And we suspect  
7 that advertising intermediaries in other domains would  
8 be similarly impacted. And I think Garrett's paper  
9 sort of points to this, and there's a few papers that  
10 are pointing to the need to sort of think about the  
11 broader competition effects of GDPR on these things.

12 And so while we find that our results aren't  
13 wholly negative on the firm side, it would be  
14 interesting to think about how that would compare to,  
15 say, Google, who might not have been as impacted by  
16 GDPR as our advertising intermediary. So we suspect  
17 that our results on the impact to a third-party  
18 intermediary would be similar. And it's interesting  
19 future work to think about how that would impact  
20 itself in a broader competition between advertising  
21 intermediaries.

22 MR. WOOD: Cool. So let me ask you another  
23 question, Guy.

24 So part of what I found fascinating about  
25 your paper was that there were these externalities



1 between different types of consumers. How is the move  
2 from -- can you dwell on a little bit more and tell us  
3 how the move from software-based data obfuscation to  
4 GDPR opt-out is likely to affect the welfare of  
5 consumers who don't have strong preferences about  
6 privacy?

7 MR. ARIDOR: Yeah. So that's a good  
8 question.

9 So I guess as an economist, I have to state  
10 the caveat that we do a reduced form metrics exercise, so  
11 we can't directly say anything about welfare. But we  
12 do argue indirectly in the paper that if you think of  
13 consumer welfare as largely depending upon the quality  
14 of services they receive, this is largely dependent on  
15 the ability of a firm to do prediction. And so  
16 particularly in our context, we find that there,  
17 there's a marginal improvement in prediction. And  
18 this may lead to other domains and better  
19 personalization and ultimately improve consumer  
20 welfare.

21 There's obviously settings such as where  
22 firms are using this prediction to do price  
23 discrimination where, you know, arguably it would  
24 reduce consumer welfare. So the way we try to frame

1 alignment of preferences between firms and consumers  
2 in terms of how they use their data.

3 But I think it would be -- and again, we  
4 point this out the paper -- it'd be interesting to do  
5 a proper structural analysis to really decompose the  
6 welfare benefits to these policies.

7 MR. WOOD: Cool. Let me turn back to  
8 Garrett.

9 So, Garrett, while the California Consumer  
10 Privacy Act is sometimes compared to GDPR, there are  
11 some differences. Do you think the CCPA -- or if you  
12 want you could imagine a different hypothetical  
13 federal privacy legislation. Do you think that sort  
14 of legislation would lead to similar increases in  
15 concentration that you find?

16 DR. PRINCE: I think it would have different  
17 effects on competition. So I think the main  
18 difference is that the GDPR has a data minimization  
19 principle, and that places pressure on firms to limit  
20 their datalimit

1 allows consumers to avoid data sharing. And we know  
2 from research, like Christine's and Guy's and my own  
3 works, that opt-out rates, at least according to our  
4 stuff, is like 5 percent to 15 percent when sites have  
5 to display this prominently. But the CCPA insists on  
6 this colorful language which is, "Do not sell my  
7 personal information" for the opt-out button, which I  
8 would speculate -- it would be interesting to hear  
9 what Christine would say about this -- I would think  
10 this could increase the opt-out rates.

11 So while I don't think this is going to have  
12 an effect on vendors, I do worry this could have an  
13 effect on the publisher side. In particular, large  
14 websites may have an easier time gaining consent than  
15 smaller and less recognizable websites. And our work  
16 examining over a thousand firms using Adobe Analytics  
17 data and the GDPR is consistent with this finding. We  
18 see a larger reduction in recorded web outcomes for  
19 smaller websites in our data.

20 MR. WOOD: Okay.

21 Christine, did you want to speculate on the  
22 effects of the CCPA's -- what's the exact wording,  
23 Garrett?

24 DR. PRINCE: "Do not sell my personal  
25 information."

1 MR. WOOD: Is that a good notice?

2 MS. UTZ: Actually, we already did some  
3 investigation of that. So we took a look at a couple  
4 of -- I don't know how many -- a couple of thousand of  
5 US websites, and we looked at how they implement the  
6 CCPA link. And we saw really, really big variance in  
7 how this link is named. Often, it's "do not sell" and  
8 "do not sell my info," "do not send my personal info."  
9 There were dozens of variants on that.

10 Yeah, this makes you wonder how the sites  
11 will deal with the rest of the CCPA requirements if  
12 they're already having kind of difficulties complying  
13 with this simple requirement like just put in a link  
14 that has this wording.

15 MR. WOOD: Yeah. My understanding -- and I  
16 haven't been following it super closely -- was that I  
17 think the California Attorney General might be  
18 producing guidance. I don't know if they have a  
19 deadline. But the guidance is -- you know, if they  
20 read your paper, the guidance might be great.

21 So let me ask a sort of very broad question  
22 of you, Jeff. What's the most important points about  
23 privacy policy that you think privacy policymakers  
24 should be taking from your research?

25 DR. PRINCE: Oh, wow, that is a big one. I

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1 guess, you know, one of the takeaways for us was there  
2 was a very noticeable similarity in both the relative  
3 and, even in a lot of ways, the absolute preferences  
4 for the different types of privacy. I think many  
5

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1 -- it seems like that sort of structural similarity  
2 makes me a little more confident in the survey-based  
3 approach. It seems like a method producing  
4 something -- the real preferences -- if we're finding  
5 consistency across different countries and across  
6 different groups of people.  
7

1 processing. Like, for example, in the case if you  
2 have an embedded YouTube video, you can say, okay, if  
3 you don't agree to YouTube setting cookies, then you  
4 just will see a gray box or something and not the  
5 embedded video, something like that.

6 MR. WOOD: Okay. So we did get one --  
7 actually, two audience questions. And one of them is  
8 about Privacy Shield. And that's a big area, so we're  
9 not going to touch that yet.

10 But the other one is a somewhat more  
11 specific question for Christine. So we only have  
12 about a minute left. But, Christine, if you feel like  
13 you can do justice to this, how can data protection  
14 authorities, who often review consent statements for  
15 consent but not other factors, incorporate your  
16 research into their day-to-day work?

17 MS. UTZ: Okay. Yeah, I think they could  
18 maybe feel encouraged to issue -- to come up with some  
19 guidelines. I mean, we already have some guidelines.  
20 One was recently published by the EU. And we have  
21 some other guidelines by different EU member states.  
22 But I'm sure there are still lots of uncertainties  
23 what constitutes valid consent.

