Computational Social Science: where are we now?

Mark Elliot
Good afternoon, and welcome to day four of the research methods e-festival. I'm really pleased to be introducing our third keynote, Noshir Contractor. Noshir is professor of behavioural sciences at Northwestern University based in three different schools, the McCormick School of Engineering and Applied Science, the School of Communication and the Kellogg School of Management. That threefold affiliation reflects Noshir's truly interdisciplinary contribution. Indeed, it's no overstatement to say that he's been at the forefront of three emerging interdisciplines: network science, computational social science, and web science. He has received many awards and accolades in his career, for example, the prestigious US National Communication Association Distinguished Scholar Award, honouring a lifetime of scholarly achievement in the study of human communication. In 2015, he received the title of International Communication Association fellow, in recognition of a distinguished scholarly contributions to the broad field of communication, and he's now president elect of the same International Communication Association. He's published more than 250 research papers representing a substantial body of work on communication networks. Fundamentally, Noshir expresses a passionate interest in how social and knowledge networks form and perform in domains including business, scientific communities, health care, and space travel. And his talk today will cover all this and more. So over to you Noshir.

Noshir Contractor
I am delighted to be joining you at the Research Methods e-festival organised by the National Centre for Research Methods in the United Kingdom. My name is Noshir Contractor and the longest sort of title, title of my talk is 'reimagining theories and methods to understand and enable the algorithmically infused changing nature of work'. Or the shorter title that Mark Elliott gave me 'Computational social science: where are we now?' I'm going to put this in the context of technology and the changing nature of work. So while I'm going to talk about issues that are broadly based in the area of social computational social science, my specific focus here today is going to be looking at how it has changed the ways in which we understand the nature of work. And in particular, for example, how technologies have played an influential role in that respect.

If you go back to the 1990s, there has been a lot of recent technological developments that have come, starting with groupware, internet, social computing, clouding, crowdsourcing. And most recently, there has been a big spurt of interest in what is called as 'enterprise social media'. Enterprise social media was the late reckoning by folks in the enterprise that they should be bringing to the enterprise, the same kind of social media that was so popular outside the enterprise. So if we can have Facebook and Twitter and society, why can't we have similar platforms within the enterprise, and indeed, many such platforms have emerged in the last few years. Microsoft Teams Slack, JIRA, Jive, Trello, Zoom, which we're using at this very minute is another example of those kinds of platforms that are being used to be able to have impact that goes beyond direct email. And there are scholars who try to understand what is it that makes this different from email.

And one way of looking at it is in terms of technological affordances, that are provided by enterprise social media, for example, association, looking at something on a wall, when it's mentioned, as opposed to in a private IP email means that it helps reveal who knows who and who knows what within the organisation. It enhances evaluability because you're now able to evaluate other people's information for your recommendations, comments, liking or tagging. It increases visibility. So you can see how people have responded to questions raised by others. It, of course, enables persistence, which means that you can go back even if you were not happy in the conversation at the time it was happening, you can scroll back and look at what things were said when, and then personalization, which is it allows each person to present themselves in a way that they intend to so the front stage in urban governance, terminology is enabled and made much more customizable in this space.

And in addition to these five, there are a few more: editability, you now have the ability to go back and revise information others provide after they've shared it. You're also able to make this much more pervasive today, because of the fact that a lot of us are using social media on mobile devices, in addition to laptops, we have access to this information anywhere, wherever we might be. It increases awareness of the information and updates from other people you now know when they are finishing projects when they have passed certain milestones. It certainly increases sociability because along with preference, the prevalence of social media, it means that we are also going to experience what some would call an abundance of information, and others would call information overload. Sociability becomes very important in terms of getting that information. And then finally sharing the things that we do the most commonly, and that is create groups and channels on the fly for sharing information.

In addition to everything we're seeing with technological affordances, we are also seeing a new affordance that is coming into the workplace. And that's the algorithmic affordance. The algorithmic affordance is where in addition to technology is allowing us to do things in different ways than we had done previously. Now, the computer stops being just a tool or an assistant, but actually becomes an autonomous teammate, and in some cases, even our manager. These are algorithms that tell us what to do, when, so it starts with recommendations for example, and it is important as we begin to look at the changing nature of work, that we begin to anticipate how algorithmic affordances in addition to technological affordances are changing what is happening in the workplace.

