Ep. 119 Healthcare, Computers and Consumer Choice

Judith Kelley [00:00:00] As people, we always having to make lots of choices about products we buy, about services we buy and sometimes about public goods that we avail ourselves of, including health care or schools, many other things in our in our lives. And we know from marketing and consumer theory that we are influenced by many things when we make our choices, emotions and commercials work for a reason, and giving us different types of information, too, can influence our choices. So so there's some interesting questions that arise about how does the information of of provision when it comes to things that are not typical products for us, that are maybe complex products like health care. How does that influence the choices that we make? And and if we want to guide people to make choices that are good for them, how can we go about doing that? And what are some ethical questions around that or complications that may arise in terms of the way we're guiding people? And are we getting the best outcomes for them and for everybody at the end of the day? So those are some of the questions that we're going to talk about today with Kate Bundorf, who looks at how the provision of different kinds of information might help people make complicated choices around health care provision. And I should also remember to say welcome to Policy 360. I'm Judith Kelly Dean of the Sanford School of Public Policy. And my guest today is Kate Bundorf, who recently joined us here at the Sanford School. And so thank you so much for joining me today, Kate. We're really excited to have you here as part of this podcast, but also here at the Sanford School.

Kate Bundorf [00:01:55] And thank you. It's great to be on the podcast and with you at the school.

Judith Kelley [00:02:01] So, Kate, what algorithms are we talking about here? What are they doing in this context?

Kate Bundorf [00:02:07] Yeah, so so that's a great question. So we were really focused in the context of health insurance. You know, to me, health insurance is very interesting because it's a really complicated product. Right. People really have a hard time understanding, you know, especially the coverage and the cost features associated with their health insurance plans. So one thing an algorithm could do is to help you understand how all those complicated cost sharing features of your plan might map into spending for a person like you. So that's kind of like the feel, to me, it feels like the low hanging fruit of algorithm's in the context of health insurance. You know, it's complicated for everyone. You know, lots of people face challenges doing that. Right. So that is a way in which we could use algorithms to make decision making easier in this context.

Judith Kelley [00:03:02] So your study is looking at what if we tried this and would it matter rather than necessarily this is already happening and let's see how it's working?

Kate Bundorf [00:03:13] Yeah, I think that is a great way to characterize it. Right. And I think that where the study where the study really started from is there is a growing and almost large literature documenting the many ways in which people kind of screwed up making their health insurance choices. Right. So it seems like, you know, they're not choosing the plan that minimizes their out-of-pocket spending even when there are better alternatives available. And there's this growing literature on people making choice errors or not making quite the right choice. And I felt a little frustrated by that literature. I felt, well, here we are documenting the ways in which people's decisions are kind of going wrong. What could we do to actually help people and make those choices easier?

Judith Kelley [00:04:01] So are we talking about so a tool where I'm sitting down trying to select either between different plans or different levels of coverage, and I can sort of interact with it and say, yes, I'm married, I've got, you know, son, I've got a daughter, how old they are. Here are some of the preexisting conditions in my family. And and here's how many people in my family have have maybe passed away from different kinds of ailments, sort of similar to some of the forms we fill out of the doctor's office when we're sitting there waiting to be seen by the doctor, we get those clipboards with all those questions on them. Is that kind of information we would be inputting to begin with, to help your algorithm, then give us some recommendations?

Kate Bundorf [00:04:49] Yeah, let's let's say they're they're kind of two things that you could think about. One is putting lots of inputting lots of information on your personal health history and kind of where we're going with this, is we're trying to say, oh, how does having this health history, how does that affect my likely health care use?

Judith Kelley [00:05:07] Right.

Kate Bundorf [00:05:07] And then how does that map to my plan? So one could do that. You can also say, well, you know, my insurer knows a lot about my health care use last year. Someone has lots of information on how much health care I'm using. And not only do they have information on how much health care I'm using, but they have a lot of information on how people like me are using health care. So you could pretty easily imagine someone with a lot of data developing predictions that would probably be even better than the information that you could input yourself. Our tool didn't exactly do that. I don't want to oversell our tool here. We did our research in the context of of Medicare Part D, that is the publicly subsidized insurance plan, prescription drug insurance plan for older adults. So what we were mostly interested in is people's drug coverage. And we did not have access to their historical, you know, what I would call claims data. So what we did is we asked people to input here are the drugs that I'm using today. Right. And we use that to come up with an estimate of what their spending is likely to be.

Judith Kelley [00:06:22] What what did you find? People eager to be given a recommendation and then they just go with that or were people capable of making the same sort of shortcuts mentally, even if they didn't have those algorithmic recommendations, did they end up sort of making the same choices? What happened?

Kate Bundorf [00:06:43] We found that offering the information, the people who use the information did respond to it and they responded to it in several ways. So people in response to our tool, they were more likely to switch plans. They were more satisfied with their plans. They looked like they enrolled in plans that save the money. And they took longer. They spent more time making a decision. It's hard to interpret. What does that mean? More time making a decision? So I think because we had that result, plus those other three that I talked about, we're interpreting interpreting that as probably good. Right. They were probably more engaged in the decision and more willing to kind of do the work when they have the tool. The other thing I should say about that collection of results is those results were more magnified. The effects seem to be a bit larger in the arm where the information was paired with the expert recommendation. So we solve X and it seems like they were a little bit magnified in the in the arm where they were paired with that additional kind of stamp of approval from the expert.