24 And then one big issue we still see -- this  
25 is something Garrett has already pointed out, which is

1 we do have the laws, but there's just a big -- they're  
2 not being enforced right now, or just a very, very  
3 small extent. So right now, there's really no  
4 incentive in many areas to comply with GDPR, because  
5 there's just a lack of enforcement.

6 And one big problem in this area is that  
7 data protection authorities just lack the funding and  
8 the personnel to actually enforce the law. But I hope  
9 we'll see some changes in that in the future so that  
10 the regulations can finally exist, not just in paper,  
11 but also actually in live systems.

12 MR. WOOD: Okay. Sounds reasonable to  
13 me, speaking purely for myself and not for the Federal  
14 Trade Commission.

15 I would like to thank you all again for a  
16 wonderful panel and for participating in this year's  
17 PrivacyCon. PrivacyCon will resume in about eight  
18 minutes. But for now there's a virtual coffee break.  
19 And when we resume, we'll do the last panel of the day  
20 on miscellaneous topics in privacy and security. So  
21 thank you. Thank you again.

22 DR. JOHNSON: Thanks, Dan.

23 DR. PRINCE: Thank you.

24 MS. UTZ: Thanks.

25



1           SESSION 6: MISCELLANEOUS PRIVACY/SECURITY

2           MR. HINE: Hi, everybody. Welcome to our  
3 final panel of the day, panel 6. This is sort of the  
4 miscellaneous panel. We'll call it the potpourri  
5 panel for today on privacy and security issues.

6           Just a couple of reminders. One, that you  
7 can send questions to the [privacycon@ftc.gov](mailto:privacycon@ftc.gov) mail

8

1 has examples of regulation which mandate these privacy  
2 choices. And this includes the GDPR in the European  
3 Union, as well as the CAN-SPAM Act, COPPA, and now the  
4 California Consumer Privacy Act in the US.

5 Additionally, groups like the Digital Advertising  
6 Alliance also work towards self-regulation in the  
7 advertising industry.

8 On the next slide are examples of three  
9 types of privacy choices that are commonly mandated by  
10 regulation and self-regulatory guidelines. And these  
11 include opt-outs for email communications, opt-outs  
12 for targeted advertising, as well as data deletion  
13 choices.

14 Next, I'll go over our research questions,  
15 which explore how these mandated privacy choices are  
16 provided in practice. We asked what choices related  
17 to email communications, targeted advertising, and  
18 data deletion do websites offer? Additionally, how  
19 are websites presenting these privacy choices to  
20 their visitors, and what are the potential usability  
21 issues?

22 To answer these questions, we conducted two  
23 studies. The first was a manual, in-depth content  
24 analysis of privacy choices on 150 websites. We  
25 followed up on this work by conducting an in-lab

1 usability study of a subset of these choices.

2           So next, I'll go a bit into more detail  
3 about our study protocols. To standardize the data  
4 recording for empirical analysis, for each website, we  
5 filled out an analysis template with 82 questions. An  
6 example of these questions included the location of  
7 the privacy choice, was it in the privacy policy,  
8 account settings, somewhere else on the website; the  
9 level of detail provided about each choice; the  
10 availability of links to the choice; as well as the  
11 path of implementation, for example, how many user  
12 actions were required to actually use the choice.

13           So next, I'll provide a quick overview of  
14 how we selected websites for the study. We randomly  
15 sampled 150 websites from Alexa's Global Top 10,000  
16 list as of March 2018. All 150 of these websites were  
17 analyzed between April and October 2018, and half of  
18 them were reviewed by two researchers with an  
19 agreement of .82.

20           Next, a bit more about our user study. For  
21 our user study, each study session we conducted had  
22 three portions. First, we conducted a pretest  
23 interview to understand what users already believed  
24 about data collection and privacy controls. Next, we  
25 had participants complete two study tasks.

1           First study task, we identified a set of  
2 nine websites that had common implementations of  
3 privacy choice mechanisms that we identified in our  
4 empirical analysis. We gave users scenarios to  
5 describe this privacy choice task and asked them to  
6 complete this task as they would in the real world.  
7 For some websites, the scenario would require going to  
8 the account settings, while on others, it required  
9 going to the privacy policy. And the policy  
10 mechanisms could appear as links in the policy text  
11 or it could be described within the text as  
12 instructions.

13           In the final component of the study, we  
14 asked participants interview questions after the test  
15 to capture information about their experience and  
16 understanding of the study tasks.

17           So next, I'll go over a few of our results.  
18 But I encourage you to read more in our papers. So  
19 first, some good news. From our empirical analysis,  
20 we found that privacy choices are common. Almost 90  
21 percent of websites that use email marketing or  
22 targeted advertising in our sample offered their  
23 respective opt-outs. And almost three-fourths of all  
24 sites in our sample provided a data deletion  
25 mechanism.

1                   Next slide, please.

2                   In our empirical analysis, we found that  
3 privacy choices were often provided in privacy  
4 policies. The downside of that, other than consumers  
5 largely ignoring privacy policies, is that the  
6 headings under which choices are presented are  
7 inconsistent from policy to policy.

8                   This table presents bigrams and trigrams in  
9 headings of sections that describe these privacy  
10 choices. We noticed that some terms were evenly  
11 distributed, like "your choice." However, there were  
12 more unique terms for certain types of choices, such  
13 as opt out for email communications, third party for  
14 targeted ads, and your right for data deletion.  
15 Alarmingly, no single n-gram occurred in more than 20  
16 of our analyzed policies. And this lack of  
17 consistency across websites could make it hard to  
18 locate choices in privacy policies.

19                   Next, I'll go over another reason why  
20 offering choices through privacy policies is less than  
21 ideal. From our user study, here's an example of a  
22 privacy policy that users encountered on one of the  
23 websites in the study during the scenario in which  
24 they were trying to stop seeing ads for shoes that  
25 they searched for last month. So here are some

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1 relevant information about how ad partners use cookies  
2 and beacons to decide which ads to show.

3 On the next slide, we see that the first  
4 link here is for opting out of Google Analytics. And  
5 participants often clicked that first when trying to  
6 disable cookies. But this link isn't that useful if  
7 the main goal is to disable cookies, so it's not clear  
8 why it's shown first here.