As a way of, for citing this, my colleagues and I have written two articles in the past couple of years. In 2020, we wrote an article about the next generation of computational social science, the obstacles and the opportunities. This article was published in Science Magazine about 11 years after we published the first article titled 'Computational social science' in Science Magazine as well, which got a lot of interest and has served an important role in galvanising the community. This year, earlier this year, we also, a team of us also wrote an article specifically focusing on measuring algorithmically infused societies. And here we talk about the broader societal impacts of algorithmic infusion. Today's presentation is going to focus more in looking at it specifically in the workplace. What would be an example of this in the workplace? One example, as I alluded to a minute ago, would have to do with recommendations. We spend a lot of time in the workplace forming teams, either teams being self-assembled, or teams that are staffed by other people.

If you look at this on sort of two axes, the horizontal axis starts on the continuum on the left, where we as individuals go around searching for teammates. At the extreme right, on the horizontal axis, you see the algorithmic formation driven approaches where a computer is putting together recommendations that they are giving you about how to form teams or who to form teams with. Think of this as Match.com, or Tinder, except that it's not for dating, but it's to help put together teams rather than romantic couples. The vertical axis here refers to the ways in which the teams are formed. As I mentioned, some of it may be self assembled at the bottom. On the top, you have teams that are staffed. Staffed teams are typically the norm in the workplace. Self assembly is increasingly common in in the gig economy certainly has been true in academia when we form teams and collaborations. But the staffing of teams takes on even more importance, when you think about some of the more crucial efforts that staffing teams that we will touch on later on in this presentation. For example, deciding who would be the six members of an international crew who would be going on a three year mission to Mars, where there is no voluntary options of turnover or exit from the team along the ways. And so, forming the right team, in those situations becomes incredibly important and significant.

For example, some of the research that I'll talk about later on, but I'll just preview here, we know from previous work, that people like to form teams with other people who are competent. We know from prior research that people like to form teams with people like themselves, birds of a feather, such as gender. We know from previous research that people like to work with those they worked with previously, because of familiarity in the research. Now add to that mix the mystery algorithmic recommendation. And now the question becomes: to what extent are people willing to look at these recommendations and use those in in decisions about who to team with? And, just to complicate things a little bit? To what extent will those recommendations be significantly enhanced or not? If the recommendation is being made about someone that you have already previously worked with? And so these are some of the questions that we will answer later on in the... towards the end of today's presentation.

But back to what we were talking about at the broader level. I think what we're looking at here is that computational approaches, computational social science approaches and methods and theories are helping us to understand and enable what this nature of work would look like. To give you a few examples: we now have the ability to reimagine theories. And what do I mean by that: theories that we have not been able to test at scale. In social network analysis, we've had theories about brokerage, and its impact on upward mobility for decades now, but it was only, not until recently, where we were able to use the call graph data, the telephone pole data from all the United Kingdom, for example, to begin to see how we might be able to test these theories at scale, rather than simply in a single organisation, for instance. Another example is theories of contagion. Also, a social network theory, where we've known for a long time that theories of contagion would suggest that the extent, the extent to which in this case I exercise would be impacted by the exercising activities of those in my social network. But now with the access, with the ability and the availability of wearable devices. Sinan Aral and his colleague, Christos Nikolaidis, published this article in Nature Communications a few years ago, where they were not only able to prove that this exercise contagion model does impact our exercise, but they were able to go one step further. They were able to make more nuanced claims where they were able to identify that the extent to which I exercise more or less, is not as much driven by the person who is a little ahead of me in exercising, or, but is, in fact, driven more by the person who's right behind me. And so I'm more interested in making sure that the person behind me doesn't catch up with me. And I am motivated by a desire to catch up with the person who's a little ahead of me. These are the kinds of nuances that are easy to be able to explore potentially, by looking at large tracts of data of the kind that is available by the traces, digital traces of wearable devices that we use.

