Panel 3: Empowering and Diversifying the Technical Workforce
Moderators: Willie Pearson (Georgia Tech) and Rob Rutenbar (University of Pittsburgh)
Speakers: Erik Brynjolfsson (MIT), Nancy Amato (University of Illinois at Urbana-Champaign), Sharla Alegria (University of Toronto), Nancy Cooke (Arizona State University)

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00:00:00.480 --> 00:00:03.120
Rob Rutenbar: Our panel, ah

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00:00:04.740 --> 00:00:11.010
Rob Rutenbar: Topic for the next two hours is empowering and diversifying the technical workforce.

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00:00:12.179 --> 00:00:23.970
Rob Rutenbar: So, um, we are all vividly aware of the, you know, the sort of the general history of, you know, diversity problems in the in the STEM workforce and there's been

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00:00:25.020 --> 00:00:30.720
Rob Rutenbar: Sort of a salutary but but incomplete amount of progress is sort of in the computer science and computing side of the world.

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00:00:32.010 --> 00:00:43.950
Rob Rutenbar: We certainly have a ways to go. But we now have sort of a broader and even sort of the onboard more interesting opportunity at the intersection of the CISE and SBE directorates to focus on on some of these problems.

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00:00:45.030 --> 00:00:55.710
Rob Rutenbar: There are some, you know, economic estimates that a significant fraction of today's jobs are likely to be eliminated or significantly transformed

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00:00:56.460 --> 00:01:07.590
Rob Rutenbar: At the same time, the skills needed to provide you know non economic services in a range of impactful social interactions are likely undergo substantial change. This feels like a remarkable opportunity

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00:01:08.040 --> 00:01:14.820
Rob Rutenbar: For the computer science information science, engineering folks on CISE and the social and behavioral scientists

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00:01:15.270 --> 00:01:23.580

Rob Rutenbar: In SBE to focus on, you know, what's necessary to create some tangible quality of life improvements here across all the communities that we connect with. So we've got

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00:01:24.300 --> 00:01:37.620
Rob Rutenbar: An exciting slate of four speakers and we're just going to let them go in order. And so our first talk is Eric Brynjolfsson from MIT using big data to understand the workforce: how will machine learning transform the economy.

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00:01:39.810 --> 00:01:50.010
Erik Brynjolfsson: Thank you Rob. It's a real pleasure to be here. And let me just share my screen here and give you all a chance to to see what I'm looking at. I'm

12
00:01:50.670 --> 00:02:01.890
Erik Brynjolfsson: So I'm really happy to have a chance to talk about these issues, it's been it's been fascinating to hear the discussion so far and I want to take my 12 minutes to just dive in, into a

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00:02:04.110 --> 00:02:13.860
Erik Brynjolfsson: Little piece of it that I've been focusing on which has to do with how we can use all this data that's available, big data, a lot of people call it to understand the workforce better

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00:02:14.100 --> 00:02:23.280
Erik Brynjolfsson: And in particular, I've been looking at how machine learning and related technologies are likely to change the kinds of tasks that are done in the economy.

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00:02:23.790 --> 00:02:32.010
Erik Brynjolfsson: The balance between what's done by humans and what's done by machines. What the implications are for wages, productivity,

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00:02:32.400 --> 00:02:43.200
Erik Brynjolfsson: inequality, employment, and related factors and I'm looking forward to particularly to the discussion and interaction that we'll have from this. So I look forward to your questions and comments on all of that.

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00:02:44.820 --> 00:02:54.810
Erik Brynjolfsson: Let me start by saying, Let me see if I can, yes, that that new tools beget revolutions. I don't know how many of you will recognize this guy, Anton van Leeuwenhoek.

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00:02:55.440 --> 00:03:06.810
Erik Brynjolfsson: But he's famous for, among other things, inventing the first really usable microscope. He's holding one there. I know it looks a little like an iPhone, but that's one of his early microscopes, single lens.

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00:03:07.230 --> 00:03:21.690
Erik Brynjolfsson: And with this, he was able to peer into things like drops of water and see what was in them and what he described, he wrote to the Royal Society Society in London, was a bunch of creatures swimming around there. He called them animalcules.

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00:03:22.740 --> 00:03:32.250
Erik Brynjolfsson: Unfortunately, nobody believed him. They said, look Anton, you're if- you're a nice guy and all, but please stop sending us these crazy letters about, you know, animals swimming around in drops of water.

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00:03:33.000 --> 00:03:40.500
Erik Brynjolfsson: But of course we know now that he was right. And eventually, other people had some of the same technology and were able to to

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00:03:41.220 --> 00:03:54.090
Erik Brynjolfsson: Reinvent and discover new fields. The field of microbiology. In fact, probably most of us would not be alive today if it weren't for those kinds of inventions. Today, somewhat later, that was 300 years ago,

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00:03:55.200 --> 00:03:59.460
Erik Brynjolfsson: Social scientists are beginning to get some equally powerful tools.

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00:04:00.240 --> 00:04:10.410
Erik Brynjolfsson: And I think that what we call big data is really a measurement revolution, and in particular, digitization over the past two decades or so two or three decades has made

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00:04:11.220 --> 00:04:21.720
Erik Brynjolfsson: Gigabytes, terabytes, exabytes, yottabytes of data available to researchers like us and we can peer in and see things with much greater resolution than we ever were able to.

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00:04:22.560 --> 00:04:32.520

Erik Brynjolfsson: There are hundreds of millions of job postings online and you can get them from different sources, there's LinkedIn profiles on, there's mobile phone data as I think you all know that

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00:04:33.120 --> 00:04:45.750
Erik Brynjolfsson: when you walk around with your, your phone, it's recording where you are and sharing that information with a lot of people, and we're all being tracked and that information can be used for all sorts of different kinds of purposes.

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00:04:46.230 --> 00:04:54.990
Erik Brynjolfsson: There are tens of billions of Bing searches and Google searches every, every month, and they give a lot of insight into what people care about. Every time somebody

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00:04:55.650 --> 00:05:04.470
Erik Brynjolfsson: Types in a search, they're really saying what they're interested in at that moment. And that's sort of like a collective mind reading in some ways and a prediction

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00:05:04.860 --> 00:05:14.730
Erik Brynjolfsson: Of what people are likely to buy or do or care about. And I can go on and on, but there's a whole field of computational social science and related tech

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00:05:15.510 --> 00:05:24.600
Erik Brynjolfsson: fields that have been revolutionized by these. Let me talk particularly about some of the things that you can do with job profiles. Here's one of my co-authors, Prasanna Tambe.

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00:05:25.230 --> 00:05:38.640
Erik Brynjolfsson: And you can read his LinkedIn profile, read a lot about his background, along with with tens of millions of other people, probably most of you at this conference. And you can gather this data and get collected into

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00:05:39.750 --> 00:05:49.710
Erik Brynjolfsson: organize it by, by company or by university by occupation by job skills, lots of other different kinds of ways you can look at it. And

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00:05:51.120 --> 00:05:56.490
Erik Brynjolfsson: we've argued that this is a good way to understand how the workforce is changing and

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00:05:57.420 --> 00:06:01.620
Erik Brynjolfsson: in particular, a couple of papers I wrote with Tom Mitchell at Carnegie Mellon argued that

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00:06:02.070 --> 00:06:13.110
Erik Brynjolfsson: we need to better track how technology is transforming work and and we demonstrated one way to do that was to look particularly at machine learning. And that's exactly what I'm going to do in the next few minutes to explain a little bit.

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00:06:13.530 --> 00:06:20.220
Erik Brynjolfsson: Let me, let me dive into particularly how machine learning is transforming work. And to do that,

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00:06:21.810 --> 00:06:26.370
Erik Brynjolfsson: Let me just remind you, the technological revolution that is

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00:06:27.300 --> 00:06:34.170
Erik Brynjolfsson: motivating us to look at this over the past decade, there's really been quite an impressive improvement in the basic capabilities

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00:06:34.590 --> 00:06:46.920
Erik Brynjolfsson: of machine learning, especially supervised learning systems using deep neural nets, the steep part of the curve there just around 2012 was when Jeffrey Hinton introduced deep learning techniques into vision systems and

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00:06:47.940 --> 00:06:49.830
Erik Brynjolfsson: Took databases like the one on the left,

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00:06:50.310 --> 00:07:02.520
Erik Brynjolfsson: Image net with 14 million images, and for the first time was able to really tag them quite effectively to the point now where actually the machines are better than humans at recognizing different kinds of animals and objects.

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00:07:03.150 --> 00:07:08.550
Erik Brynjolfsson: It doesn't mean that machines are better than humans in all vision tasks, but for many types of tasks, for instance,

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00:07:09.570 --> 00:07:20.910

Erik Brynjolfsson: Diagnosing breast cancer or skin cancer or reading lung X-rays, machines in many papers have been shown to match or exceed human performance for those particular tasks.

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00:07:21.510 --> 00:07:33.480
Erik Brynjolfsson: And of course it's not just image recognition. Basically, any kind of a task where you're mapping from an input 'x' into an output 'y,' but is a potentially a good category for

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00:07:34.140 --> 00:07:46.800
Erik Brynjolfsson: These deep learning systems, these machine learning systems. And there's a bit of a gold rush going on right now to understand which tasks that we currently do in the economy could be done as well or better by machines.

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00:07:47.460 --> 00:07:54.870
Erik Brynjolfsson: So what we set out to do was to do that in a more systematic way understand where machine learning was affecting the workforce.

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00:07:55.500 --> 00:08:08.790
Erik Brynjolfsson: And important premise is that we are far from artificial general intelligence or AGI. That is, we aren't anywhere close to where machines can do all the things that humans can do or the end of work, you know, that the terminators you see in Hollywood.

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00:08:09.240 --> 00:08:18.930
Erik Brynjolfsson: But we are places where you can see the machines can do certain tasks very well, and many other most tasks humans still do better. So which is which? Well,

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00:08:19.290 --> 00:08:22.590
Erik Brynjolfsson: We developed something we called a suitability for machine learning rubric.

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00:08:23.040 --> 00:08:34.050
Erik Brynjolfsson: We consulted with a few dozen of the top machine-learning researchers around the world, and we asked them the criteria they used for deciding when a task was likely to be suitable for machine learning.

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00:08:34.440 --> 00:08:41.520
Erik Brynjolfsson: And after a series of iterations we compiled a list of about 24 questions that you could ask about any task.

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00:08:41.910 --> 00:08:48.060
Erik Brynjolfsson: And it will tell you whether that task or score it as to whether that task is likely to score high or low on suitability.

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00:08:48.810 --> 00:08:59.220
Erik Brynjolfsson: We then took that rubric and we applied it to the O*NET database which many of you are familiar with, which has 950 occupations, over 18,000 occupation specific tasks.

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00:08:59.940 --> 00:09:07.560
Erik Brynjolfsson: In particular, each occupation like insurance clerk or security guard or psychologist or economist or bus driver or radiologist

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00:09:07.950 --> 00:09:20.130
Erik Brynjolfsson: Is described by a set of tasks that they typically do usually somewhere to 20 to 30, in some cases 35, different tasks and instead of trying to describe the entire occupation,

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00:09:20.580 --> 00:09:29.130
Erik Brynjolfsson: We looked at each individual tasks and scored that and used some of the questions that you see there on the left. And by doing so,

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00:09:29.760 --> 00:09:36.030
Erik Brynjolfsson: We could get a sense of whether a particular task was easy for machines to do or likely easy for machines to do or not.

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00:09:36.360 --> 00:09:45.090
Erik Brynjolfsson: And most of them I think have not yet actually had machine learning applications, but we're talking about just existing technology and just having it diffuse, which usually takes

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00:09:45.870 --> 00:09:53.100
Erik Brynjolfsson: You know a year, sometimes five or then or even more years. So to give one commonly used example: a radiologist

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00:09:53.520 --> 00:09:59.550
Erik Brynjolfsson: There. According to O*NET, there are 27 distinct tasks. It's widely discussed. It's one of the favorite ones that people talk about

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00:09:59.940 --> 00:10:11.910
Erik Brynjolfsson: And you can use some with the image recognition task. So we decided to look at that, along with the other thousand occupations

and as, as I just mentioned machines are pretty good at interpreting images.

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00:10:13.080 --> 00:10:23.430
Erik Brynjolfsson: The way human radiologists do, in fact, in most cases, better than human radiologist, but there are 26 other tasks that the humans do, for instance administering sedation.

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00:10:23.970 --> 00:10:31.770
Erik Brynjolfsson: These are not something that you'd want a machine to be doing or conducting physical exams are many other kinds of tasks and this pattern was very

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00:10:32.190 --> 00:10:44.940
Erik Brynjolfsson: Consistent for most of the occupations we looked at where there were some tasks that machines could do well and many other tasks that machines, really, were not suitable for at least with current technology or current machine learning technology.