9 On the next slide, we see that the  
10 information about disabling cookies was presented  
11 underneath that link.

12 Next slide, please.

13 So from our empirical analysis, we noted  
14 that another reason why figuring out what to do could  
15 be difficult is that websites sometimes provide  
16 multiple tools for the same type of privacy choice on  
17 different pages of the website. So take Twitter's  
18 targeted ads for example. First, in the account  
19 settings you can find the opt-out provided by Twitter  
20 itself. If you navigate to it's About Ads page, it  
21 only shows opt-outs provided by the DAA, NAI, as well  
22 as Google. If you go to its privacy policy, only the  
23 ones provided by Twitter and the DAA will show up.

24 All of these links to multiple opt-out tools  
25 spanned across multiple pages of the website may cause

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1 confusion about what tools should be prioritized and  
2 what their differences are. In fact, this is  
3 something that we observed in the lab.

4 On the next slide, we have an example of  
5 what privacy policy participants saw in one of their  
6 tasks. Participants who saw this had a difficult time  
7 understanding which of these three links would allow  
8 them to opt out of targeted advertising. While it was  
9 confusing when there were multiple links leading to  
10 different tools, when there were multiple paths to the  
11 same choice for information related to a privacy  
12 choice, we observed that it actually tended to be  
13 easier to find.

14 On the next slide, we have an example from  
15 the lab. Most participants who were assigned a data  
16 deletion task on RuneScape.com found the information  
17 they needed through searching the website support  
18 pages rather than referring to their privacy policy.  
19 And this led them to the Your Personal Data Rights  
20 page shown on the next slide, where they were able to  
21 see that the website offered this.

22 Another major result, which I present on the  
23 next slide, is that using these choices require high  
24 numbers of user actions. The user actions could  
25 include clicks, hovers, scrolls, filling out form

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1 fields, or other types of interaction. For example,  
2 we see here that on average a participant took about  
3 38 actions to exercise a privacy choice using a policy  
4 link.

5           And this average includes the reality that  
6 most users make some mistakes, like going to the wrong  
7 page, clicking the wrong item, on the way to the final  
8 correct action. When we collected data about the  
9 shortest path to each choice in our empirical analysis  
10 by performing the same tasks with prior knowledge of  
11 the location of the choices, it still required a high  
12 number of user actions. In the case of policy links,  
13 even if someone already knew exactly how to get to the  
14 final step and took the shortest possible route to get  
15 there, it would still take about 22 actions. In the  
16 lab, we uncovered some practices that required  
17 unnecessary effort.

18           On the next slide, here is an example of a  
19 part of a complicated form that some websites require  
20 to exercise a privacy choice. The example shown here  
21 is a form for deleting data on the New York Times  
22 website. Most participants dislike the number of  
23 similar-seeming options here. Further down the form,  
24 you had to select from a list of 22 different New York  
25 Times services, and you could only submit one request



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1 type at a time.

2           The next slide provides another reason why  
3 exercising privacy choices might require unnecessary  
4 effort. So websites sometimes require users to submit  
5 written requests to complete actions, such as data  
6 deletion, when a simple web form would have sufficed.  
7 There were also participants who ended up writing  
8 emails to customer service to ask for help because  
9 they couldn't find a simpler way to do their task  
10 through the website itself. And it sometimes wasn't  
11 easy for participants to articulate what they wanted  
12 to do. For example, one participant who was given the  
13 shoe ad scenario I described before wrote this email  
14 to ask for help.

15           So after hearing so many issues, you might  
16 wonder, how do we improve the usability of website  
17 privacy choices?

18           On the next slide, we show that one way  
19 regulation could help improve visibility is to have  
20 explicit requirements that dictate parameters like the  
21 location of controls and the way that controls are  
22 presented. And the findings from our user study  
23 suggest that the CAN-SPAM Act has likely been  
24 effective in making email unsubscribing more usable.  
25 It mandates the look and placement of email opt-out

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1 links in commercial emails, and users thus expect to  
2 find the unsubscribe link in that location.

3           Additionally, the next slide shows another  
4 way that policy could play a role, which is by  
5 standardizing policy section headings so that choices  
6 are easier to find. Such practice has been adopted by  
7 the US financial industry as a model privacy form to  
8 help financial institutions comply with the GLBA.  
9 Though it may not be perfect, it's definitely a good  
10 start, and research has shown that the standardization  
11 effort of the GLBA contributed to less ambiguity in  
12 privacy policies.

13           As summarized on the next slide, another way  
14 that choices could be made more usable is through  
15 unified settings. This could simply mean matching  
16 user expectations by always having privacy choices  
17 easily accessible within websites' account settings,  
18 rather than buried elsewhere on the website or its  
19 privacy policy. There is also the possibility of  
20 further unifying choices for users by offering more  
21 universal mechanisms, such as through a web browser  
22 that's able to parse privacy policies or use  
23 machine-readable privacy policies to help users  
24 exercise preferences across multiple websites with  
25 less effort.

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1           Thank you, and I'd like to pass it off to  
2           the next speaker.

3           MR. HINE: Great, thanks. And that will be  
4           Ido Sivan-Sevilla.

5           DR. SIVAN-SEVILLA: Right. Thank you,  
6           Jamie. Good afternoon, everyone.

7           I'll be presenting our research today about  
8           the extent that third-party trackers in websites  
9           persistently identify users across websites or, more  
10          specifically, across social contexts. And this  
11          research was conducted with the research group in  
12          Cornell Tech, including Wenyi Chu and Xiaoyu Liang,  
13          two Cornell Tech Master's students, and Professor  
14          Helen Nissenbaum, Professor of Information Science in  
15          Cornell Tech. And we gratefully acknowledge support  
16          from NSA and NSF for this research.

17          Next slide.

18          Okay, so a little bit of background. If you  
19          think about the web, the web is an array of different  
20          social contexts. We go to the web when we want to  
21          look for information about our medical problems or  
22          express our educational aspirations or consume news.  
23          And advertisers take advantage of the fact that the  
24          web is an array of all these different things to  
25          conduct cross-context inference about individuals.

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1 The fact that the web is an array of social contexts  
2 coming together is really profitable for this  
3 industry.

4 Think about, for instance, how advertisers  
5 can cross information about users' medical problems,  
6 educational interest, and news consumption habits.  
7 They become in a better position to know when a  
8 consumer can be turned into a purchaser and make  
9 purchasing decisions.