Other examples include working in areas where the theories that are focusing on attention on new or at least increasingly prevalent phenomena. Things like contagion and exercising going on forever. But more recently, there has been an interesting team assembly as I gave in the previous example, collective intelligence, the wisdom of crowds, there's been a lot of interest in this, we've had this for a long time, but this is becoming much more prevalent these days, and coming up with theories in that area. This article that appeared from by Richard Mann and Dirk Helbing, is an example of trying to understand the optimal incentives for collective intelligence. Yet other theories look to new ways of being able to look at variables that we had not looked at before. Today, we have the ability to be able to mesh together, blend together data that we collect from brain connectivity networks, dynamics, and combine that with social network dynamics. And so all of a sudden, you have the opportunity, as was taken upon by colleagues, Dr. Danielle Bassett, Jean Vettel, Emily Falk, and their collaborators and put together new theories of why we engage in certain social networking behaviours that are based upon our brain networks, and then in turn, how our brain networks themselves are being modified based upon what we pick up from our social networks.

Next, I want to talk about how we can reimagine methods. After all, that is indeed, the main topic of this e-festival. And one of the areas I want to talk about, as an example of how we are able to reimagine methods is networks as relational effects. Until relatively recently, when people were studying network dynamics, they were relying on what I would call 'panel forms of network', data collected at time one, time two, time three, and so on. But increasingly, what we began to see is that a lot of the data we're getting is network data that is collected by timestamps. So we know every single relational event as it is happening. A is sending a message to B at this time, C liking this post at this time. These are the kinds of relational events that we didn't have access to in the past. And therefore there was not very much need to develop methods to study data that we did not have. And then the moment we began to get more of this timestamp data largely from digital traces, that really spurred the social networks community, to think through new methods to be able to take advantage of these data. And elational event modelling is an example of that, which started out with, I remember just a panel or two at previous conferences that have now become burgeoned into dozens of panels at more recent social networks conference, the interest in relational events has really taken off. And I think a large part of that credit goes to the fact that we had the digital trace data, which you can think of as the tail that was wagging the dog, which was these new methods such as relational event methods.

Another recent development in methods that has been prompted by large scale data on teams in particular, is what is called as hypergraph methodology. Hypergraphs is not new. We've known of hypergraphs for decades, maybe even more than that. The idea of a hypergraph is based on the premise that if you have graphs, which are networks, which have edges, which are connecting two nodes at a time, hypergraphs have what are called as hyper edges. And hyper edges are not confined to collecting just two nodes at a time. Hyper edges could include one node, two node, three nodes, or phonons. Why is that interesting? Well, it becomes interesting to social sciences, because now all of a sudden, when you want to study teams, you realise that there is no simple way in network terms, in graph theory terms to identify a team of say, A, B, and C, by simply showing edges between A and B, B, and C and A and C, because what that network does not allow you to distinguish is whether this was one theme made up of three individuals, or three separate teams made up of say, A and B, B and C and A and C, which both would look the same in a network. Enter hyper edges and as you can see, on the right hand side, a hyperedge, E sub 1 can show by this colouring, the vertices participants in the team V1, V sub 2 and V sub 3, and then you see edge two, which is a team made up of only two vertices V sub 2 and V sub 3, and so on. So the bottom line here is that all of a sudden, there has been a renewed interest in hypergraph methodology because of the large amounts of digital trace data, which allow us to study teams at scale much more so than we did in the lab a few years ago.

Another place where we're beginning to see teams is when you see new methods is understanding teams through computational modelling, again, agent based modelling and computational modelling is not new, per se. But the interest in looking at these from a computational modelling point of view is now available because of the computational capabilities that we had that we didn't have a few years ago. And what that means is that we no longer have to rely only on building toy models, if you may, or intellective models as they are sometimes referred to where you come up with an idea, and then you come up with hypothetical data, you put in some relationships based on your intuition between why people engage in certain activities, and you run it. Now, because we have access to large amounts of computational infrastructure, we are able to actually calibrate these models not arbitrarily, but using empirical data. These models, unlike the intellectual models, that we talked about a minute ago, are referred to sometimes as emulator model. An emulator model is actually emulating real data. So the kind of work we've been doing, for example, in this case that I'll talk about later, is modelling crew relations on a simulated mission to Mars. And so you're the four astronauts, and we're trying to understand at any given moment, which astronaut has a positive effect towards another one, who thinks of the other as a hindrance, who has a good booking behavioural relationship with someone, and who is shares information with other people. And we're able to calibrate these data because we're collecting empirical data from the same crew members and use that to estimate and fit the model using behavioural search genetic algorithms in the process.