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00:10:45.450 --> 00:10:52.170
Erik Brynjolfsson: In fact, it was not a single occupation in our data set where machine learning just ran the table and was able to do all of the tasks.

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00:10:52.770 --> 00:10:59.220
Erik Brynjolfsson: But almost all of them, the vast majority of them, machine learning could do at least some of the tasks.

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00:10:59.550 --> 00:11:12.510
Erik Brynjolfsson: So that one of the takeaways is that machine learning is likely to lead to a lot of reorganization and reinvention of work, but not the wholesale elimination of tasks in our occupations and in big lumps.

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00:11:13.140 --> 00:11:23.370
Erik Brynjolfsson: And overall, There are about $700 billion worth of tasks that could easily be done with machine learning right now. That's just the ones that are very top of the 98th percentile of suitability.

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00:11:23.910 --> 00:11:33.000
Erik Brynjolfsson: So, the ones who are quite confident machine learning could do, you could probably increase that number, if you consider other tasks that are somewhat suitable for machine learning.

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00:11:33.900 --> 00:11:46.470

Erik Brynjolfsson: And you can cluster the tasks in different ways. For instance, you can see the clerical workers and factory workers tend to have a lot of tasks that are suitable for machine learning. Scientists and interestingly therapists and clergy are not so

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00:11:47.790 --> 00:11:58.140
Erik Brynjolfsson: High on suitability for machine learning, but every different group of occupations that we saw in the economy could be scored and many of them clustered together regardless of what industry they were in

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00:11:58.590 --> 00:12:04.140
Erik Brynjolfsson: You can also score them by what wages are being paid for instance on this

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00:12:04.740 --> 00:12:15.120
Erik Brynjolfsson: way of organizing the data we rank all the occupations from zero to 100 based on what the wages were. The ones on the left were the ones that were lowest paid, and the ones on the right were the highest paid

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00:12:15.600 --> 00:12:20.880
Erik Brynjolfsson: And as you can see, lowest paid occupations tended to be more likely to have a lot of tasks that are suitable for machinery.

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00:12:21.240 --> 00:12:29.580
Erik Brynjolfsson: For instance, cashiers we've already seen, you can go through a lot of checkout counters and the machines can can read and recognize, you know what the bananas look like and so forth.

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00:12:30.420 --> 00:12:43.620
Erik Brynjolfsson: But there's some high paid occupations like pilots that also scored pretty high. I couldn't resist peeking, some of you may be curious where economists score, you know, not as high on suitability for machine learning and maybe not as high paid some of us would like.

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00:12:45.330 --> 00:12:56.010
Erik Brynjolfsson: You can also look at it by industry. If you want to group it and aggregate it that way up, food services, transportation, retail, trade tend to have a lot of tasks that are suitable for machine learning.

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00:12:56.700 --> 00:13:02.910
Erik Brynjolfsson: You can do it by geography, as you know, the kinds of work, people do in Kansas is different than what they do in

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00:13:03.810 --> 00:13:15.990
Erik Brynjolfsson: Illinois or New York or Florida. On average, there's a lot of similarities as well. But you can see that the different parts of the comp- country will be affected quite differently as machine learning defuses through the economy.

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00:13:16.500 --> 00:13:24.180
Erik Brynjolfsson: And you can also start making recommendations for specific companies, for instance, here's one company where we peered in using the data from some of these data sets.

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00:13:24.570 --> 00:13:33.840
Erik Brynjolfsson: And you can see that, for instance, personal bankers and tellers have a lot-- the bars, the red bars are pretty large there on the left. That means that a lot of their tasks are suitable for machine learning.

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00:13:35.070 --> 00:13:42.690
Erik Brynjolfsson: You can imagine different futures for them. And one of the things we did with our analysis was we took those personal bankers and said, Well, some of them could reinvent themselves into a

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00:13:42.900 --> 00:13:46.620
Erik Brynjolfsson: Personal banker 2.0. Does that mean I'm running out of time?

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00:13:48.810 --> 00:13:50.910
Erik Brynjolfsson: But others a

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00:13:51.000 --> 00:13:59.820
Erik Brynjolfsson: minute, one minute. Okay. One minute. Thanks so others could develop new roles. Others are at higher risk. And so this kind of gives a map of which sorts of

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00:14:01.380 --> 00:14:13.050
Erik Brynjolfsson: Occupations have the smallest skill gaps in the biggest skill gaps and what are easier or harder. You go through a lot of other analyses, just using these existing data and making it accessible to people. So up to, to summarize,

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00:14:14.310 --> 00:14:22.260
Erik Brynjolfsson: Big data is transforming work, but it's also transforming the way that we measure work and gives us a lot of new tools for understanding it better.

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00:14:22.980 --> 00:14:29.820
Erik Brynjolfsson: We can assess suitability using this rubric and aggregate it in lots of different ways, occupation, geography, firms, industry.

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00:14:30.510 --> 00:14:36.810
Erik Brynjolfsson: As I mentioned, an important takeaway is that we didn't see any occupations that would be fully automated at least not with these technologies.

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00:14:37.110 --> 00:14:45.360
Erik Brynjolfsson: But at the same time, none of them are immune and will be unaffected. Instead, the big story is that almost every job will have to be reorganized and

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00:14:46.740 --> 00:14:54.360
Erik Brynjolfsson: reconfigured in order to take full advantage of the technology and that's what entrepreneurs and managers and I think social scientists are looking at to understand better.

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00:14:54.990 --> 00:15:03.450
Erik Brynjolfsson: And we can create a roadmap for how to get out on the other side of this, the COVID crisis, and in this transformation, where

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00:15:03.900 --> 00:15:13.230
Erik Brynjolfsson: companies are the future, cities, nations even, can reorganize their workforce to have more of the kinds of tasks that humans are especially good at

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00:15:13.500 --> 00:15:26.670
Erik Brynjolfsson: even as machines take over many of the tasks where they have a comparative advantage. There's lots more at my website, the papers that I described are there, and I welcome any questions or comments you may all have. Thanks very much.

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00:15:28.080 --> 00:15:28.620
Rob Rutenbar: Thanks, Eric.

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00:15:30.150 --> 00:15:37.530
Rob Rutenbar: I think the plan is we're, we're going to do the talks back to back to back, and then we have a 30 minute chunk for

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00:15:38.940 --> 00:15:40.410
Rob Rutenbar: Free for all questions at the end.

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00:15:41.970 --> 00:15:42.750
Erik Brynjolfsson: Sounds good to me.

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00:15:43.710 --> 00:15:44.070
Okay.

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00:15:45.240 --> 00:15:59.730
Rob Rutenbar: So next up is the Nancy Amato from the Computer Science Department, University of Illinois at Urbana-Champaign and Nancy is going to talk about pathways to computing growing and diversifying the workforce. Nancy, you're up.

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00:16:01.020 --> 00:16:02.970
Nancy Amato: Hello. Are you guys seeing my screen.

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00:16:03.540 --> 00:16:10.530
Nancy Amato: Yes. Okay. And let's see. Let me move to the, I don't see myself anymore but

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00:16:13.440 --> 00:16:14.370
Nancy Amato: Do you still see it?

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00:16:17.010 --> 00:16:17.220
Alondra Nelson: Yes.

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00:16:17.250 --> 00:16:17.970
Nancy Amato: Can you hear me.

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00:16:18.270 --> 00:16:25.380
Nancy Amato: Yes, yeah. Okay. Cool. Alright, so, as Rob mentioned, I'm going to talk about pathways to computing. I'm

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00:16:25.800 --> 00:16:36.990
Nancy Amato: department head at University of Illinois Urbana-Champaign, a position which Rob used to have. And actually I'm going to be talking about some of the things that he started here. Um, so first off let's

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00:16:38.610 --> 00:16:44.910
Nancy Amato: There we go. Just to kind of set the stage. Um, there's actually was a recent Chronicle of Higher Ed

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Nancy Amato: Article that, just from April 15, that kind of summarizes the state pretty well. I'd encourage you to look at it.

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Nancy Amato: But bottom line is I think most, at least in CISE, we're all very familiar with this, but there's been a huge demand for computing.

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00:17:00.750 --> 00:17:09.630
Nancy Amato: Since 2007, the number of CS majors has more than quadrupled. According to the article, there's something on the -- more than 300,000

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00:17:10.620 --> 00:17:21.660
Nancy Amato: Nationally CS majors or people that are, would like to be. And on top of that, departments also face to face a huge demand for courses by non majors.

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00:17:22.350 --> 00:17:34.410
Nancy Amato: So what are the challenges here? There's, in order to kind of meet this demand, we on top of that, we have a huge competition for faculty from industry. So it's hard for us to hire and get enough faculty.

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00:17:35.340 --> 00:17:46.560
Nancy Amato: And another thing is we've been working for a really long time since, you know, at least two decades to try to improve the gender balance and the representation of students in our majors.

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00:17:46.920 --> 00:17:59.250
Nancy Amato: And now that we have this huge demand where many institutions are having to put in place enrollment caps and then this is disproportionately impacting students from these groups that we're trying to really bring into the field.

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00:18:00.300 --> 00:18:07.620
Nancy Amato: Again, another thing is this big demand for computing and this kind of increasing tilt towards the tech curricula

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00:18:08.070 --> 00:18:19.230
Nancy Amato: can create friction with other disciplines basically competing for resources. So what is this though? This has put us in a place where there's a really great opportunity.

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00:18:19.860 --> 00:18:32.160

Nancy Amato: The need to accommodate this demand has driven curricular innovation and has really set us up for really exciting new cross disciplinary interactions. So

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00:18:33.480 --> 00:18:34.080
Nancy Amato: Let's see.

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00:18:36.480 --> 00:18:43.890
Nancy Amato: So this is kind of a broad spectrum of there's many, there's opportunities for many new pathways and on ramps to computing

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00:18:44.760 --> 00:19:00.750
Nancy Amato: First off are, and I'm going to talk about a couple of these in more detail going forward, but I just kind of want to set the stage. Here is our CS + X degrees. So, these are basically blended degrees, they're not double majors, and they're mostly so far been undergraduate degrees.

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00:19:01.860 --> 00:19:10.380
Nancy Amato: Many institutions are experimenting with this: University of Illinois and Stanford were some of the early ones. Northwestern, UMass, Columbia. There are many of them.

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00:19:10.920 --> 00:19:14.190
Nancy Amato: I'll talk about the experience at the University of Illinois in a bit

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00:19:14.880 --> 00:19:26.070
Nancy Amato: Another thing have been like boot camps and other training programs. These are like typically shorter things. They don't usually lead to formal degrees, maybe they get a certificate

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00:19:26.580 --> 00:19:43.470
Nancy Amato: They have very, very widely varying costs and success rates. And then there are these so called bridging programs. These are kind of more formal academic programs that are designed to prepare students with undergraduate degrees for graduate degrees in computing

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00:19:45.270 --> 00:19:54.330
Nancy Amato: There's been actually a long time ago. In fact, I kind of came into the field through such a program that Berkeley had. It was called the reentry program was back in the 80s.

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00:19:54.810 --> 00:20:02.490

Nancy Amato: But now there's been kind of a resurgence of these, Northeastern's Align program is a one, that they are kind of spreading out throughout

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00:20:03.000 --> 00:20:11.790
Nancy Amato: The country. We are starting one here. We're calling it the iCan program. I will go into that in a little bit more detail. Columbia, Georgia Tech, and more of these are coming online.

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00:20:12.330 --> 00:20:21.060
Nancy Amato: And I think that's another way that we can bring more students into the field. So now what I'm going to talk about is the CS + X programs here

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00:20:21.750 --> 00:20:34.770
Nancy Amato: At University of Illinois. So basically, the idea here is that these are different ways to bring computing together with other disciplines.

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00:20:35.760 --> 00:20:45.240
Nancy Amato: NSF has recognized that this is, that computing is ubiquitous and essential to everyone. I think that's, you know, partly why we're here today and discussing some of these things.

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00:20:46.050 --> 00:20:56.040
Nancy Amato: Now the CS + X degrees are degrees. Again, they're not double majors. They're really specially designed for, to bring together these two different disciplines.

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00:20:56.400 --> 00:21:03.180
Nancy Amato: And the student ideas that the students are going to learn the core concepts from computer science and the other the X discipline.

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00:21:03.450 --> 00:21:15.450
Nancy Amato: And upon graduation, they're prepared to go on for a career that would be either in the computing area or the X discipline or to go on to graduate study in either one of those disciplines.

136
00:21:16.050 --> 00:21:25.650
Nancy Amato: So at the University of Illinois in fact, for the longest time, there were two of these degrees from math and computer science and statistics and computer science.