10 One more click.

11 And the fact of the matter is that we are  
12 never alone in the web. Embedding third parties in  
13 websites became an inevitable and disturbing social  
14 norm. According to recent statistics, there are 9  
15 trackers on average per website and overall 33  
16 tracking requests per page. And these trackers have  
17 the potential to undermine the integrity of our  
18 context and the way we browse the web and violate our  
19 privacy according to our approach of privacy as  
20 contextual integrity.

21 Next slide, please.

22 So this approach was also used in a previous  
23 paper presented by Madelyn Sanfilippo in this  
24 conference. And we argue that privacy is the  
25 appropriate flow of information based on informational

1 norms in a given context. Privacy is not about  
2 control, whether information is public or private.  
3 It's about how we use information.

4           So think about some examples of privacy  
5 violations according to this theory. So think about  
6 employment decisions based on religious affiliations.  
7 Think about the display of advertisements based on  
8 sensitive health information. Think about clinical  
9 tagging based on voice assistant data. These are all  
10 examples in which information was taken out of its  
11 original context, based on, without -- against the privacy  
12 expectations of the data subject that their  
13 information is about.

14           Next slide, please.

15           So what we're trying to do here is to apply  
16 this context-sensitive approach to online tracking.  
17 And when you look at previous studies, you see  
18 that online tracking was studied in bulk, across  
19 thousands of website, without distinguishing their  
20 social contexts. And our approach here was to apply  
21 a context-sensitive analysis to online tracking,  
22 comparing tracking across different social contexts  
23 of the web.

24           So what does it mean? Let's try to  
25 visualize what we're doing here. So one more click.

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1                   So for instance, if you go to WebMD.com, one  
2   of the third parties you will see there is  
3   DoubleClick.net. DoubleClick uses a user ID cookie  
4   and assigns you an ID, in this example the string, one  
5   to nine.

6    1Totsss Tc(           NYTimeso for 0 1Tc(Tc(of                   Olsg1.08 6





1 websites.

2                   According to user surveys, and some of them  
3 were discussed in previous sessions in this  
4 conference, people are not comfortable with trackers  
5 navigating their data between different contexts to  
6 get a better understanding of their profiles. And  
7 this is what we're trying to measure in this study.

8                   Next slide, please.

9                   So about our data analysis approach, so for  
10 each experiment, we were matching ID cookie aproa moeir da1.94 0

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1 healthcare websites. And this is especially alarming  
2 in our times of the global pandemic, when healthcare  
3 websites are becoming extremely popular, when users  
4 seek health information.

5 Next slide, please.

6 Okay, this figure is trying to start and

7

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1 websites after health websites, you see 69 persistent

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1 means that a different number of trackers are actually  
2 following this trend of persistent identification.

3 Next slide.

4 Okay. Three takeaways from this study. So  
5 first, we see that users who consume their news or  
6 visit educational resources after browsing at  
7 healthcare websites are potentially more vulnerable  
8 for manipulation by the advertising industry. Like I  
9 said, this is especially alarming in times of the  
10 global pandemic.

11 Secondly, what matters for users' privacy is  
12 not only the amount of tracking within a given  
13 context, but also the extent that trackers link  
14 information about users between those contexts for  
15 potentially better targeting purposes.

16 And, finally, like I said, healthcare  
17 websites, which were regarded in previous studies as  
18 less dangerous for users' privacy because they had  
19 less number of third-party trackers that were  
20 following you, are actually the most alarming ones  
21 when it comes to persistent identification trends.

22 And next slide, that will be my last one.

23 So to conclude, we argue that this is a  
24 first modest step to apply contextual understanding to  
25 online tracking. We argue that this is a rather

1 unaccounted privacy violation. We should all work for  
2 keeping the integrity of our different social contexts  
3 when we go online, no matter how profitable their  
4 conflation might be for certain parties, in this case  
5 third parties and advertisers.

6 And, ultimately, this work is a call to  
7 apply a more context-sensitive analysis to online  
8 tracking in order to better understand this rather  
9 unaccounted privacy violation. So more, of course, is  
10 in the paper. And I'm looking forward for your  
11 questions and comments.

12 Thank you.

13 MR. HINE: Daphne, you have the floor.

14 DR. YAO: All right. Thank you, everyone.  
15 Thank you, Jamie.

16 I'm Daphne Yao from Virginia Tech. Today,  
17 I'm going to talk about payment card security. And  
18 this is work published in ACM CCS 2019 last year. And  
19 it was in collaboration with my PhD student, Sazzadur  
20 Rahaman, who just defended his PhD thesis yesterday,  
21 and my colleague, Gang Wang, from University of  
22 Illinois.

23 Next slide.

24 PCI stands for Payment Card Industry. The  
25 body behind the data security standard, the DSS, are

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1 big banks, so Visa, MasterCard. They formed what is  
2 called the Security Council -- PCI Security Council.  
3 The standard, it started in 2004, many years ago.

4 A little bit of history. Before there was  
5 DSS 1.0, Visa came up with data security standards on  
6 its own. And quickly, many other companies --  
7 MasterCard, Discover, American Express -- followed  
8 suit. And then it was so confusing. The payment  
9 ecosystem had so many intertwining components. The  
10 acquirer banks, the issuer banks, the merchants, they  
11 have to work together on transactions. And so it's  
12 very confusing to have one standard for Visa and  
13 another standard for MasterCard.

14 And so the big banks have formed the  
15 Security Council and decided that let's just unify all  
16 the data security standards. The current version is  
17 3.2.1, which has evolved tremendously since its first  
18 version. The 4.0 version will come up in 2021.

19 So I got very interested in PCI.

20 Next slide.

21 So I got very interested in PCI DSS because  
22 of the Target data breach. I wrote an article  
23 explaining the details of the Target data breach. It  
24 occurred in 2013. And some of you may know the  
25 initial entry point of the attacker was this air



1 conditioner system. So [indiscernible] Fazio  
2 Mechanics. One of the employees there fell victim to  
3 a phishing attack. And, eventually, that person's  
4 credential was used to access internal Target networks  
5 because of the lack of network segmentation. And,  
6 eventually, malware, what is called the BlackPOS, was  
7 installed on point of sale devices in Target. Forty  
8 million credit card numbers were compromised.