And then finally, we also have access to new methods of looking at data based upon machine learning techniques in machine translation, and so on. When I was a grad student back in the in the mid 1980s, empirically, sort of exploratory data was considered a little bit of a four letter word in some context, or at least in terms of exploratory data that people would then make inferential claims from. Because of the nature that you could see, for example, the factor analysis is like reading tea leaves at the bottom of a cup, you could squint your eyes and come up with all kinds of interpretation. I believe that that criticism is no longer valid, primarily because we have so much of data, that while we could still engage in reading tea leaves with some training data, we have the ability then, to make more causal inferences by seeing the extent to which those kinds of data are now able to be tested in in additional data, things that we did not have the luxury of doing in the past as much as we do now. And then of course, what that does also is it allows us to think about new ways in which we can be coming up with hypotheses. And by that I mean that in the past most of our hypotheses in the social sciences were driven by the logic of things like regression, or ANOVA, or time series analysis, or even exponential random graph models, for example in networks and stochastic actuarial models, in all of these models, we typically were saying things like, as A increases, B increases or decreases, interaction effects might happen. Or based on a certain variable, we might see differences in x and y's. Those are the kinds of logics that we've used that. But today, because of the kinds of new machine learning techniques that have gotten more attention, classifier algorithms, for example, what it allows us to do is to begin to take those kinds of findings we get from classifier algorithms, and turn them into hypothesis. I argue that that brings in Boolean logic, if then claims into our hypothesis testing much more front and centre than it has been in the past. And in addition to that, it allows for the fact that something that system theorists have believed for a long time, and that is the principle of equal finality, where a certain outcome is not just going to be driven by one set of antecedents, but could actually be accomplished. For example, an outcome like satisfaction could be accomplished by a variety of different combinations of variables, each of which provide equal final paths to the final outcome. And so these are again, important ways for us to be reimagining methods. I spent some time talking about theory, data and methods. And before I go into some empirical examples, I want to touch on a cautionary note that has been made about the fact that today, we are so reliant on certain types of data.

A common- a common cautionary note, is associated with this cartoon, which says that today, we are so hungry about getting data that we go and look at the data that we have, rather than the data that we might want to collect in order to test theories. Not unlike the drunken mαn who in this particular picture has lost the keys to his car, and is looking around everywhere for it, but decides that the best place to look for the key of the car is under the lamp. And when he was asked why he wants to look for the key under the lamp, he says 'Well, that's because that's where the light is', rather than where the key might have been in that particular case.

Today, we are criticised in some circles that some of our social media conferences in particular, are all focused so much on Twitter, to the point where some people say that we're not studying sociology, for example, but we are studying Twitterology. Now, I think that while that is a valid criticism, I would like to broaden that criticism and say it does not apply only to the data. It also applies to theory and methods, we sometimes get so locked into our existing theories or our existing methods, that we do not allow ourselves the luxury to ask questions that might require us to reimagine theories and reimagine methods. And I hope that the examples that I've given so far, will help us get more motivated to do exactly that. Now on to the specific examples that I want to talk about, and that's going to be in the area of what I call as 'People analytics'. So back in 2013, there was an article that was published that said how Google is using people analytics to completely reinvent HR, HR being human resources. And indeed, in the New York Times an article in 2016, talked about what Google learned from its quest to build a perfect team. New research reveals surprising truths about why some work groups thrive and others falter. What they spent two years doing was studying 180 teams, the most successful ones amongst them shared these five traits, first, among them, psychological safety, second, dependability, and so on. My main point here is that the ideas and the traits they came up with were all individual traits. I think we can do better than that. And so in- in conjunction with my colleague, Paul Leonetti, who is at UC Santa Barbara, we published this article in 2018, Harvard Business Review titled 'Better people analytics: measure who they know, not just who they are'. The basic message being social network analysis research over the decades has told us a lot about what we can know about what's happening in the workplace based on who they know, networks rather than who they are. The big challenge therefore, is why should we stick with people analytics only looking at individual trades and state data, when we should be combining attribute analytics with relational analytics, individual network data, team network data, organisation and this is where we wanted to move from attribute analytics to relational analytics.