137
00:21:26.040 --> 00:21:39.840

Nancy Amato: But starting about in 2014, and Rob was department head when this started, and I think this was really, really visionary. There have been 11 new ones started that spanned four different colleges. I have a, you know,

138
00:21:41.040 --> 00:21:42.420
Nancy Amato: Graphic on the next page.

139
00:21:44.250 --> 00:21:58.050
Nancy Amato: Now the idea here is that they really bring together people faculties from both disciplines to come together and design these things. And each one of them is a special partnership between those two

140
00:21:58.500 --> 00:22:07.740
Nancy Amato: Different disciplines. We're starting since they have really kind of these new ones have really been around only for like five or six years, and many of them are just coming online now,

141
00:22:08.040 --> 00:22:18.540
Nancy Amato: We don't have a lot of experience with bringing people together. But the idea is it hopefully these are going to also spark new research collaborations and we have one that's coming online now.

142
00:22:18.780 --> 00:22:27.000
Nancy Amato: We have a new Center for Digital Agriculture that's co-led by the College of Engineering and Computer Science and the College of Agriculture.

143
00:22:29.970 --> 00:22:46.350
Nancy Amato: So this is animated. So this is kind of shows you the different types of degrees that we have and in the different colleges. So many of them are between engineering, computer science and engineering, and College of Art liberal arts and sciences.

144
00:22:47.400 --> 00:22:56.580
Nancy Amato: The original two, math and statistics, were there. And then we've added anthropology, astronomy, chemistry, linguistics GIS, philosophy, and economics.

145
00:22:57.120 --> 00:23:14.940
Nancy Amato: In the College of Fine Arts, there's CS + Music; in agriculture, there was crop sciences; and the new one that's coming on this next year is Animal Sciences and advertising was one of the original ones too, early ones. So here's some numbers, some statistics.

146

00:23:16.020 --> 00:23:24.450
Nancy Amato: Some of them are maybe what you would expect them. Some of them I found a little bit surprising and some of them I think are some of the questions that we might

147
00:23:24.870 --> 00:23:29.280
Nancy Amato: Be interested to study at the interface of CISE and SBE.

148
00:23:29.820 --> 00:23:39.450
Nancy Amato: So you can see on the left, there's basically showing our undergraduate enrollment. The orange at the bottom are the kind of plain computer science majors.

149
00:23:39.870 --> 00:23:51.930
Nancy Amato: The gray and gold are the math and statistics ones and then the blue ones are the additional, uh, the new CS + X majors.

150
00:23:52.560 --> 00:23:59.580
Nancy Amato: And as you can see we're getting to the point where about half of our enrollment our computer science majors.

151
00:24:00.000 --> 00:24:14.220
Nancy Amato: Another maybe 25% are the math and statistics and CS, and then another 25% are the others. And you can imagine how exciting it is like in the freshmen courses where we have this

152
00:24:14.580 --> 00:24:21.180
Nancy Amato: great diversity of students in class together. It's really exciting. Some of the things that are

153
00:24:22.110 --> 00:24:26.580
Nancy Amato: We kind of were thinking when we started this is that this would help us, for example,

154
00:24:26.850 --> 00:24:33.630
Nancy Amato: Increase our diversity of our student body. So certainly it's increasing the diversity of their background in there.

155
00:24:33.840 --> 00:24:40.080
Nancy Amato: There are other things that they're studying so they're coming to the classroom with many different experiences and they have. They know different things.

156
00:24:40.470 --> 00:24:48.630

Nancy Amato: But we're also thinking and hoping that it would improve our gender balance and our in participation of underrepresented minorities.

157
00:24:49.320 --> 00:24:57.210
Nancy Amato: Now, if you look at this though you see that our computer science major, that's the one that see us in Grainger Engineering,

158
00:24:57.540 --> 00:25:06.390
Nancy Amato: That actually has the highest percentage of women at 30% and also the highest percentage of the others amongst the underrepresented minorities.

159
00:25:06.960 --> 00:25:13.320
Nancy Amato: If we look at those kind of longer standing blended degrees math and CS and statistics and CS

160
00:25:14.010 --> 00:25:30.420
Nancy Amato: They actually have there the least gender balanced with about 21% women and less than 4% underrepresented minorities. The other CS + X majors, we, I would have thought they would have had greater gender balance than

161
00:25:31.890 --> 00:25:38.400
Nancy Amato: Computer Science, the engineering degree. But they don't, and neither are the under represented minorities. So this is something

162
00:25:38.850 --> 00:25:50.430
Nancy Amato: That we're trying to understand why that is. I think that it's, there has been a lot of care and attention placed on recruiting and trying to

163
00:25:51.030 --> 00:25:59.070
Nancy Amato: Make sure that students felt that computer science was a good major for them and that they would feel welcome to them and that has

164
00:25:59.280 --> 00:26:09.990
Nancy Amato: Maybe paid off. And maybe that's why our numbers are better there. We need to work a little bit more on to understand really what's going on. But I think, again, this is a something that would be really interesting to study together.

165
00:26:11.250 --> 00:26:12.210
Nancy Amato: Now, the next

166

00:26:13.290 --> 00:26:17.310
Nancy Amato: Type of new pathway I want to talk about is something that we're just starting

167
00:26:19.680 --> 00:26:30.060
Nancy Amato: So here, the idea is, again, there are many students that would like to come into computing and that if we bring them in, are going to increase the

168
00:26:30.570 --> 00:26:42.420
Nancy Amato: Basically they are enrich us up everywhere as a field. There's also a very strong interest in studying computer science from people who have an undergraduate degree or higher.

169
00:26:42.870 --> 00:26:52.560
Nancy Amato: And they maybe aren't, don't feel very equipped to kind of jump right into our MCS program or they don't feel like they have the right ba- background for that.

170
00:26:53.430 --> 00:27:00.540
Nancy Amato: So what we're doing is we're starting a new program we're calling it the iCAN program for Illinois Computing Accelerator for Non-specialists

171
00:27:00.930 --> 00:27:07.920
Nancy Amato: And basically, what it is is about, about a year's worth of coursework that would provide the CS fundamentals in terms of like

172
00:27:08.280 --> 00:27:12.990
Nancy Amato: Coding, data, structures, algorithms, and some systems, understanding of systems.

173
00:27:13.350 --> 00:27:20.040
Nancy Amato: And when a student finishes that, they will have enough background to go comfortably into any of our graduate programs.

174
00:27:20.250 --> 00:27:30.450
Nancy Amato: Or professional master's program or the research based, you know, thesis master's program or even a PhD and in fact I'm hoping many of them would be interested in going onto PhD.

175
00:27:31.500 --> 00:27:42.900
Nancy Amato: This program is, the Northeastern Align program has been running for a few years and they've been pretty successful and they're trying to encourage and help other institutions

176
00:27:43.170 --> 00:27:48.660
Nancy Amato: Really get this going on. Carla Brodly at Northeastern is a dean there and she's been spearheading this.

177
00:27:49.140 --> 00:27:58.920
Nancy Amato: And so, Illinois, Georgia Tech and Columbia, are you know have joined this consortium and many other schools have joined now. I think they're up to about 10.

178
00:27:59.760 --> 00:28:07.230
Nancy Amato: We're planning to launch our program in this fall. We've hired a director of this program, Tiffany Williams. That's who's pictured there on the left.

179
00:28:07.590 --> 00:28:20.760
Nancy Amato: She actually was working with the Northeastern Align Program in Charlotte, and we recruited her way, and she's joined us. We were originally planning to launch it on campus in Champaign-Urbana this fall.

180
00:28:21.180 --> 00:28:23.760
Nancy Amato: And then we're planning to move into Chicago

181
00:28:24.240 --> 00:28:25.500
Nancy Amato: And online.

182
00:28:27.120 --> 00:28:48.090
Nancy Amato: Has kind of caused us to read replan and now we're moving to offered online first and then in Chicago in Urbana, but next. So I'm pretty excited about this. Okay. And here's the last slide, I have just some thoughts. I had about things that I think would be

183
00:28:49.500 --> 00:28:57.330
Nancy Amato: Good opportunities for collaboration between size. Researchers at SP on looking at some of the questions about these programs.

184
00:28:57.630 --> 00:29:07.050
Nancy Amato: Now, why do some of these CS plus x programs fail, for example, Stanford, you know, that made me sad. I'm a Stanford alum, but they they can their programs. Earlier this year, or last year.

185
00:29:07.650 --> 00:29:17.970

Nancy Amato: And some of them are thriving like ours. Why is the gender balance and some of these CS plus x majors worse than in the either the X or the Cs, and why is it better than others.

186
00:29:18.930 --> 00:29:26.640
Nancy Amato: What can we do to increase the participation of success of these underrepresented groups in the CSP sex and other pathway programs.

187
00:29:27.120 --> 00:29:41.070
Nancy Amato: And finally, how can we provide the community and support needed for these non traditional and at risk students in online and remote settings that we're going to have to do now that is something that really worries me a bit. I'm not sure how to go about that.

188
00:29:42.150 --> 00:29:43.800
Nancy Amato: Okay, that's, that's

189
00:29:47.730 --> 00:29:49.650
Rob Rutenbar: Awesome. Thanks, Nancy.

190
00:29:52.950 --> 00:30:04.620
Rob Rutenbar: Thanks, that was great. I will, I will also say apropos moderators privilege that hanging out with all the X-departments when I was the head of computer science at Illinois was like one of the single funnest things I ever got to do.

191
00:30:05.700 --> 00:30:11.340
Rob Rutenbar: So I'm certainly as excited about where the CS + x stuff might, maybe going next as Nancy is

192
00:30:12.960 --> 00:30:29.550
Rob Rutenbar: So, um, let us move on to our next speaker. So, Sharla Alegria from the University of Toronto is going to talk about structural challenges and practical questions for empowering and diversity technical work in the new economy. So, Sharla, take it away.

193
00:30:40.290 --> 00:30:44.700
Sharla Alegria: Thanks very much. I hope everybody can see my slides and screen at this point.

194
00:30:47.520 --> 00:30:49.020
Sharla Alegria: So thanks for

195
00:30:54.570 --> 00:30:57.720

Sharla Alegria: Thanks for including me in this exciting panel. I'm Sharla Alegria and

196
00:30:58.650 --> 00:31:08.310
Sharla Alegria: As Rob just mentioned, I'm a Professor of Sociology at the University of Toronto and I actually just only moved to north of the border here. My research focuses on the US tech workforce.

197
00:31:08.910 --> 00:31:13.800
Sharla Alegria: I'm going to focus today on three areas and first I'll provide a brief

198
00:31:14.160 --> 00:31:21.240
Sharla Alegria: overview of some of the demographic profile of the tech workforce and uh, to give a bit of context to the conversation about diversity and then dig in a bit to focus on

199
00:31:21.600 --> 00:31:27.540
Sharla Alegria: The division of labor within the tech workforce to provide a sense for how to think about diversity in the process of producing computer related technology.

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00:31:27.990 --> 00:31:33.870
Sharla Alegria: Next I'll provide a bit of context for what's at stake in the efforts towards moving towards a more diverse competing workforce and

201
00:31:34.140 --> 00:31:41.310
Sharla Alegria: Expand by showing how shifting workforce practices that we might associate with a quote unquote new economy can make our solutions obsolete.

202
00:31:41.880 --> 00:31:51.240
Sharla Alegria: Finally, I'll conclude by sharing some of the questions and directions I'm excited about, freezing social and computational science to identify and address the challenges of diversity in a power-technical workforce.

203
00:31:52.950 --> 00:31:57.540
Sharla Alegria: But first, I think it's more to share but but how I came to this topic. The question that really motivated me is

204
00:31:57.990 --> 00:32:05.730
Sharla Alegria: How can there be so little change in women's representation of computing, despite so much investments. What you see here is the new USPS

205
00:32:06.120 --> 00:32:15.000
Sharla Alegria: stamp for STEM education. And on the righthand side of the screen is a collection of swag from the Grace Hopper Celebration of Women in Computing.

206
00:32:15.840 --> 00:32:29.130
Sharla Alegria: So we can see private companies and federal government, the NSF included, put lots of investment into recruiting, and retaining women in tech work, and competing work generally, and the trends don't reflect the level of investment.

207
00:32:30.000 --> 00:32:34.050
Sharla Alegria: But my work instead of focusing on the choices that women may or may not make

208
00:32:35.100 --> 00:32:41.340
Sharla Alegria: I look more at the structure of the field, how work gets done by its processes and when gender might matter in these choices.

209
00:32:42.900 --> 00:32:51.720
Sharla Alegria: So with that said, I'll try to focus on the demographic picture which matters for how we understand diversity and the division of labor, which is critical if we want to think about how diversity and empowerment at the same time.