9           So as I was reading about the Target data  
10 breach, Target was actually in compliance with DSS,  
11 the Data Security Standards, back in 2013. And that  
12 was one of the main arguments that Target's CEO Gregg  
13 Steinhafel used to say, oh, we are in compliance; we  
14 got breached; it's not our fault. But as you look  
15 into the standards, you realize that a lot of those  
16 measures were just a sanity check. It was just a  
17 baseline. So I will explain a little bit more about  
18 the exact measurement we did.

19           Next slide.

20           So as you look into a bit closer about the  
21 DSS standards, you realize that regardless of which  
22 merchant size you are -- I mean, you can be Walmart,  
23 you can be a mom-and-pop shop, 7-Eleven -- you have to  
24 satisfy this, what is it called, a quarterly scanning  
25 report. It is an external scan of your network, the

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- 1 payment network of the merchant, and to ensure that
- 2 all the system that touches the credit card has to be
- 3 compliant with a set of standards.
- 4

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1 application that sells electronics. It has a card  
2 payment system. It has different options for the user  
3 to design their purchases. And so we used this as a  
4 testbed and embed altogether 35 vulnerabilities. But  
5 only 29 of them can be scanned externally. So we only  
6 need a scanner to find out 29 of them.

7           And so we find out there's numerous -- more  
8 than 100 -- scanners to choose from. And, of course,  
9 from a scientific research group, we have a limited  
10 budget. But we tried to cover high-end scanners and  
11 low-end ones. And, luckily, some of them offer free  
12 trials. And so we selected a few of them to test.

13           The way that we tested the scanning services  
14 is we just do a baseline scan and see how many  
15 vulnerabilities they can find. And then we'll follow  
16 their instructions to fix some of them, but then only  
17 the minimum amount of fixes. And so, eventually,  
18 we'll have a version that all of the testbeds  
19 indicating the minimum fix and a testbed that can pass  
20 the certification.

21           So next slide.

22           A quick summary of our findings. I'm going  
23 to explain a bit more. Five out of six scanners  
24 knowingly certified vulnerable merchant websites. And  
25 this is somewhat expected, also somewhat

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1 disappointing. And I'll explain more why it's somewhat  
2 expected. In addition, we also put up our own  
3 scanner, a lightweight one. We scanned a whole bunch  
4 of websites -- a majority of them are not fully PCI-  
5 compliant.

6 Next slide.

7 A quick summary of the findings on the  
8 scanners. We eventually settled six scanners. Two of  
9 them are advertised as two different products, but  
10 they use the same engine. Two other scanners, 3 and  
11 6, are not approved. They are not approved ASVs. If  
12 you look at this, the last column is the most  
13 important one. Only one scanner, scanner 2, does not  
14 allow vulnerabilities knowingly to exist in a  
15 certified version, even though there are seven  
16 vulnerabilities it cannot detect out of 29. So this  
17 is a very disturbing result. The must-fixes has to be  
18 a vulnerability score greater than 4.0. And it was  
19 defined in the ASV scanning guideline to have to be  
20 automatic failure. You have to -- the scanner has to  
21 fail the website. But most of them don't.

22 Next slide.

23 More information about the certain type of  
24 vulnerabilities called application security -- and  
25 those are the typical cross-site scripting, cross-site

1 request forgery, SQL injection, the harder one, the  
2 harder vulnerabilities -- failed miserably. On the  
3 right last four columns, those are research products.  
4 They are top-of-the-line web scanners. Some are  
5 research products, some are commercial products. They  
6 also don't do very well. So this gives you a serious  
7 pause, what's going on here.

8           Next slide.

9           Good news is that when we use our scanner  
10 scanning websites, a majority of them, even though  
11 they are not fully PCI-compliant, some of the typical  
12 issues don't exist, you know, default MySQL  
13 username/password, weak hash in certificates,  
14 browseable directory. Those are dot, dot, slash, and  
15 you can go back. And those are gone, which is good.  
16 Animation, one click, please. However, we've seen  
17 wrong domain names, vulnerable OpenSSH versions,  
18 expired certificates. And those are the issues that  
19 PCI compliance prevents but that still exist.

20           Next slide.

21           And, of course, that's not very surprising.  
22 If you have inadequate scanners certifying insecure  
23 websites, you inevitably will have vulnerable  
24 websites.

25           And so this is a first quantitative study

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1 measuring PCI scanner capability. But then the issue  
2 is much, much more beyond the PCI by itself. We  
3 tested web scanners; they don't do well. We tested  
4 research product; they don't do well either on certain  
5 types of more complicated web application  
6 vulnerability.

7           So what does it mean? And so if you can  
8 remember one thing, that's this slide. For all  
9 various stakeholders, everyone needs to improve. This  
10 is definitely not some work to say scanners, you know,  
11 you should be blamed. No, no, no. Everyone needs to  
12 improve.

13           The research community needs to have more  
14 deployable solutions. For cross-site scripting, a  
15 concept that's been around for a long time, there's no  
16 good open source deployable grade solutions.  
17 Regulatory authorities, how can we improve the  
18 specifications? And then part of it is to have a  
19 holistic measurement of system security as opposed to  
20 just one check, one check, one check, put them all  
21 together. Scanner evaluators, how to improve, more  
22 importantly, more robust testbed.

23           Next slide. Last slide here.

24           PCI specification, very comprehensive. We  
25 were very impressed about the completeness, but

1 enforcement is tough. Research needs to catch up. We  
2 also disclosed our findings with the Security Standard  
3 Council and got positive feedback. And this is a  
4 problem that needs everybody in the community to  
5 improve.

6 That's it for my talk. Thank you.

7 MR. HINE: Excellent. Thank you so much,  
8 Daphne.

9 Yixin, final presentation.

10 MS. ZOU: Thank you, Jamut9y2Hi, ,lTdphne. 4

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1 security practices, potentially leaving them at risk.

2 Next slide, please.

3 What we don't know, however, is whether this  
4 low adoption pattern also persists to other online  
5 safety practices, such as those for privacy and  
6 identity theft protection. Moreover, there's limited  
7 knowledge about what happens after consumers adopt  
8 advice, such as how often they abandon this advice and  
9 why.

10 Next slide, please.

11 For our research questions, we scoped them  
12 with security, privacy, and identity theft as three  
13 key dimensions for online safety. First, which online  
14



## PrivacyCon

1                   Next slide, please.

2                   Here I want to give an overview of practices

3 we examined. Security practices include two-factor

4 authentication, antivirus, cautious clicking

5 behavior, good password habits, and so forth. Privacy

6 practices include a management of one's browser

7

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1 or were not aware of.