The good news is that some of this data is now available much more easily. And we are able to look into these kinds of networks in ways that we were not able to do previously. This is not unlike what people do when they look into the brain. They have microscopes that go into the brain and are able to look at what are the differences in patterns between the brain of a control person in good health and how that might compare to the brain of somebody afflicted with schizophrenia, for example. In the case of work like this, they rely on microscopes. I argue that social networks, we don't need a microscope, we need a mɑcroscope. If we rely on a microscope and look into this pixelated image we don't see much. But as we begin to zoom out, there we are, just like the Henri Matisse's famous pointillist painting that you're looking at, we now have the ability to zoom out and see patterns in the networks in ways that we couldn't see previously. But where are these patterns coming from? They come from digital trace, they come from places where we could leverage digital trace data to better understand our organisations from the same enterprise social media platforms that I spoke to you about before. And this kind of data is only going to be increased.

Gartner said that the social software and collaboration revenue will double by 2023. They made this prediction before the pandemic. Turns out, we've already doubled it partly accelerated because of the pandemic. The activity networks I'm talking about are things when employees send messages to other people, when they send files to other people, they give badges, they thumbs up and like other people, they also in some cases, sending messages the old fashioned way. And as you look at this network, and you have that Microsoft, you can look at structural signatures. In the article in Harvard Business Review, we showcase six structural signatures that have been known to social network analysts for decades. So there's nothing new about this, it's just that now we have the ability to do something that social network researchers have not been able to do quite as effectively. And that is have access to a lot of relational trace data, digital trace data, the signature on the left talks about the ideation signature, the extent to which a person, if they have a network, where they're connecting to people who are not connected to each other, they have the ability to have the potential to come up with a lot of good ideas. If they connect to people who are connected to a lot of people, then they have the ability to influence the network, just like we know from PageRank algorithms that Google uses, or the other kinds of eigenvector centrality measures that people in social networks have been using for a very long time.

At the team level, we can talk about looking at the network to identify how likely a team is to be efficient. If members of the team are all getting along well with one another, have strong ties, this team is going to get this work done on time. But if you're interested not in the team getting its work done on time, but are they going to come up with innovative ideas, you need to come down here and look at the extent to which members of the team have links to people outside the team, when not connected to each other. Because it's that ability to tap into external resources that are distinct from one another amongst team members, that makes the team likely to be innovative. At the organisational level, you can zoom out and see the extent to which the team is siloed. The organisation is siloed, where you may have different departments where they're not talking to one another, or the extent to which the organisation is vulnerable to an external supplier or vendor that has connections to various people within the organisation who are not connected to each other. And therefore the person on the outside might have a competitive edge at being able to put together ideas that exist within the companies. But because these people within the companies are not connecting, they become vulnerable to this outside supplier taking their idea and running. How do we make this kind of signatures actionable?

At the organisational level, we can see how these kinds of signatures are going to help our recent efforts and building momentum in the area of diversity and inclusion. A lot of demographic data has already been collected and is being collected by corporations and organisations around the world. In order to help us measure more carefully the extent to which our organisations and workplaces in general is diverse. However, inclusion is a much tougher challenge. Inclusion is looking at the notion that not only do you have diverse people on the team, but to what extent are we engaging with the diverse individuals? To what extent are the diverse individuals engaging with us, and that is much better measured by looking at the Relationship Analytics, the extent to which in the back and forth of interaction, you see the extent to which these diverse individuals are engaging with one another.

A second example is an area of succession planning. Succession planning is typically relied on looking at people's resumes, knowing on a tacit where, how a person in the organisation or outside, comports themselves. But today, we have access to troves of digital trace data, where we can begin to more systematically inform our succession planning decisions by looking at the networks of the individuals and seeing to what extent those networks might have a bearing in helping them do the job to which you are hoping they will succeed.