Judith Kelley [00:07:52] Mm hmm. So so you did find this is good, right, that you did find that people were responding to having information and they were responding to having recommendations. Did it make sense to you when you looked at the participants in your study? Was it the was that the the right folks that were responding to the information in the sense of the ones who needed it most?

Kate Bundorf [00:08:20] Yeah, so that was another key finding of our study. And it was something that was interesting and a little bit surprising to us at the time, but I think kind of consistent with some of the research. So let me tell you what that was so so we the way we structured the study, we invited people to participate and a lot of people by the people to participate in the trial, just telling them very basic information about what the trial was, was about. And a lot of people did not take us up on that offer and they did not participate in our trial. But that represented an opportunity because we had administrative data on those people so we could look at the people who did not participate in the trial and the people did participate in the trial. And then we'd use some fancy machine learning methods in order to estimate what we think the treatment effect of the intervention would have been among the people who did not enroll in the trial if they had enrolled. Right. And that turned out turned up some interesting results. When we did that, we found that the people who didn't enroll in the trial, on average, it looks like the intervention would have had a relatively large effect on their choices. Another way of saying that is they probably would have responded more, change their plans, more moved to plans that offered and more likely to move to a plan that offered more generous coverage than the people who actually took up the intervention. So if you put that together, a bunch of people didn't enroll in our trial. You know, that was sad, a little bit sad for us. But the more important kind of policy implication is those people that didn't enroll look like the people who might benefit from a little assistance in this making this complex financial decision.

Judith Kelley [00:10:21] So if we do end up with a policy tool like this that's broadly available, you know, some of the the theory that we have on nudges, which suggests that you let people opt out of something rather than opting into them, would suggest that with something like this, we might we might want to default to presenting recommendations and having people to opt out.

Kate Bundorf [00:10:47] Yes. I think we walked out of our study thinking, well, if this type of advice is going to work for folks and not kind of magnify differences that already exist in financial outcomes, we need to maybe think about it a little differently or do an intervention which is more active. So default is one you could also think about, you know, it could be even a little softer, right. In the sense that, you know, here's an alternative intervention. Instead of asking people to come to us or to use our tool, know, we had a lot of information on what plan folks were enrolled in and how these different plans may have covered their drugs better. We could send out just that information. Right. Make it more clear we could only send it to the people that we think could benefit from it and we don't have to send it to everyone, right? So if we can reach out to people with that information, maybe that's enough. But I think this does open up a, you know, and lots of people are working on this in lots of different domains. So I should say it it fits in with lots of work that folks are doing to try to make these types of tools, whether they're algorithms or machine learning based or whatever, to make these these ways to help people make decisions a little more accessible. The other thing I want to emphasize in our study is we did find another finding, which is a little bit more subtle, but let me run with it. So when when I talked about the results, I talked about how the effects were magnified in the arm in which people had information and the expert advice.

Judith Kelley [00:12:36] Yes.

Kate Bundorf [00:12:37] The expert advice takes those planned characteristics and kind of weights them in a way known only to the expert and then makes the recommendation. That weighting is potentially important. Right. That weighting is saying things like, well, I think, you know, out of pocket costs are probably a little bit more important than how consumers rate the quality or rate the experience of interacting with this plan, maybe even the network of pharmacies, those, that weighting, was chosen by the expert and in domains where people care about those those those different aspects of the plan and maybe weight them differently. We have to be, I think, a little concerned about the weight, like how we're using expert recommendations. Right. And kind of the long and the short of it is we might be moving people away from things that we care about if we're not very aware of what's going into an expert recommendation in this type of context.

Judith Kelley [00:13:43] I mean, that is a poignant observation, right? Because we are increasingly learning in general that when we start to apply algorithms and machine learning that these may not affect all populations equally and that there are marginalized populations in particular that may be disserved by some of these algorithms of where these expert assessments or evaluations don't fit everybody in the same way.

Kate Bundorf [00:14:16] Yep, absolutely. We need and I think as part of that, we need some sort of mechanism to evaluate the algorithms and to help people understand, you know, what the algorithm is doing for their Decision-Making. That's such an incredibly important point.

Judith Kelley [00:14:30] Well, Kate, it's absolutely fascinating. And also, you know, it's something that potentially extends to to other fields as we think about a society in which we have different choices, both in private provision of goods, but also public provisions of goods, schools, car insurance, elderly care, you know, there are many things where we have to make choices to avail ourselves of different services, and as we think more and more about tailoring our experience to the individuals as the American society very much likes to do and soon we'll be able to just get clothing that's completely tailored to us, et cetera, et cetera. You know, it's worth thinking about who who is benefiting and what are some of the some some of the trade offs as we potentially move into a system like this and how can we make it work for everybody? So I think this is really fascinating, the step that you've taken with this with this research.

Kate Bundorf [00:15:26] OK, thank you. We really enjoyed the project and I enjoyed talking to you about it.

Judith Kelley [00:15:30] Kate Bindoff is the S. Malcolm Gilles distinguished professor of public policy. She's a core faculty member here at the Sanford School of Public Policy and a core affiliate faculty member also at the Duke McCulloch Center for Health Policy. So we'll be back in a couple of weeks with another conversation. Thank you for joining me today. I'm Judith Kelly.