210
00:32:53.430 --> 00:33:05.550
Sharla Alegria: Here is a graph of the National Science Board's Science and Engineering Indicators report. What I want to show you here is actually that the trend in general for women's representation across science and technology and engineering fields broadly is up you can see most of these

211
00:33:06.150 --> 00:33:09.780
Sharla Alegria: Most of the trend lines here head in this re, generally positive direction.

212
00:33:10.680 --> 00:33:23.460
Sharla Alegria: Computer science is an exception. Computer mathematical science stands out for actually decreasing gender diversity despite all this investment, which you can see here, it's the lighter green line is kind of heading in the general downward direction.

213
00:33:25.140 --> 00:33:30.390

Sharla Alegria: And here just to quickly show you as the 2019 breakdown by race and gender for computing occupations

214
00:33:31.380 --> 00:33:38.160
Sharla Alegria: And overall workforce participation using data from the Bureau of Labor Statistics. What you should see here is that women's representation

215
00:33:38.460 --> 00:33:44.010
Sharla Alegria: Is much lower in computing and in the overall workforce and while computing may initially appear more racially diverse,

216
00:33:44.730 --> 00:33:52.470
Sharla Alegria: this is actually different primarily by high representation of Asian workers, and black and latinx workers are less well-represented in tech than in the US workforce overall.

217
00:33:54.540 --> 00:34:10.080
Sharla Alegria: And here's a look at the division of labor among tech workers at the 177 largest Silicon Valley firms on this is data from the Center for Employment Equity at the University of Massachusetts, my alma mater, where so they're using EEO-1 reports here, and without fail, I'm just going to cycle through,

218
00:34:11.490 --> 00:34:21.270
Sharla Alegria: And you can see some different information here, but what I want to most focus on is the division of labor among tech workers. So even though Asian workers are over represented in computing drops broadly,

219
00:34:21.780 --> 00:34:24.870
Sharla Alegria: They aren't moving into managerial and executive positions where

220
00:34:25.380 --> 00:34:38.250
Sharla Alegria: decision making authority. We see white women's increasing representation and management, but not in executive positions. And white men's representations increases generally across positions with more decision making capacity and authority.

221
00:34:40.860 --> 00:34:51.030
Sharla Alegria: Next I'll show some areas where limited diversity has consequences for technical products and we've mentioned some of these already today. I think these are areas where intellectually diverse teams from social science training and

222
00:34:52.680 --> 00:35:02.340
Sharla Alegria: And in addition to demographic diversity, what helped the tech workforce better understand the implications of assumptions built into algorithms, the social production of machine learning, training materials, and broad

223
00:35:02.640 --> 00:35:07.050
Sharla Alegria: And develop broad critical thinking about the social world that could help to create more critical technology.

224
00:35:11.790 --> 00:35:17.640
Sharla Alegria: But first, I need to define a couple of terms. We can think about diversity in two ways, like with intellectual and demographic diversity.

225
00:35:18.300 --> 00:35:26.190
Sharla Alegria: Excellent work with Laurel Smith-Doerr and Tim Sacco where we investigate the perceived diversity for improving innovation, problem solving, and productivity and team science.

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00:35:26.610 --> 00:35:34.410
Sharla Alegria: In the context of team science, diversity sometimes refers to demographic diversity in terms of the general racial or ethnic makeup of the team, and other times

227
00:35:34.800 --> 00:35:42.690
Sharla Alegria: Folks are referring to intellectual diversity in terms of the common approach and disciplinary background of team members. I think we've argued a bit today that both of these matter.

228
00:35:43.200 --> 00:35:47.520
Sharla Alegria: But in every study we could find, intellectually diverse teams outperform single discipline teams.

229
00:35:48.030 --> 00:36:01.050
Sharla Alegria: The results were mixed for demographically diverse teams, but what we saw across the empirical research was that inclusion is key. When minority scientists are fully included as members of the team, demographic diversity pays off-- the positive effects we're looking at go up.

230
00:36:02.190 --> 00:36:12.240
Sharla Alegria: But when they're not fully incorporated, it's as if the team was operating short handed. So we need both demographic, and we need

demographic diversity and in conjunction with inclusion to make a difference.

231
00:36:12.840 --> 00:36:18.960
Sharla Alegria: Still, we keep seeing examples of why diversity and tea-in tech work matters. Many of these folks have pointed to today.

232
00:36:19.500 --> 00:36:27.660
Sharla Alegria: Safiya Noble's book, Algorithms of Oppression, demonstrates how search algorithms based on frequency and driven by profit, profit seeking, seeking to

233
00:36:28.500 --> 00:36:32.160
Sharla Alegria: Sorry leads to search results that denigrate and pornify black women's bodies.

234
00:36:32.610 --> 00:36:41.040
Sharla Alegria: In 2011, for example, a search for the phrase "black girls" in Google, you'll have nearly all links for pornography on the first page. And an image for the search for the word

235
00:36:41.400 --> 00:36:53.910
Sharla Alegria: A certain image search for the word gorillas in 2016 resulted in pictures of a young black couple. Similarly Ruha Benjamin's new book, Race after Technology: Abolitionists tools for The New Jim Code, describes case after case of racial bias and seemingly

236
00:36:55.080 --> 00:36:59.400
Sharla Alegria: Neutral technology, including many examples that folks have referenced here today.

237
00:37:00.480 --> 00:37:09.660
Sharla Alegria: Part of the challenge as these scholars and folks today have pointed out is the seeming objectivity of search algorithms, machine learning, and AI-- they become black boxes hiding assumptions

238
00:37:09.960 --> 00:37:14.640
Sharla Alegria: And allowing damaging user biases and programmers assumptions about technology.

239
00:37:15.150 --> 00:37:24.450
Sharla Alegria: And what's more, as the companies that produce these technologies are actually really good about fixing these problems, um, but never really saying people have biases and limitations that result in the problems in the first place.

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00:37:24.870 --> 00:37:33.270
Sharla Alegria: Those are present in our training materials and our programmers that, that enter the assumptions into the algorithms in the first place.

241
00:37:33.600 --> 00:37:42.270
Sharla Alegria: Our technology reflects the biases of the social world. And we'd like to think that more diverse teams would hopefully realize these problems before the technology gets released, but

242
00:37:43.140 --> 00:37:51.390
Sharla Alegria: in my own research, I found that the Division of Labor, on the ground, and tech companies may limit the volume of the underrepresented voices that even our present.

243
00:37:51.750 --> 00:38:01.500
Sharla Alegria: These findings have particular consequences for how we think about diversifying and empowering a technical workforce. I spent about a year and the field attending conferences and interviewing tech workers about their jobs and career paths.

244
00:38:03.570 --> 00:38:12.420
Sharla Alegria: I find that by mid career, many of the white women I interviewed had moved out of technical positions and into managerial roles after a supervisor identified their, quote unquote, people skills.

245
00:38:12.750 --> 00:38:21.510
Sharla Alegria: Technically, these were promotions, but they didn't appear to lead to executive positions. None of these women were in the executive trajectory, at least at the time when I interviewed them.

246
00:38:21.990 --> 00:38:28.800
Sharla Alegria: Nor could they point to any woman in their company who had entered an executive level position from a technical one.

247
00:38:29.400 --> 00:38:38.370
Sharla Alegria: And in some cases, these managerial positions actually have lower status in the eyes of their engineering coworkers. Still, the moves improved women's quality of life, it made sense for them personally.

248
00:38:38.880 --> 00:38:42.660
Sharla Alegria: They improved schedule flexibility and often they got to modify them across engineering teams.

249
00:38:44.340 --> 00:38:52.350
Sharla Alegria: As is the case for Alex who explains, "I was an extreme minority and there were a lot of difficulties that I faced in my tenure in IT.

250
00:38:52.680 --> 00:39:00.450
Sharla Alegria: I just said, You know what, I'm not going to fight this battle anymore. I'm just, this person obviously thinks that I'm skilled and keep contributing all that. So I'm just going to go for it and move into the business side."

251
00:39:00.870 --> 00:39:08.790
Sharla Alegria: And this was after a manager had encouraged her to pursue the management track and leave her, what was at the time, hostile engineering team.

252
00:39:13.950 --> 00:39:21.120
Sharla Alegria: These seemingly kind of haphazard moves or accidental moves for a white woman just simply didn't happen for the women of color that I interviewed, including Asian women.

253
00:39:23.250 --> 00:39:31.260
Sharla Alegria: None of the women of color interviewed found themselves encouraged and supported to pursue management due to the strength of their people skills, just like white women had. Instead, like Zheng,

254
00:39:32.100 --> 00:39:42.480
Sharla Alegria: Those that did move into management did so through deliberate and determined effort. They pursued MBAs, they changed jobs, and they trained for new credentials before they're able to obtain management positions if that was a goal that they had.

255
00:39:46.200 --> 00:39:52.800
Sharla Alegria: What became clear in the course of this research was that the structure of work has moved in ways that limit diversity among technical decision makers.

256
00:39:53.160 --> 00:40:05.580
Sharla Alegria: Companies increasing the geographic spread and increasing sort of, increased the need for good communicators who understood the technology and communicate it with the business side of the company, as well as coordinating to spread across the globe.

257
00:40:06.480 --> 00:40:14.760

Sharla Alegria: These translators, as I call them, may have had some say in the direction of the technology, but their assumptions were not the ones written into the algorithms that guided the technology.

258
00:40:15.330 --> 00:40:24.000
Sharla Alegria: Meanwhile tech companies are among those relying increasingly on contract contingent labor. Practically, this means limited opportunity for upward mobility or on-the-job training.

259
00:40:24.600 --> 00:40:35.580
Sharla Alegria: In tech work in particular, where labor staffing agencies hire workers on H1B Visas and contract with other firms to provide these workers to complete backend tasks, opportunities for promotion and training review are limited.

260
00:40:36.000 --> 00:40:48.210
Sharla Alegria: Technical workers on the leading edge of new economy workplace restructuring where fewer workers have full time permanent positions where they can learn new skills on the job and expect regular promotions in recognition of increased skills and experience.

261
00:40:50.730 --> 00:40:57.750
Sharla Alegria: So where does all this leave us? If the Division of Labor and Technical Work limits the potential returns to the already limited diversity of the workforce,

262
00:40:58.110 --> 00:41:12.030
Sharla Alegria: We know that limited diversity and the products of technical work shows tendency to exacerbate existing inequalities, and broad workforce changes appear to dilute the potential results of broad representation efforts by emphasizing flexibility over workforce development.

263
00:41:14.250 --> 00:41:17.730
Sharla Alegria: Here are three areas that I think are open for exploration and that I'm excited about,

264
00:41:18.060 --> 00:41:28.650
Sharla Alegria: Particularly with crosscutting work between social and behavioral computer sciences. First, diverse teams matter in academic, the government and even public/private partnerships have the opportunity to lead the way here.

265
00:41:29.070 --> 00:41:42.390
Sharla Alegria: The NHS, sorry the NIH and NSF are already building models for this. Even when it's not clear what every member will do,

answering questions, making/taking for granted logics clear, and considering alternative solutions makes for better science. Diverse teams can help with us.

266
00:41:45.090 --> 00:41:53.520
Sharla Alegria: Second, private sector labor practices have long been moving in a direction that limits the power and potential of the average worker and dilutes the effectiveness of diversity efforts.

267
00:41:53.970 --> 00:42:03.150
Sharla Alegria: Contingent contract and generally flexible labor practices reduce labor costs and make sense when the consequences for creating technology that exacerbates inequalities are trivial.

268
00:42:03.930 --> 00:42:06.210
Sharla Alegria: This is a space for creative cross kind of thinking

269
00:42:06.870 --> 00:42:14.130
Sharla Alegria: These are labor practic, sorry these are labor force problems that reshape what work means. Social scientists have tools to study work

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00:42:14.400 --> 00:42:18.750
Sharla Alegria: And labor practices, but as more of the job search hiring and even the work itself move online

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00:42:19.110 --> 00:42:34.080
Sharla Alegria: And become less formalized in the traditional ways, we need new tools that are adaptable to better understand the digital world, and many of these tools may come from computational social science, computer science, more probably. Ideally, this will help help us build more diverse teams

272
00:42:35.100 --> 00:42:38.400
Sharla Alegria: And better tools understand how the workforce is changing.

273
00:42:41.100 --> 00:42:54.240
Sharla Alegria: Finally access and training are both important and unequally distributed, especially as technical workers are expected to take increasing responsibility for constant training and upgrading skills. We've heard about great training programs to develop technical skills.

274
00:42:54.240 --> 00:42:54.480

Regan: But

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00:42:54.510 --> 00:42:59.250
Sharla Alegria: We don't know as much-- thanks just wrapping up-- but we don't know as much about

276
00:43:01.230 --> 00:43:05.700
Sharla Alegria: For whom and under what conditions these training programs result in new and improved job opportunities.