2 Next slide, please.

3 At the end of the survey, we collected  
4 information about demographics, technical background,  
5 and prior negative experience. All participants'  
6 gender and income distributions are representative of  
7 the US population, but are skewed to younger and more  
8 educated people.

9 Next slide, please.

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1 authentication. What we found is that assisted  
2 practices were adopted significantly less than manual  
3 or automated practices.

4 Next slide, please.

5 We also examined factors related to the user  
6 that influenced adoption. Experts had higher levels  
7 of adoption than nonexperts. And we further unpacked  
8 this difference and found that computer science and IT  
9 expertise, more so than privacy and security  
10

1 inconvenient and difficult to use consistently. For  
2 instance, saying if "I'm in the middle of doing  
3 something, I won't be able to install this software  
4 update," or saying that "it's hard to keep track of  
5 unique passwords for different accounts."

6 Next slide, please.

7 Regarding reasons for abandonment, 20  
8 percent of participants who used but then abandoned a  
9 practice say they don't need the practice anymore, as  
10 it does not provide sufficient values to guarantee  
11 continuous usage. Like, "I have used it, but don't  
12 find it all that helpful for private browsing."  
13 Another 14 percent reported abandoning a practice when  
14 the perceived risk has diminished after a negative  
15 event. For example, "I had a credit freeze due to  
16 suspected identity theft in 2012." But after some  
17 years, they decided to not use the freeze anymore.

18 Next slide, please.

19 We discuss how our research has implications  
20 for how experts can provide online safety advice to  
21 consumers to increase adoption and reduce abandonment.

22 Next slide, please.

23 To bridge the gap that security practices  
24 were adopted much more than privacy and identity theft  
25 practices, it's important to show the synergy that

1 exists between practices, especially in cases when  
2 multiple practices could add additional protection  
3 layers. For instance, to combat phishing scams,  
4 avoiding clicking on the links is a common security  
5 tip. But this advice could be complemented by  
6 recommending users also actively monitor their  
7 financial accounts as an identity theft protection  
8 tip, but also an important mitigation practice after  
9 one has fallen for phishing.

10 Next slide, please.

11 Using an FTC's online article for identity  
12 theft self-protection as an example, this could be  
13 improved by giving more guidance as to which practices  
14 are most important to adopt and the connections  
15 between different practices and how they mutually  
16 benefit each other. For example, with measures for  
17 keeping your personal information secure online versus  
18 offline, we can illustrate how they work together and  
19 why it's important to do both. Moreover, it's  
20 important to identify the most effective and urgent  
21 actions to be prioritized so that consumers are not  
22 overburdened to take all actions at once.

23 Next slide, please.

24

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1 experiencing identity theft drives the adoption of  
2 online safety practices. In case of a data breach,  
3 consumer-facing data breach notices can be a possible  
4 venue for education. Consumers reading these notices  
5 will be highly motivated to resolve the situation and  
6 mitigate future risks. And so resources that  
7 encourage and explain how to adopt protection  
8 practices will be most effective at that moment,  
9 though the advice must be actionable.

10 Next slide, please.

11 We discussed how current tools for consumer  
12 online safety protection can be improved.

13 Next slide, please.

14 We found that usability issues prevented the  
15 full adoption of practices across all three domains.  
16 This echoes previous research in computer security  
17 about 2FA, password managers, software updates, and  
18 encryption, et cetera. Though these are security  
19 practices, in our study, we also found evidence of  
20 usability issues with privacy and identity theft  
21 protection practices as well.

22 Next slide, please.

23 This calls for more systematic research to  
24 better understand what these usability issues are and  
25 how to solve them. And another potential idea, more

1 relevant to lawmakers, is to require usability testing  
2 for provided tools so that they are not made hard to  
3 use intentionally, which can reduce the burden on  
4 consumers.

5 Next slide, please.

6 As examples for requiring usability testing,  
7 we can think about requiring readability testing in  
8 data breach notification laws to ensure that breach  
9 notifications are readable and reduce the chances of  
10 them being lengthy and full of jargon. We can also  
11 think about auditing dark patterns in mandated privacy  
12 notices and controls to give consumers real autonomy  
13 in privacy and data choices.

14 Next slide, please.

15 To summarize, for our study we studied the  
16 adoption and abandonment of various online safety  
17 practices. We find different patterns of adoption and  
18 abandonment between security, privacy, and identity  
19 theft protection practices. This implies the  
20 importance of expert advice to ensure that emphasis is on



1 details and reach out to me if you have any questions.

2 Thank you.

3 MR. HINE: Excellent. Thanks so much,  
4 everyone. We really appreciated those presentations.

5 Let's move into Q&A. Just a reminder, if  
6 you have any questions, feel free to send them through  
7 the [privacycon@ftc.gov](mailto:privacycon@ftc.gov) address, and we'll try and  
8 reach out and get to some of those.

9 So the first question I have actually is for  
10 Hana. I wanted to first ask you, you know, one of the  
11 conclusions that you reach in your paper is about  
12 notice and consent, which you rightfully mention is  
13 sort of a dominant approach here in the United States.  
14 But you suggest that consent mechanisms have failed to  
15 provide consumers meaningful privacy protections. And  
16 so my question for you is whether your analysis  
17 justifies some type of an alternative approach. And  
18 the hard part of the question is, if there is one,  
19 what do you think that should be?

20 MS. HABIB: Yeah, I think going forward  
21 there still is a place for notice and consent. But it  
22 really needs to look a lot different from what it  
23 currently looks like now, which is typically you go to  
24 a website, you see a wall of text, and then you click a  
25 box that says, I agree, which doesn't necessarily

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1 translate to meaningful notice or meaningful consent,  
2 because people don't really know what they're agreeing  
3 to.

4           We can potentially replace that with  
5 interfaces that allow people to make their preferences  
6 known up-front. Like I mentioned in my presentation,  
7 there is a potential for having tools built into the  
8 web browser, for example, where you set your  
9 preferences there, and those preferences are  
10 automatically communicated to websites without the  
11 user having to do anything, other than that initial  
12 step of setting those preferences to begin with.

1 or you think differently about that.

2 DR. SIVAN-SEVILLA: I totally agree with  
3 Hana's approach. I think consent became a meaningless  
4 term in our digital society. Users do not really  
5 understand what they agree for. They don't have a  
6 real alternative to choose from to get the service.  
7 Recent studies from Helen Nissenbaum and Kirsten  
8 Martin about what users actually think about  
9 information flows reveal that when users get aware of  
10 what's happening, they would never consent to what's  
11 going on behind the scenes of our favorite websites  
12 and mobile apps. And I think user awareness is  
13 critical to pivot around and change what's happening  
14 in this industry.

15 And one way to increase awareness is to  
16 visualize what's happening. There is an add-on to  
17 Firefox from Ghostery, a commercial company, to  
18 actually visualize what's happening, how many third  
19 parties are approaching you dynamically. And it's  
20 starting to get a sense of what's actually happening  
21 when you go to your favorite websites. So this is one  
22 step forward.

23 Users need to be much more aware of what's  
24 happening. And a complementary part of that is to  
25 require more transparency from these companies. How



1 question. First, we need to obligate service  
2 providers to provide alternatives for consumers.  
3 Firefox has done a very interesting step by preventing  
4 third-party cookies altogether. This is a great step  
5 for our privacy. But you see that the industry is now  
6 calling this the post-cookie area and moving to other  
7 ways to identify us and create fingerprints for our  
8 browser habits and operating system characteristics to  
9 know that we are the same person as we go over the  
10 web.

11 So the industry will always find sneaky ways  
12 to circumvent and go around. It's kind of a cat-  
13 and-mouse race for our privacy. So we need to make  
14 them more transparent about what they actually do to  
15 us. And then once we have this in place, it's for us  
16 consumers to decide what we actually want to do and  
17 weigh our options. But we have to have alternatives  
18 for the first place. And, unfortunately, we have no  
19 transparency and no alternatives. And the situation  
20 is not so encouraging.

21 MR. HINE: Great. I want to open it up.  
22 Yixin or Daphne, do either you have any  
23 response to that?

24 DR. YAO: I agree.

25 MR. HINE: Okay. Sounds good.

1           So, Daphne, I want to pose the next question  
2 to you. One of the things that struck me so much in  
3 your findings was that scanners, at least in the PCI  
4 context, it appears, need some significant  
5 improvement. And it sounds more generally like some,  
6 either off-the-shelf or even open-source scanners,  
7 sometimes outperform ones that cost thousands of  
8 dollars, or for some things, like cross-site scripting  
9 or SQL injections for example, you may not really be  
10 able to find a reliable scanner to identify those  
11 vulnerabilities.

12           And I think about that in the context of the  
13 FTC and the work we do in the privacy division, where  
14 a number of the companies that are under order are  
15 required as part of those orders to engage in scanning  
16 and use tools to identify vulnerabilities as part of  
17 their assessments. So I guess the question to you is,  
18 are your findings more broadly applicable or are you  
19 just finding this to be a problem within sort of the  
20 PCI world?

21           DR. YAO: Great question, Jamie. It's  
22 definitely more broadly applicable. Some of the  
23 products that we tested are packaged as web scanners.  
24 So they have no mention of PCI, but then they still  
25 fail in some of -- a lot of the application level

1 tests.

2                   And part of the struggle that we find is it  
3 just is so complicated. Because if you think about  
4 it, I would not -- now I will -- but a typical  
5 researcher would not say, okay, I have tenure to  
6 complete, I have a PhD thesis to devise, let's choose  
7 to build a deployable-grade cross-site scripting  
8 detector. No one in their right mind will do it,  
9 because the minute you submit the paper, you will  
10 immediately get rejected. The reviewer in most  
11 conferences will say, oh, this is not novel. We know  
12 about this attack. We know there is some way of, you  
13 know, conceptually how to detect it. Why am I reading  
14 this?

1           And so a lot of the -- I think it's widely  
2 applicable. It's not just the web scanner. Many,  
3 many other aspects of security also need those kind of  
4 tools, the open-source tools that will be able to push  
5 the standards of the industry up. If you think about  
6 the profitability, you know, for-profit companies, the  
7 minute they put up a product, they will not list all  
8 the limitations, being against their interest. And so  
9 they will vaguely say, oh, you know, we cover this, we  
10 cover that. And then so it's only -- if researchers  
11 don't do this, don't do the measurement, don't provide  
12 transparency, no one will.

13           And then your security is something that  
14 there is no silver bullet, everyone knows, and there's  
15 no guarantee. And it's all, you know, the devil is in  
16 the details. And so you have to know what cases to  
17 cover, so what is the gap, what is missing, what is my  
18 attack surface. So that needs a lot of work.

19           MR. HINE: So I want to move over to Yixin  
20 quickly. But I want a quick follow-up, Daphne. I'm  
21 curious if you could very briefly talk about what the  
22 reaction from PCI was. Because if you've identified  
23 scanners and you believe that there may not be  
24 commercially available scanners to find certain types  
25 of vulnerabilities, how does an organization that



1 requires that type of compliance reconcile the fact  
2 that there may not be tools out there that reliably  
3 identify those vulnerabilities?

4 DR. YAO: Yeah, great question. So the  
5 person that I had a long conversation with from the  
6 Security Council fully acknowledged our findings, and  
7 I do understand their struggle. So basically, they  
8 have two testbeds, they test the scanners. But then,  
9 because the industry practice is a lot -- the level  
10 that we understand how to solve those problems is  
11 together collectively low, but then they have to  
12 certify some scanners, and so they have to reduce  
13 their bar to a certain extent.

14 And then PCI, they have built a very strong  
15 community. I really was very impressed that they help  
16 scanners to pass their tests. And so in that kind of  
17 thing, you know, they do have scanners. They said  
18 they kick out a lot of scanners out of their approval  
19 list. But then it's a problem that they have, they  
20 also struggle with, that if everyone fails the test,  
21 then this test is not very meaningful.

22 MR. HINE: Excellent. Thanks so much,  
23 Daphne.

24 Yixin, I wanted to talk about -- your  
25 research touches on usability. And it includes

1 recommendations, for example, practices and tools, to  
2 improve security, privacy, and identity theft. And so  
3 my question to you is, what do you think is driving  
4 this disconnection between users and interfaces? Is  
5 it just poor interface design? Is it just developer  
6 laziness or could it be consumers? Are consumers just  
7 simply unwilling to take responsibility for their  
8 privacy and protection on the web?