277
00:43:06.210 --> 00:43:15.600
Sharla Alegria: Complicating this imperative, as the wide range of for-profit training programs, community-based boot camps, University-sponsored skill workshops, and online badging and credentialing opportunities.

278
00:43:16.230 --> 00:43:24.690
Sharla Alegria: And adding to this range of different training programs and opportunities, the ways of signaling to potential employers about skills folks have, we know that

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00:43:25.350 --> 00:43:30.630
Sharla Alegria: From Tressie McMillan Cottam's work that race and gender inequality further stratify access to continuing education.

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00:43:31.470 --> 00:43:35.640
Sharla Alegria: And in my own work, I only have a few cases to to start to look at this, but it appears

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00:43:36.090 --> 00:43:43.410
Sharla Alegria: That those with brand name bachelor's degrees and non-technical areas like literature, history are able to move into technical roles with with simple credentials.

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00:43:44.040 --> 00:43:51.060
Sharla Alegria: This is an exciting area for cross cutting research since searches for new employees often use machine learning, along with human resources to sort out resumes and recruit.

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00:43:52.410 --> 00:43:56.580
Sharla Alegria: And another area that I think is right for cross-disciplinary research. Thanks very much!

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00:44:03.240 --> 00:44:04.590

Rob Rutenbar: Sharla, thanks. Thanks. That was great.

285
00:44:05.760 --> 00:44:22.140
Rob Rutenbar: So, um, our fourth and final speaker for the session is Nancy Cooke from Arizona State, and she's going to talk about The Future Workforce: Human AI Robot Teaming. So Nancy take it away!

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00:44:22.500 --> 00:44:30.660
Nancy Cooke: Yes, thank you. So I'm interestingly trained as a cognitive psychologist. I'm working in a Human Systems Engineering program, and

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00:44:31.320 --> 00:44:40.230
Nancy Cooke: we're located within the College of Engineering so a lot of this work is, has been done with the collaborations between social scientists and

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00:44:41.130 --> 00:44:53.040
Nancy Cooke: engineers, computer scientists. I'm also directing the Center for Human AI and Robot teaming out of of ASU, which is under the global security initiative that Nadya Bliss leads and there we assemble

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00:44:53.700 --> 00:45:02.010
Nancy Cooke: Lots of different disciplines, including social scientists and computer scientists, in order to study this problem with human AI robot teaming.

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00:45:03.090 --> 00:45:05.310
Nancy Cooke: One of the plugs I want to put in for

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00:45:06.540 --> 00:45:09.150
Nancy Cooke: For teaming is that in some cases, we know that

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00:45:10.500 --> 00:45:23.190
Nancy Cooke: AI or machine learning can excel, do the job better than a human and other cases humans do better. But still, in other cases humans teamed with AI, such as in centaur chess do better than

293
00:45:24.570 --> 00:45:28.320
Nancy Cooke: the best chess expert in the world or the best AI.

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00:45:34.320 --> 00:45:34.620
Okay.

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00:45:37.260 --> 00:45:55.320
Nancy Cooke: So what I'm going to do next 10 minutes or so let's talk about how we can draw from social science principles of human teaming to inform the development of human AI and robot teams. There's a lot of things that can be learned. And it's not as simple as just putting

296
00:45:56.490 --> 00:46:01.740
Nancy Cooke: Random robots, AI, and humans together. This can be done systematically.

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00:46:03.000 --> 00:46:17.550
Nancy Cooke: One of the things we know about human teams is that team members, by definition, have different roles and responsibilities. What does this mean for human AI robot teams? I think one of the things this means is that we don't need to replicate ourselves. I'm not really

298
00:46:18.900 --> 00:46:25.830
Nancy Cooke: All about general AI. I think that we know how to replicate ourselves just fine, and there's some things that we can't do.

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00:46:26.280 --> 00:46:39.420
Nancy Cooke: Rather, we need the AI and the robots to be doing that part of the task which either we can't do, or we don't want to do, and we should be doing the things that we're skilled at. I think that in the future of work,

300
00:46:40.980 --> 00:46:52.260
Nancy Cooke: it would be, we would assemble teams for that test, teams that include humans who are skilled at doing that particular part of the task, and then you bring in the AI and the robots that are similarly skilled.

301
00:46:55.110 --> 00:47:02.130
Nancy Cooke: Another thing we know about human teams is that effective teams understand that each team member has different roles, responsibilities, and

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00:47:02.580 --> 00:47:11.760
Nancy Cooke: because of that they need to avoid role confusion, but also back each other up as necessary. So it's kind of complex, fuzzy line between

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00:47:12.270 --> 00:47:19.680
Nancy Cooke: Being able to do everything that the other person does, but being able to back up the other person. So what does this mean for you and then AI robot teams?

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00:47:21.120 --> 00:47:28.770
Nancy Cooke: I think this means that technology needs to understand the bigger team task in order to have this kind of understanding in order to be able to back up.

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00:47:29.730 --> 00:47:46.860
Nancy Cooke: We've been doing some work in my lab in which we have a synthetic agent teamed with two humans to control the single Unmanned Aerial system and we find out that the synthetic teammate is not a very good team player-- it doesn't really anticipate, it acts like it's the only

306
00:47:47.880 --> 00:47:59.130
Nancy Cooke: Agent on the team. It doesn't anticipate the information needs of its fellow teammates and so the whole team as a result starts going downhill in its ability to respond flexibly and adaptively.

307
00:48:00.030 --> 00:48:08.850
Nancy Cooke: So what is the problem there with our synthetic agent? The problem was that it didn't have an understanding of others' tasks. It had an understanding of its tasks, but not an understanding

308
00:48:09.270 --> 00:48:21.630
Nancy Cooke: Of the other parts of the task, and some people talk about theory of mind, that this is something that the AI has to have. And I'm not sure, but it has to have at least an understanding of the bigger task.

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00:48:25.080 --> 00:48:25.650
Nancy Cooke: Another

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00:48:26.760 --> 00:48:38.310
Nancy Cooke: Principle or fact about human teams is that with team practice, effective teams share knowledge about the team goals and about the current situation, and this facilitates coordination and implicit communication.

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00:48:38.940 --> 00:48:45.420
Nancy Cooke: That is, teams don't start out being effective teams. It takes time. It takes practice. And what does this imply?

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00:48:46.020 --> 00:49:00.000
Nancy Cooke: I think this means that we have to expect that humans and technology will need time to train together. So we talked about training

the workforce so that they can work with AI, with robots. But I think that training has to happen together on both sides of the coin.

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00:49:04.470 --> 00:49:12.900
Nancy Cooke: Another principle is that effective teams have team members who are interdependent, and thus they need to interact to communicate even when direct communication is impossible. This is the

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00:49:13.320 --> 00:49:21.360
Nancy Cooke: key feature of teams is that they are interdependent with different roles and responsibilities, and they need to communicate, but sometimes that

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00:49:21.780 --> 00:49:31.380
Nancy Cooke: direct communication is not possible. I have an inflation of a hot air balloon where you have to coordinate with the person who's holding up the crown line and the person who's

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00:49:32.040 --> 00:49:36.630
Nancy Cooke: who's the pilot, and who's inflating the balloon. How does that coordination have to work?

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00:49:37.350 --> 00:49:46.020
Nancy Cooke: Well, to me, this means that interaction for human machine teams is important, but natural language communication may be unnecessary.

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00:49:46.560 --> 00:50:06.840
Nancy Cooke: I like to think about other types of teams, such as human-dog teams, and they are very big teams. They're very well practiced at doing one particular thing, both the human and the dog practice together and they communicate or they interact, but they don't communicate in natural language.

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00:50:08.190 --> 00:50:09.000
Nancy Cooke: So I'm thinking

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00:50:10.560 --> 00:50:16.230
Nancy Cooke: Signaling or maybe some other form of controlled or restricted natural language.

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00:50:18.330 --> 00:50:23.130
Nancy Cooke: And finally, interpersonal trust is important to teams and earlier today, we heard a lot about trust.

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00:50:24.510 --> 00:50:38.790
Nancy Cooke: There's been a lot of work now going on looking at trust in AI, trust in robots, and in this research, transparency and explanation seem to be of critical importance.

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00:50:42.090 --> 00:50:55.530
Nancy Cooke: So those were just some principles that we might take some of the social science of teams and apply it to assembling human-AI-robot teams, but there's also a lot of social science research that can inform human-AI-robot teaming so

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00:50:56.610 --> 00:51:05.610
Nancy Cooke: We in our lab have synthetic task environments in which we bring the real world into the lab so we can study it under more controlled

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00:51:06.570 --> 00:51:16.260
Nancy Cooke: Circumstances. These testbeds, for instance, we have a testbed for looking at driver interaction with driverless vehicles,

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00:51:16.890 --> 00:51:23.340
Nancy Cooke: in which we have small robots running around on a track that are either controlled by a human or autonomous.

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00:51:23.760 --> 00:51:37.920
Nancy Cooke: We also have another testbed where we could have three agents flying an unmanned aerial vehicle. These testbeds are of critical importance because we need to be able to understand how the team is going to function and how agents are going to work

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00:51:39.750 --> 00:51:41.460
Nancy Cooke: in, without having to

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00:51:42.720 --> 00:51:52.680
Nancy Cooke: not having to implement them, um, before they're ready. So I think one of the problems is that people who are roboticists and AI often

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00:51:53.310 --> 00:52:04.950
Nancy Cooke: jump in and start building the AI, building the AI agent or the robot without consideration of its use and its use with humans. And so these testbeds allow us to be able to study

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00:52:06.390 --> 00:52:10.650

Nancy Cooke: That interaction in a relatively controlled environment.

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00:52:11.910 --> 00:52:24.300
Nancy Cooke: Finally, we also are strong believers in what's been called the Wizard of Oz technique from the Wizard of Oz classic. What that technique is, is having a human

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00:52:25.500 --> 00:52:41.250
Nancy Cooke: simulate a robot or an AI agent, and we call it Wizard of Oz because the human is sort of behind the curtain and that the participant who is interacting with the so called robot or AI agent does not know that they're interacting with a person.

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00:52:43.140 --> 00:52:51.960
Nancy Cooke: That is a critical paradigm for studying human-AI-robot teaming for the very reason that you can

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00:52:52.530 --> 00:53:02.160
Nancy Cooke: answer some of these questions before the AI agent is developed or before the robot is developed. We are looking at things like how do you do, what is the best way to do explanations

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00:53:02.700 --> 00:53:13.530
Nancy Cooke: In robots and that kind of information once we find out empirically what it is can be fed to people who are designing the actual robot planning algorithms.

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00:53:16.380 --> 00:53:25.020
Nancy Cooke: So in conclusion, I think that there's principles from social science of teams that have implications for even AI-robot teaming and I think, in many cases, the team can be

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00:53:26.160 --> 00:53:32.910
Nancy Cooke: You know more than the sum of the parts. And so we can make pretty effective teams that do better than either human alone or the AI alone.

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00:53:34.110 --> 00:53:40.620
Nancy Cooke: And the testbeds and Wizard of Oz method can provide human subjects data on interactions with robots and AI, head of the robot,

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00:53:41.820 --> 00:53:44.880
Nancy Cooke: and support the AI development.

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00:53:46.020 --> 00:53:48.000
Nancy Cooke: So I didn't even get the bell, and I think I'm done!

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00:53:52.650 --> 00:53:55.350
Rob Rutenbar: Okay, we can, I think we can ring the bell if you want.

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00:53:58.800 --> 00:54:02.760
Rob Rutenbar: I think, I think the other Wizard of Oz team behind the curtain can make that can make that happen.

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00:54:05.940 --> 00:54:06.390
There we go.

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00:54:08.070 --> 00:54:15.570
Rob Rutenbar: Okay. Okay, cool. Um, so thank you so much to all the panelists for all this great great material and great stuff to think of

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00:54:16.800 --> 00:54:25.740
Rob Rutenbar: So, um, we have 30ish minutes, um, for for Q & A for

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00:54:26.820 --> 00:54:28.740
Rob Rutenbar: **Willie Pearson** and I to be

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00:54:29.760 --> 00:54:35.730
Rob Rutenbar: reading some of the questions that the the ops team has been curating from the various

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00:54:37.140 --> 00:54:42.780
Rob Rutenbar: input channels. Um, Willie, do you want to pick one and start or do you want me to pick one and start?

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00:54:50.220 --> 00:54:51.930
Willie Pearson: There was some general-- can you hear me?