9 MS. ZOU: Thank you, Jamie. That's a great  
10 question.

11 So I guess my immediate response would be, I  
12 don't believe it's the incompetence of developers,  
13 designers, and engineers. I think we have people  
14 capable of doing this. The issues I see are probably  
15 threefold. First is the lack of understanding for  
16 usability issues. Like, in my work, I see this is  
17 well covered for security practices and for some of the  
18 privacy practices, but I have yet to see like  
19 comprehensive audits of major identity theft  
20 protection tools, even though our study has shown  
21 anecdotal examples from certain survey respondents.  
22 But we need a better understanding of what the issues  
23 are in order to solve them.

24 And then second is not to blame users, but  
25 we need to realize the fact that most consumers don't

1 have comprehensive understanding of technology, have  
2 limited knowledge, literacy, and also time. So for  
3 consumers, we need better education, more targeted,  
4 effective education to make them realize these are the  
5 available tools and how to use them, by giving very  
6 actionable guidance.

7 And then the third part, I think more for  
8 regulators, is to think about how to motivate  
9 companies to design usable tools. And things like  
10 what I mentioned in my presentation, of the audits or  
11 patterns throughout mandated privacy notices and  
12 controls that I think regulators are already working  
13 on this, this will be a very meaningful step to ensure  
14 companies are incentivized to solve their usability  
15 issues, not intentionally making them hard to use  
16 because that's for their own profits.

17 MR. HINE: Hana, would you also like to  
18 comment on this? I think some of your work touched on  
19 some of these issues.

20 MS. HABIB: Sure.

21 So yeah, as Yixin mentioned before in her  
22 presentation, I think the need for user testing is  
23 there. Like you can't really produce these tools and  
24 expect them to work great off the bat. Developers  
25 aren't their users, so unless they have the actual

1 tool in front and interfaces in front of real people  
2 who are using these tools as they would in their  
3 normal lives, they really have little to go on in  
4 terms of what problems people might encounter and what  
5 might be difficult for people to understand.

6 And, additionally -- and I wanted to make  
7 another point -- I don't think it's that people are  
8 incompetent in terms of -- or that they don't really  
9 care about their privacy and security. In fact, I  
10 think the opposite is true. And that's what the  
11 research overwhelmingly shows. I think it's more that  
12 security and privacy typically aren't people's primary  
13 tasks. They're usually -- people are using websites,  
14 using applications to do something else really, not  
15 really to come up with a strong password, for example,  
16 anything like that. So typically, privacy or security  
17 might be in the way of them doing their primary task.

18 So rather than putting the burden on users  
19 to make sure their privacy and security is taken care  
20 of, it should really be on the part of companies to  
21 have better privacy and security practices. And I  
22 think that's where regulation can have a major role.

23 MR. HINE: Okay. So there was one question  
24 from the audience. And that is to Hana. And we'll  
25 finish up with that.

1           And the question is, did you notice any  
2 patterns in terms of the type of site and how  
3 difficult or easy it was to find opt-out information?  
4 So for example, were e-commerce sites more challenging  
5 to navigate versus gaming sites or popular news  
6 sites?

7           MS. HABIB: Yeah. I didn't get into this in  
8 the presentation, but we provided a little bit of  
9 details about this in our paper. So the way we  
10 sampled the websites was that we picked the really  
11 popular websites from the top 10,000 list as well as  
12 some less popular sites and sites that really probably  
13 most people haven't heard of. So we call them top,  
14 middle, and bottom sites in our paper.

15           And one positive note that we noticed is  
16 that, across the three different categories there  
17 really wasn't a difference in terms of the number of  
18 privacy choices being offered. But how and where they  
19 were offered seem to vary. So for top sites, for  
20 example, they generally had controls within the  
21 account settings as well as somewhere else in the  
22 website, like a privacy policy, or even like an About  
23 Ads page, dedicated About Ads page for websites that  
24 had targeted advertising, whereas the middle and  
25 bottom websites relied more heavily on the privacy

1 policies to provide consumers these choices.

2 Additionally -- oh, I guess that's the time.

3 MR. HINE: Oh, no. Please finish your  
4 thought, sorry.

5 MS. HABIB: Okay. Yeah, so additionally,  
6 the way that these choices were provided in the case  
7 of targeted advertising opt-outs, for example, the  
8 more popular top websites tended to have their own  
9 implementations of these tools and a setting within  
10 that, a setting for that, whereas other types of  
11 websites relied more heavily on third-party opt-outs  
12 offered through like the Digital Advertising Alliance  
13 or the NAI.

14 MR. HINE: Excellent.

15 Well, on that note, I just want to thank all  
16 the panelists so much. This has just been an absolute  
17 pleasure to moderate. The research is fantastic. I

1 CLOSING REMARKS

2 MR. HINE: Well, that brings us to the end  
3 of our fifth PrivacyCon. We are so thankful for  
4 having everyone here today. As Elisa mentioned  
5 earlier today and was obvious to everybody who was  
6 here, we moved things virtual and I think it went  
7 really well. There were a lot of changes that  
8 happened moving from a live event to a virtual event.  
9 And we just want to thank everybody for your  
10 indulgence today. We want to thank all of the  
11 panelists. Please know that they worked really,  
12 really hard to deal with technology and to make this  
13 such a great event.

14 Just a few thank yous again. I know that  
15 Elisa thanked a lot of people today, but I just want  
16 to thank all of the moderators. I want to especially  
17 thank Elisa, who worked so hard with me to help put  
18 this together. I want to thank all of the support  
19 that we had.

20 There are people like Leah Singleton, who  
21

1 got the word out on social media.

2           There are so many other folks behind the  
3 scenes at the FTC that had to work twice as hard to  
4 make this happen virtually. We want to thank all of  
5 you.

6           A few last remarks. We will have the video  
7 up on the event webpage on the FTC.gov in a couple of  
8 days. You'll be able to go revisit and see all the  
9 presentations again. On the agenda, almost all the  
10 papers are linked, so you can access all of those  
11 papers. If there are updated versions in the next few  
12 weeks or months, we'll update them accordingly.

13           And I just want to remind everybody that  
14 PrivacyCon is an event that we started sever.941 0 11.94 lio.94



7/21/2020

PrivacyCon

1 we want to thank everybody for participating. And we  
2 hope to see you next year. Thanks again. Take care.

3 (The workshop was concluded.)

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