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00:54:52.710 --> 00:55:00.360
Willie Pearson: Yes. Okay. There were some general questions that came out, and we might need to have a little bit more clarification. I think Eric and then

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00:55:00.810 --> 00:55:10.590
Willie Pearson: towards the end Nancy C. spoke to some of this. Could you discuss a little bit more about the future of work? There are some questions that came in

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00:55:11.280 --> 00:55:20.100
Willie Pearson: That would be helpful if we know a little bit more about what you mean by the future of work and the kind of activities associated with that in terms of skills and so forth and so on.

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00:55:22.200 --> 00:55:38.610
Erik Brynjolfsson: Sure, I'll take a first cut of that. I mean, it's obviously a very big, broad question. We see some amazing technologies being developed and many of them can either automate or augment or otherwise affect the kinds of tasks that humans can do

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00:55:40.770 --> 00:55:49.320
Erik Brynjolfsson: What we see is that there are a lot of differences between the kinds of things that machines are good at, at least the current wave of machines, and the kinds of things that humans are good at.

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00:55:49.920 --> 00:56:06.480
Erik Brynjolfsson: They say we're very far from artificial general intelligence. So, so my take on it is we're not going to see any kind of a wave of mass unemployment or wholesale replacement because there are so many things that need to be done, and only humans can do them in our economy. In particular,

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00:56:08.220 --> 00:56:18.900
Erik Brynjolfsson: I put them in two broad categories. One is creative work-- thinking outside the box, invention entrepreneurship, scientific work, artistic work, all those kinds of

358
00:56:19.410 --> 00:56:28.590
Erik Brynjolfsson: tasks. Another really big one, even bigger I think, is tasks that involve the human touch and interpersonal interactions where we really

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00:56:28.860 --> 00:56:42.960
Erik Brynjolfsson: Prefer to have a human involved. I wouldn't want a robot taking care of a two year old or trying to motivate a kid soccer team or an adult group of folks, for that matter. So persuasion communication,

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00:56:44.820 --> 00:56:55.260
Erik Brynjolfsson: Human Interaction, and physical human interaction as well, those are all things where humans have a big advantage. And there are some jobs like a lot of nursing and other jobs that combine

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00:56:55.590 --> 00:57:03.030
Erik Brynjolfsson: These different categories. At the same time, there are many things machines are increasingly good at obviously a lot of computational work and

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00:57:03.360 --> 00:57:10.530
Erik Brynjolfsson: Arithmetic routine information processing, those have already been affected. And as I showed in my talk, there's a whole set of talk tasks.

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00:57:10.800 --> 00:57:20.070
Erik Brynjolfsson: Like in pattern recognition, which we're used to, and image recognition, which you used to think were beyond machines and they were a decade ago, but now machines are learning how to do

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00:57:20.400 --> 00:57:25.500
Erik Brynjolfsson: Them. So going forward, my main takeaway is is that there's plenty of work for humans to do.

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00:57:26.100 --> 00:57:30.690
Erik Brynjolfsson: It involves different kinds of tasks than what we've been doing in the 20th century by and large,

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00:57:31.170 --> 00:57:36.240
Erik Brynjolfsson: more creative and more interpersonal, which I think is mostly good news because most people probably prefer those kinds of tasks.

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00:57:36.720 --> 00:57:48.420
Erik Brynjolfsson: It also involves a lot more cooperation and interaction, because as I showed, we found no, no place where machines could just run the table and do everything that a human was doing in any given occupation. Instead,

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00:57:49.020 --> 00:57:56.760
Erik Brynjolfsson: as several of the other speakers pointed out, there are opportunities for humans and machines to interact and and do more than either one of them could have separately.

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00:57:58.710 --> 00:58:01.200
Willie Pearson: Nancy C, can you speak to part of that as well?

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00:58:03.480 --> 00:58:16.110

Nancy Cooke: Yeah, I mean, I agree with what Eric was saying. And I think the future of work, there will be work for humans. It will be a different kind of work. And one of our projects where we're looking at the future of work though, interestingly, we find out that

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00:58:17.910 --> 00:58:32.490
Nancy Cooke: Many humans prefer repetitive mundane tasks that machines are taking. They don't really want to do the the deep thought kind of work. So that is one kind of barrier to to finding

372
00:58:33.870 --> 00:58:44.700
Nancy Cooke: To re-skilling the workforce and having them engage with with the AI and with the robots in ways that maybe are foreign to them, they do not like.

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00:58:47.370 --> 00:58:59.370
Nancy Cooke: I think this is so, I mean we are already there. And also we're already teaming with AI, and if you want to know what the future of work is, I think the future of work is now, it's what we're doing right now. We're

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00:59:00.030 --> 00:59:11.820
Nancy Cooke: teaming over um, we're teaming virtually, and I think that's also going to play a big role in the future of work. I think more and more, work will be done like this, unfortunately.

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00:59:14.280 --> 00:59:18.810
Willie Pearson: Rob, there are a couple more global questions. One has to do with the

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00:59:20.040 --> 00:59:32.190
Willie Pearson: CS + X program and that kind of curricular approach. And so one question is, have those particular programs been rigorously evaluated by third party?

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00:59:36.060 --> 00:59:47.130
Nancy Amato: So, some of these are still quite early, right? So, in many cases, we're having, so for most of the new ones, we're having our first graduates come through now.

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00:59:47.700 --> 01:00:03.570
Nancy Amato: And we're just enrolling like the first class of freshmen now. Some of them have been going on for a long time, like the math and statistics and computer science ones, but these are, you know, this is I think one of the areas for potential collaboration for us to really work together.

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01:00:04.800 --> 01:00:11.580
Nancy Amato: Most of the ones, and here, Rob actually knows more than I do. I think that, but many of our, our

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01:00:12.000 --> 01:00:28.200
Nancy Amato: Programs really have been, we haven't designed that many new courses that are specifically for the students in these blended majors. We've been trying to identify the courses that we've already got and kind of put together them in a,

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01:00:28.860 --> 01:00:37.050
Nancy Amato: The right kind of major, but I think that, you know, this is something we really need to. And I think it's exciting thing to do in the future.

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01:00:37.800 --> 01:00:44.100
Willie Pearson: Related question had to do with, is the curriculum informed by people in education on your campus?

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01:00:46.380 --> 01:00:46.830
Nancy Amato: In?

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01:00:47.340 --> 01:00:48.300
Willie Pearson: In terms of pedagogy?

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01:00:49.230 --> 01:01:01.830
Nancy Amato: Well, we have our, our, many of our faculty, in fact, our researchers in computer science education, and they work together with colleagues in the College of Education. So I would say yes.

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01:01:02.820 --> 01:01:13.140
Nancy Amato: This is true both for our, you know, playing what's called "playing" computer science courses as well as these new courses we're trying to put together.

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01:01:14.400 --> 01:01:24.480
Nancy Amato: Okay. In fact, computer science education is emerging as its own discipline like and we are, we're building this up as a research area in our department.

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01:01:25.440 --> 01:01:28.560
Willie Pearson: You know, another global question has to do with the

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01:01:30.000 --> 01:01:42.840
Willie Pearson: Reproduction of inequities in terms of jobs, workers, and specifically dealing with people of color who are already underrepresented in the fields, but also some women in their social class issues.

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01:01:43.350 --> 01:01:52.020
Willie Pearson: So I guess one of the questions that came up in the chat was, will these particular new types of jobs and new types of work

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01:01:52.440 --> 01:02:01.350
Willie Pearson: To simply reproduce where that the same people who are disenfranchised now will continue to be disenfranchised and the future and what some of the chat

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01:02:01.740 --> 01:02:11.580
Willie Pearson: Described as precarious positions. In other words, jobs that have very low probability of sustaining a decent wage and so forth and so on.

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01:02:18.960 --> 01:02:19.260
Willie Pearson: So,

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01:02:19.380 --> 01:02:23.250
Nancy Amato: I'm not quite sure what the question is there, but I would say that

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01:02:23.640 --> 01:02:30.240
Nancy Amato: Part of the reason why, you know, for example, we want to design more of these. Let's call them kind of on ramp

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01:02:31.200 --> 01:02:43.950
Nancy Amato: Programs is to provide more avenues for people from all areas and, particularly, you know, we're mostly one of my primary interests in starting this new bridging program is precisely to bring in

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01:02:44.490 --> 01:02:54.810
Nancy Amato: Opportunities for for students from diverse backgrounds all over. So that's, that's kind of our primary motivation for wanting to have this program be successful.

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01:02:55.320 --> 01:03:04.110
Nancy Amato: But one of the challenges I'm quite concerned about right now, frankly, is with COVID and you know the, we know that

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01:03:04.920 --> 01:03:08.820
Nancy Amato: Providing students a sense of community and that support system,

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01:03:09.150 --> 01:03:27.660
Nancy Amato: We, you know it's tough. And it's, it really did benefit from this interpersonal and this community building thing. And so my question is how are we going to be able to do this in this new way of being? For the first for the next year, I think this is a big challenge.

401
01:03:28.440 --> 01:03:29.640
Erik Brynjolfsson: And if I could build on that.

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01:03:30.660 --> 01:03:42.630
Erik Brynjolfsson: I see these tools as being incredibly powerful, but they are just that: they're tools, and that means it can be used in lots of different ways. I'm quite convinced there's no predetermined outcome in terms of

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01:03:43.140 --> 01:03:54.240
Erik Brynjolfsson: Which sets of people will be winners and losers, or how things will play out. I certainly see many examples of these technologies being used to amplify existing inequities and to

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01:03:54.870 --> 01:04:05.880
Erik Brynjolfsson: Multiply the effects of the types of discrimination that humans were already doing when you put them into a machine learning program that that replicates what the machines were doing, you're going to get more of it at warp speed.

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01:04:06.270 --> 01:04:10.200
Erik Brynjolfsson: But that's only one way to use it. You can also use these technologies

406
01:04:10.380 --> 01:04:12.060
Erik Brynjolfsson: To increase diversity to

407
01:04:12.630 --> 01:04:19.590
Erik Brynjolfsson: Enrich work, to, as Nancy was saying, have more people get an on ramp and and get education and skills.

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01:04:19.920 --> 01:04:32.490

Erik Brynjolfsson: I think these are very much choices. And one of the reasons I'm happy you guys are organizing this this workshop here is to keep that front and center that there are lots of different ways of applying it both in terms of research and in terms of

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01:04:33.690 --> 01:04:38.550
Erik Brynjolfsson: Managers and business executives who are adopting these technologies and

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01:04:39.600 --> 01:04:48.090
Erik Brynjolfsson: I'm hopeful that if we keep that front and center, we will use these technologies to create not just more prosperity, but more widely shared and inclusive prosperity.

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01:04:48.480 --> 01:04:52.170
Willie Pearson: Okay, thank you. Rob, you have some other questions before we go on?

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01:04:52.890 --> 01:04:53.940
Rob Rutenbar: Sure, um,

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01:04:54.960 --> 01:04:55.950
Rob Rutenbar: There were a couple of

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01:04:57.480 --> 01:05:03.090
Rob Rutenbar: Granular CS + X questions that I thought might be interesting. Um, so um

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01:05:04.290 --> 01:05:05.130
Rob Rutenbar: So from

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01:05:06.990 --> 01:05:16.470
Rob Rutenbar: One correspondent: "I appreciate this type of curriculum design at my technical university. We are ramping up a program like this CS + X

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01:05:18.210 --> 01:05:25.050
Rob Rutenbar: Idea informed by other CS and informed by other fields, but one major issue is that technical universities like mine do not have funding

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01:05:25.530 --> 01:05:28.650
Rob Rutenbar: And are not investing in the humanities and social sciences infrastructure.

419
01:05:29.130 --> 01:05:35.430
Rob Rutenbar: And I'm concerned with austerity, this will get worse and at under-resourced places, become a way to rhetorically integrate humanistic concerns

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01:05:35.760 --> 01:05:44.250
Rob Rutenbar: while actually shifting focus away from current spaces for Humanities Research and tech institutions." So this is sort of a, Can CS + X crowd out X

421
01:05:45.420 --> 01:05:47.190
Rob Rutenbar: Because CS + X sounds cooler?

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01:05:49.860 --> 01:05:55.590
Rob Rutenbar: That would be terrible. A terrible, terrible outcome for CS + X, but Nancy. Nancy, what do you think?

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01:05:57.810 --> 01:06:15.810
Nancy Amato: Well, one thing, and Rob you, you probably have experienced this, you know, from the beginning, one thing that I find really exciting here at the University of Illinois is the CS + X program is exciting for everyone. It provides a way to

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01:06:16.980 --> 01:06:25.200
Nancy Amato: Provide commu- competing education to more students on campus. Many more than we could serve as computer scientists alone.

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01:06:25.830 --> 01:06:37.320
Nancy Amato: But it also is giving kind of a breath of fresh excitement to some of these other majors that were were concerned about this, you know, and it is a way for them to get

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01:06:38.040 --> 01:06:43.050
Nancy Amato: You know, have more resources, they can hire more faculty if they can bring in more students

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01:06:43.380 --> 01:06:53.340
Nancy Amato: And it, it is important for their faculty's research as well. So I think overall, you know, as long as it's managed well, it's actually good for everyone.

428
01:06:54.090 --> 01:07:04.740

Nancy Amato: It helps spread so so let's just think about the load on a computer science department, a CS, a plain CS major is going to graduate taking more computer science courses than a CS + X

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01:07:05.280 --> 01:07:16.860
Nancy Amato: Major. So the, you know, we can have more majors if more of them are CS + X majors and offer them more opportunities. And then in the X department,

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01:07:17.250 --> 01:07:30.810
Nancy Amato: That's a way for them to also kind of share in the excitement and interest in computing. So I think if it's done well, it helps everyone. One thing here at the University of Illinois that

431
01:07:32.190 --> 01:07:43.710
Nancy Amato: I don't think has come up, that we didn't talk about yet is all of the Xs are not in engineering. There is not a Computer Science + Mechanical Engineering or Computer Science +, you know, Civil Engineering yet.

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01:07:44.760 --> 01:07:53.940
Nancy Amato: One of the reasons for that is because these engineering degrees have these kind of accreditation concerns and they're worried about, oh, they won't be ABET accredited

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01:07:54.270 --> 01:08:05.940
Nancy Amato: if they, you know, this will be a new nightmare. But in talking with some of the department heads here in engineering, they're actually very interested in in starting these types of programs too.

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01:08:06.270 --> 01:08:19.560
Nancy Amato: And they are thinking, well, that we won't worry about those new programs getting that same formal accreditation as like our regular civil engineering degree. So I think they have the potential to really enrich everyone.

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01:08:20.910 --> 01:08:30.090
Rob Rutenbar: Yeah. Interestingly enough, it was easier to work through all the regular- regulatory approval things for Xs far away from engineering.

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01:08:31.860 --> 01:08:34.920
Rob Rutenbar: And I, I, I, when I always used to tell this anecdote.

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01:08:36.660 --> 01:08:43.380

Rob Rutenbar: The program generates, has generated a lot of excitement on the Illinois campus and there was a point at which we started asking people to sort of

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01:08:44.670 --> 01:08:53.820
Rob Rutenbar: fill out an application, sort of a proposal. Like, like, like getting into grad school, like, you know, why do you want to be an X? because we just needed to know that people were serious.

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01:08:54.900 --> 01:09:04.170
Rob Rutenbar: And and we're being thoughtful about what the organic connection between CS and X, plus, and the single best proposal for being CS + X was the philosophy department.

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01:09:05.640 --> 01:09:21.420
Rob Rutenbar: Right. And in hindsight, it's like duh! You know, those guys are those guys are designed to argue and convince and it was just, it was brilliant. And it was compelling and you know I mean like, they literally said to, like, hey Turing, remember us? Bull, remember us?

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01:09:22.530 --> 01:09:28.590
Rob Rutenbar: Ethics, hello! You know, and, and, you know, and so they are there, they are there, they are represented. So

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01:09:29.070 --> 01:09:38.820
Rob Rutenbar: Um, it's also the case, at least for the Illinois experiment that there are departments on the Humanities and Social Sciences side that had seen declining enrollments that have seen organic growth.

443
01:09:39.630 --> 01:09:51.180
Rob Rutenbar: Right? And there are, there are, there are departments where 10%, 20%, 30% of the underground population are now CS + X, and they they have some really serious existential concerns

444
01:09:51.630 --> 01:10:01.170
Rob Rutenbar: prior to this, so I, you know, I would, I would, It would be a horrible thing if CS + X was, was just some some optics to get rid of X.

445
01:10:02.490 --> 01:10:12.930
Rob Rutenbar: That would be, that would be a dreadful, dreadful outcome. What was always exciting about the CS + X stuff was authentically, energetically interested X people who said, yeah, we'd love to talk to you guys.

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01:10:17.430 --> 01:10:19.440
Rob Rutenbar: Okay Willie, want to pick some more questions?

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01:10:19.980 --> 01:10:23.820
Willie Pearson: Yeah, I'll take a couple more. There's

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01:10:25.470 --> 01:10:47.700
Willie Pearson: I think one in particular that we might need to address that we haven't really talked about that much. And here's one of the questions, and this for Nancy and Sharla. And the question is, how does your data differentiate between Cs and data science training? Are these collapse in your analysis?

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01:10:53.580 --> 01:11:11.730
Sharla Alegria: I can probably speak to that pretty quickly, actually, um, I, I interviewed um, tech workers and paid attention to where they came from. Many of them had two degrees and training in Computer Science, Engineering, or Mathematics that was uh, through a CS route.

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01:11:12.900 --> 01:11:15.930
Sharla Alegria: And others entered some other way.

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01:11:18.060 --> 01:11:26.970
Sharla Alegria: Certainly a few through computational social science pathway or something like that, because the most I was interviewing hadn't really had that opportunity when they were in school.

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01:11:27.960 --> 01:11:34.620
Sharla Alegria: But several of them came through different kind of one off training programs and it really seemed like that for the folks that were really be able to get into

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01:11:34.920 --> 01:11:44.820
Sharla Alegria: like software programming development engineering positions, there were folks that you know, had a degree in Japanese literature from, you know, a flagship university.

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01:11:45.960 --> 01:11:50.610
Sharla Alegria: And, you know, kind of looks the part already. And then for the folks that didn't already look the part

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01:11:51.330 --> 01:12:02.670

Sharla Alegria: That I interviewed, they were mostly in like, Help Desk positions. Right? So they had taken every certificate program that was offered through their local community training center and

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01:12:03.270 --> 01:12:10.140
Sharla Alegria: had spent nine years in a contingent position doing help desk work in that. And those training programs were not moving them in any way.

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01:12:11.430 --> 01:12:11.730
But

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01:12:13.530 --> 01:12:28.770
Nancy Amato: So I can say at Illinois, they are di- quite different actually. So that the CS + X really is computing. This, the students that graduate through this, they have that computing and computer science, you know, background. They can code.

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01:12:30.420 --> 01:12:38.640
Nancy Amato: The we're working on, actually, and will should be happening in this coming academic year, a new program that's called data science, I mean

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01:12:39.150 --> 01:12:47.940
Nancy Amato: X + data science. So it's so the CS + X, CS + X, now we're kind of, there's three departments that are working together, actually four I would say, but

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01:12:48.210 --> 01:12:59.580
Nancy Amato: Computer science, math and statistics. We're working to design, together with iSchool also, some courses that would form the kind of the foundation, the core of a data science curriculum.

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01:12:59.910 --> 01:13:14.160
Nancy Amato: And then other you know departments will then kind of make their, their X + data science as a new major and it's it's modeled in some sense pa- like the CS + X, but it's putting the the main discipline first.

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01:13:14.460 --> 01:13:29.880
Nancy Amato: And these I'm very excited to see how these work out but they, you know, we really are trying to distinguish the data science and computer science as separate, you know, separate tracks with different kind of key competencies

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01:13:33.240 --> 01:13:34.500
Willie Pearson: Hey Rob, you have another one?

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01:13:36.090 --> 01:13:51.120
Rob Rutenbar: Sure. So there was a, I think a broad abroad question. Um, how do hum- so that sort of popping back up above the CS + X stuff. Um, how do human teams that rely on a command- control structure translate to machines?

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01:13:54.510 --> 01:13:55.290
Rob Rutenbar: So this is maybe Nancy?

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01:13:55.380 --> 01:13:56.640
Nancy Cooke: Yeah, so

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01:13:57.930 --> 01:13:58.410
Nancy Cooke: In our

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01:13:59.910 --> 01:14:04.860
Nancy Cooke: Unmanned Aerial system ground control task, it's a miniature command -control structure.

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01:14:06.360 --> 01:14:12.600
Nancy Cooke: We have, this is doing exactly what I said not to do, we have an agent in place of the

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01:14:13.800 --> 01:14:21.870
Nancy Cooke: The air vehicle operator or the pilot communicating in a command-control way with the payload operator and with the navigator

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01:14:23.280 --> 01:14:32.430
Nancy Cooke: It's doing what I suggested you don't do because we're kind of replicating the human, but in this case, we're working with the Air Force is interested in using these as

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01:14:33.240 --> 01:14:44.100
Nancy Cooke: training systems so you can get your team training anytime, anywhere by hooking up to the internet and and training with these agents. But that said,

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01:14:45.540 --> 01:14:47.250
Nancy Cooke: I think one of the important things about

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01:14:48.480 --> 01:15:00.870
Nancy Cooke: Control and these agents, is that having done on a team does not mean that we have no control over them. And I know there's a lot of talk about autonomy, but I firmly believe that

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01:15:01.590 --> 01:15:09.900
Nancy Cooke: We, the human needs to be in charge here and there's no reason that you can't have a team where you have different levels of control.

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01:15:10.560 --> 01:15:20.100
Nancy Cooke: There's maybe a team leader who is in control of the other. So I think command-control is a good example of that, where we don't want to see to control to

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01:15:21.300 --> 01:15:26.310
Nancy Cooke: AI agent or robot. Not sure if that answers the question, but

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01:15:27.870 --> 01:15:29.160
Nancy Cooke: I think it's an interesting question.

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01:15:29.220 --> 01:15:32.970
Rob Rutenbar: per user. These are all hard questions and interesting questions so

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01:15:33.420 --> 01:15:47.790
Willie Pearson: There, there's another one and quote, "if you are trying to just do solve-compute-design, the impact and vulnerabilities/inequities are often considered out of scope.

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01:15:48.840 --> 01:15:52.830
Willie Pearson: How do you get CS people to become more comfortable being vocal?"

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01:15:55.980 --> 01:16:03.030
Erik Brynjolfsson: I think that's a really important question. I have talked to some very prominent CS people, AI folks who who

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01:16:03.630 --> 01:16:16.620
Erik Brynjolfsson: Had the attitude that their job was just to make the tools and the impacts were not, were beyond the scope of what they should worry about. And that's the philosophy I strongly disagree with. Some people

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01:16:18.510 --> 01:16:25.920
Erik Brynjolfsson: mock it as saying, you know, our job is to send the missiles up, where they land is someone else's department. And I don't think we should have that kind of an attitude.

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01:16:26.670 --> 01:16:36.270
Erik Brynjolfsson: The way that you design the systems can have a profound effect on the kinds of outcomes that occur and that should always be considered in scope.

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01:16:36.690 --> 01:16:45.450
Erik Brynjolfsson: The performance metrics should not just include, you know, profit and loss or productivity and revenue of metrics, but a broader set of values and goals.

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01:16:45.810 --> 01:16:49.170
Erik Brynjolfsson: And I think, as I said earlier, as we get more and more powerful tools,

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01:16:49.800 --> 01:17:00.750
Erik Brynjolfsson: by definition, that means we have more power to change the world. And I think, by definition, that also means that our values are proportionally more important. So one of the things I like

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01:17:01.260 --> 01:17:09.630
Erik Brynjolfsson: That I'm seeing the past few years is bringing ethics and values much more, not just in CS, but all of engineering and economics and other fields

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01:17:09.960 --> 01:17:20.370
Erik Brynjolfsson: To a much greater extent than the past. And I think that's a natural consequence of the fact that these tools are having first order effects on our society in our economy, and

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01:17:20.730 --> 01:17:31.740
Erik Brynjolfsson: The people who designed them need to have those consequences top of mind in our, in our training, our courses, and should be part of lifelong learning for people who are already in the workforce.

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01:17:34.560 --> 01:17:48.780
Sharla Alegria: Sorry, can I jump in here as well? I think that there's a structural problem where it's possible to, you know, design technology, feel like we've solved a problem, and release into the world official recognition software protocol or whatever, that's

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01:17:49.170 --> 01:17:56.760
Sharla Alegria: Not going to recognize dark skinned faces. And if you need to open a door or phone or whatever it is to do that, then you haven't actually solved the problem.

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01:17:57.060 --> 01:18:03.360
Sharla Alegria: But we seem to keep seeing these things get released anyway. Right? And so I think there's, there's, like, well,

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01:18:03.840 --> 01:18:11.070
Sharla Alegria: Part of the problem is how we define the scope right in the first place. So if it's not going to work for all the people then maybe you haven't solved it in the first place.

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01:18:11.820 --> 01:18:21.510
Sharla Alegria: But then the other piece of this is that the structure of work actually makes it hard for people to speak up. So if you know if we've got some folks who are on the back end, you know, coding their way through

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01:18:21.810 --> 01:18:32.370
Sharla Alegria: A certain set of, a certain set of tasks that aren't linked up with the design on the other side, then it's really hard to even know when the work is done, and especially if there's a

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01:18:32.730 --> 01:18:42.210
Sharla Alegria: release schedule that needs to be met, there's not even time for that. Right? And so I think part of it is is how we define the scope of the work that needs to be done in the first place.

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01:18:48.990 --> 01:19:00.240
Willie Pearson: We have another question. And this one is actually kind of directed towards Nancy Amato, and the question refers to, I guess, the first part of your talk.

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01:19:00.750 --> 01:19:08.220
Willie Pearson: Using a systematic approach based upon what values and goods? Is this for business interests? Skill development?

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01:19:08.940 --> 01:19:23.370
Willie Pearson: And the person quotes, "I am concerned about embedded assumptions. There is a growth in CS majors and gaps in reaching men and women of color. This gap is quite serious. Would you respond to that please, or anyone else?

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01:19:26.670 --> 01:19:31.290
Nancy Amato: I guess I'm not quite certain I understand the question.

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01:19:32.670 --> 01:19:38.940
Willie Pearson: I think what the person is saying that maybe you've mentioned about using a systematic approach to

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01:19:40.050 --> 01:19:43.410
Willie Pearson: Your program. And so what the person is asking

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01:19:44.460 --> 01:19:53.310
Willie Pearson: What assumptions do you base it on? Whose values, what goals is the interest of that program directed towards? Business interests, skill development?

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01:19:53.640 --> 01:19:56.340
Nancy Amato: Maybe the- the new program we're starting is maybe what they're

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01:19:56.880 --> 01:19:57.330
Nancy Amato: Going to

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01:19:57.690 --> 01:20:13.800
Willie Pearson: The issue is the overall issue is, there is the growth in CS majors and gaps in reaching men and women of color, in other words, is still under-represented and so the bottom line here is that the person is concerned about this gap that remains.

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01:20:15.450 --> 01:20:27.720
Nancy Amato: We are too, very much so. I think we have been, that as a field computer scientists have been very concerned about this over the years and have been working hard.

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01:20:28.290 --> 01:20:45.810
Nancy Amato: And I would say many computer science programs have made some measurable progress in improving the gender balance in undergraduate programs. But frankly, if you look at the participation of underrepresented minorities and other you know

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01:20:47.430 --> 01:20:53.460
Nancy Amato: People with disabilities, etc. and in our graduate programs, we're not where we want to be at all. So,

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01:20:54.450 --> 01:21:07.350
Nancy Amato: And the, the pressure, the enrollment pressure on the programs has the potential to make that even worse. That's why I think it's, you know, imperative that when we're designing these new programs,

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01:21:07.770 --> 01:21:16.110
Nancy Amato: That we keep this in mind, and we want to provide multiple pathways into the field so that we can provide these opportunities to everyone.

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01:21:16.920 --> 01:21:30.000
Nancy Amato: This, this new program that, this new bridging program that we're developing that's designed for students who already have an undergraduate degree, but not in computing, that's our primary motivation frankly of wanting to

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01:21:30.630 --> 01:21:39.510
Nancy Amato: Build this program and we are working, you know, with everyone that we can to try to do a good job. And I think that

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01:21:39.870 --> 01:21:56.370
Nancy Amato: This is the kind of program that part of, you know, partnering with people, for example, from SBE can help us do a better job with this. But i think it's it's a concern. I wouldn't say anyone would say we have solved this problem. And we're worried about it getting worse.

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01:21:56.700 --> 01:21:58.110
Willie Pearson: Okay. Thank you. Rob?

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01:21:58.560 --> 01:22:01.620
Erik Brynjolfsson: Me to say something brief about that, which is that

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01:22:02.160 --> 01:22:11.910
Erik Brynjolfsson: There are lots of examples of this actually is getting worse as some of the especially the machine learning systems that use historical data and they just replicate and amplify it

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01:22:12.210 --> 01:22:24.450
Erik Brynjolfsson: But I don't think that's at all inherent in the technology. In fact, I'm kind of optimistic machine learning systems can do better than humans. It's very hard to keep people from having implicit

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01:22:24.780 --> 01:22:33.630

Erik Brynjolfsson: Bias and people, there are a lot of programs to try to address that. Machine learning systems, to the extent that they are reproducible and they can be audited,

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01:22:33.960 --> 01:22:38.940
Erik Brynjolfsson: Um, you can go in and see how they behave on different kinds of data sets and

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01:22:39.390 --> 01:22:47.880
Erik Brynjolfsson: build systems that are less biased in different dimensions. I don't think they'll ever be perfect on all dimensions. In fact, mathematically, it can be shown that

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01:22:48.090 --> 01:22:56.610
Erik Brynjolfsson: You can't simultaneously solve all different kinds of criteria that you'd like to solve at the same time, but they are something you can explicitly model and reproduce in a way that

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01:22:57.060 --> 01:23:05.250
Erik Brynjolfsson: Ultimately, these systems can be more fair than some of the ways we currently, say, do loan systems or hiring or parole systems or medical systems.

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01:23:06.360 --> 01:23:06.720
Willie Pearson: Thank you.

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01:23:07.050 --> 01:23:15.360
Nancy Amato: That's actually a great point on that Eric mentioned that I kind of wanted to follow up on is one of our challenges is admissions right. We have, you know,

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01:23:15.660 --> 01:23:31.440
Nancy Amato: Tons of applications and we, how do we make to try to identify who we're going to allow into our programs. So this is some place where we can try to use machine learning to help make sure that we don't you know

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01:23:32.460 --> 01:23:37.590
Nancy Amato: You know propagate these biases. Or our graduate programs, you know, this year we

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01:23:38.010 --> 01:23:49.560
Nancy Amato: Tried some really hard work to improve the way that we did our graduate admissions and I think bringing in place machine learning to help us, not to make the decisions for us, but to help us

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01:23:49.980 --> 01:23:58.440
Nancy Amato: Not miss those qualified applicants that would be able to succeed is simply is, is a direction where we might be able to make progress.

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01:23:59.610 --> 01:24:00.090
Willie Pearson: Rob?

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01:24:02.160 --> 01:24:18.990
Rob Rutenbar: Yeah, I'll do a partial answer and then I'll do another one. One of the, you know, I'm echoing what at what Nancy said one of the aspirational ideas of CS + X is you got the opportunity to go connect with X departments who may have just a very different historical demographics

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01:24:20.040 --> 01:24:22.590
Rob Rutenbar: Than than than a STEM disciplines, so

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01:24:23.610 --> 01:24:39.450
Rob Rutenbar: There is a CS + Chemistry degree. The chemists look a lot like the engineers, right? That diversity is about the same. Um, there's a CS + advertising degree, the advertising department is 1/6 African American. There's amazing, amazing different

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01:24:42.120 --> 01:24:53.790
Rob Rutenbar: Demographics and they're a very interesting unit because they're sort of half a social science department, you know, sociology, psychology, anthropology,

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01:24:54.450 --> 01:25:03.810
Rob Rutenbar: You know, and half a department that wants to do data, right, to be able to manage those kinds of problems. And what's just very interesting is that

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01:25:04.320 --> 01:25:15.960
Rob Rutenbar: That aspiration has not sort of shown up in the numbers yet right for the way the demographics are working out, which is just a super interesting question, which is, when Nancy showed showed all those, you know, showed the the

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01:25:16.530 --> 01:25:23.910
Rob Rutenbar: Spreadsheet and those those pie charts. So, you know, definitely need some more work there. Let me, let me read a broader question.

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01:25:24.810 --> 01:25:35.520
Rob Rutenbar: So question for all panelists: Eric started this panel by suggesting that machine learning is likely disproportionately threatens low wage jobs. Sharla and

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01:25:35.910 --> 01:25:52.560
Rob Rutenbar: Nancy argued that we have to value and build diversity and the technical workforce, but aren't these two things mutually exclusive in important ways? If we consider class diversity as valuable and desirable, how do we include the role of low-wage/high-tech labor in these conversations?

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01:25:58.710 --> 01:25:59.550
Rob Rutenbar: A tough question!

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01:25:59.910 --> 01:26:01.140
Rob Rutenbar: Yep. Yeah.

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01:26:02.100 --> 01:26:06.630
Erik Brynjolfsson: I'll start. It is a tough question. I don't think that they're they're mutually

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01:26:07.740 --> 01:26:24.240
Erik Brynjolfsson: Exclusive or contradictory. There are certain tasks that machines can do better. But humans are incredibly diverse and have multiple different kinds of skills and capabilities and we haven't come close to tapping into the full potential of most people.

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01:26:25.440 --> 01:26:39.390
Erik Brynjolfsson: You know, maybe I'm biased because of the industry I'm in, but I think that the first thing I put on my list of ways to to address that is education that we could do a lot more to invest in education across the board from K-12 colleges, lifelong learning.

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01:26:40.470 --> 01:26:46.770
Erik Brynjolfsson: And give people the kinds of skills that are increasingly in demand. They're not just creative

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01:26:47.790 --> 01:26:52.440
Erik Brynjolfsson: Skills. They're also interpersonal skills as I mentioned earlier, and our

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01:26:52.770 --> 01:27:06.120

Erik Brynjolfsson: Education for most of the 20th century was not, was geared actually to the opposite. It was geared towards getting people to sit quietly in rows of desks and follow instructions and memorize facts. All the things that we know now machines can do pretty well so

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01:27:06.900 --> 01:27:12.780
Erik Brynjolfsson: it uh. On the other hand if, you know, if you put a piece of paper and a pen or pile of blocks in front of a three year old,

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01:27:13.050 --> 01:27:20.040
Erik Brynjolfsson: The first thing they're going to start doing is something creative. Kid, humans love being creative. They love playing. They love interacting with other people. They love teamwork.

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01:27:20.760 --> 01:27:24.480
Erik Brynjolfsson: So I think that there's a huge amount of untapped potential that we've been

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01:27:25.320 --> 01:27:33.510
Erik Brynjolfsson: Actually intentionally quashing out of people to make them more suitable for 20th century technology, but with 21st century technology, I think if we let

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01:27:34.140 --> 01:27:44.220
Erik Brynjolfsson: Those kinds of personal interactions and creativity flourish, we'll have lots of people who can do lots of the kinds of tasks that are going to be needed going forward.

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01:27:48.030 --> 01:27:48.330
Rob Rutenbar: Okay.

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01:27:49.650 --> 01:27:51.510
Rob Rutenbar: Other other responses from anybody?

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01:27:52.050 --> 01:27:55.350
Sharla Alegria: So I think I can jump in here. I think that

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01:27:57.060 --> 01:28:05.910
Sharla Alegria: There are a variety of things that I like worry about in this landscape and low-wage/high-tech work is, you know, I think that

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01:28:06.810 --> 01:28:18.930
Sharla Alegria: Considering the increasing demands for continued skill building, we really need to think about alternative pathways into

technical jobs and those might actually look like low wage technical jobs.

561
01:28:19.260 --> 01:28:33.450
Sharla Alegria: But I'm honestly like concerned more not about like, you know, the future of work, meaning jobs, you can go away. But actually, that it's making, making low-wage work more invisible right so we still need, as Eric was pointing out, like care work.

562
01:28:34.110 --> 01:28:42.660
Sharla Alegria: Particularly especially care work that we tend to associate with women's labor isn't going to go away. But we found ways to make it less visible and also

563
01:28:43.470 --> 01:28:55.170
Sharla Alegria: Through through platforms like task rabbit and Instacart right and and and and to pay people less for doing it. And we're also finding ways I think of making work that we think of as well paid

564
01:28:56.130 --> 01:29:07.620
Sharla Alegria: Less rewarded right by through the, through these kinds of platforms, too. So I think that when we think about diversity and team building, we need to think about teams that have

565
01:29:08.640 --> 01:29:17.190
Sharla Alegria: A variety of disciplinary backgrounds, and that includes folks that maybe didn't get on to these onto these teams through the traditional education pathways.

566
01:29:22.260 --> 01:29:22.890
Rob Rutenbar: I think we're out of time

567
01:29:23.430 --> 01:29:23.910
Willie Pearson: Time's up.

568
01:29:24.450 --> 01:29:39.330
Rob Rutenbar: for this section. Yeah. Okay. Um, big, big thank you to all for all four of the great speakers for for their for their time and their prep and their willingness to be here and answer tough questions. Interesting questions, um,

569
01:29:40.350 --> 01:29:43.470
Rob Rutenbar: So I think we're turning this back over to

570

01:29:45.000 --> 01:29:49.920
Rob Rutenbar: Beth and and and also the leadership from the CISE and SBE directorates

571
01:29:50.610 --> 01:29:51.390
Erik Brynjolfsson: Yes, thank you very much!