And then finally, if you look at post-merger integration, it is well known that billions of dollars every year are being spent on mergers and acquisitions. It is also well known unfortunately, that many of these M&As don't go so well. And we submit that looking at networks amongst the two entities before the merger, or the acquisition, give us the ability to identify exactly the right individuals in these two entities, that might be brought together to help streamline and leverage more effectively the process of merger for the process of acquisition.

The next slide organises around how relational analytics can be actionable for teams. Unlike the previous slide, in this case, I'm not just going to give you hypothetical examples, I'm going to give you research that we have done with our collaborators from around the world, that have shown us how we have made relational analytics actionable for teams in the area of self assembly, in the area of team staffing, in terms of predicting team performance, as well as in predicting team conflict. As I said, it all starts with the fact that until recently, the social network insights have already been there. What was missing was a social network data. Survey data can be time consuming, it can get a low response rate and it can get obsolete pretty quickly, because people change their networks. So we began with the premise: what if we could have survey data at minimal cost with 100% response rate and data that was not obsolete because it was being updated 24/7?

Well, one way in which we can get this kind of survey data is if we could predict it, using enterprise social media. So this project that we did with our collaborators at Fudan University, as well as UC Santa

Barbara, was basically taking enterprise their social media data. Of the kind we have, yes, we collected data, this particular example that I'm going to give you was collected from 66 employees at a Chinese company that was using an enterprise social media platform, not unlike Slack, but similar to as you can see, and what we did was, we began to ask the question: could we take this digital trace data that we were collecting from them, in this case between in the month of April and May of 2019, more than a year before the pandemic, and see if we could use it to predict what people would say in a survey that we asked them to complete a month and a half later. Actually, just over a month later. And questions that we were asking them in the survey would be questions that are typically asked in organisational network analysis, you know, identify the person who provides you with a sense of purpose, who do you rely on for leadership, who do you go to for help or advice at work. And we used approaches like exponential random graph models to predict the probability that any hypothetical time will occur.

And as we did this modelling, we got some pretty interesting results. As we looked at the coefficients, conceptually, we could answer questions right, such as if an employee sends someone at least one message a day, they're 15.2% times more likely to say that that person provides them with a sense of purpose. Employees who spent 10% more messages than they received from them are 26.7 times more likely to say that a person provides them with a sense of purpose compared to a pair of people with an even split. Not only did we get these kinds of nuggets of insights, but if you look at the entire table, we get log odds ratios, and for all a variety of different patterns that all help us predict, along with the joy walk messaging, which is the name of the platform that we're using, ideas about how likely somebody is to list the other person as providing a sense of purpose. We repeated the same thing for 'who do you rely on for leadership'. Again, I'm not going to go through the details in the interest of time.

We did the same thing for 'who do you go to for help for advice'. Here again, we found some interesting insights along the lines we talked about. And then we took this model and said: how can we take this model and start predicting social relations? And so we were then now looking at these data, and essentially running this model that we had estimated in simulations and seeing the extent to which we could predict whether a tie that we said was not going to be there was also observed not to be there. And the extent to which we might have predicted a tie was there, was also then observed. As you can see from the accuracy we were at about 89.46%. But of course, that's a little misleading, because we need to look at precision and recall, on this particular plot, and depending on where you are on the plot, you can begin to see that we can have pretty high levels of precision and recall, depending on what special values we use to estimate whether a tie is or is not present, we did the same thing for relying on leadership, we did the same thing for advice of work.

We then used these to make things actionable by providing companies with a prototype dashboard that we call the relational analytics dashboard. Behind the dashboard is the ESM data that is being collected the digital freestate. That data then gets fed into the exponential random graph models that were estimated that I just showed you, and from that are predicted survey type. So what look, what the network you're looking at here, could have been collected in a survey, but was in fact predicted data from the enterprise social media data that were the digital trace data that had been sent through the exponential random graph, modelling prediction machine and we could use this then to learn more about an employee, to see where this person sits in the network, we can see whether this person is more or less likely to generate a good idea using the ideation signature that we showed in the Harvard

Business Review article, what is the risk of resignation, looking at the fact that when people are about to leave a company, they begin to shrink their networks, the ability to generate buying or influence, which was the influence signature that we talked about in the HBR article, and learn a lot more about different individuals and how they might be putting people into teams, for example.

There are lots of these I'm not going to go into great detail yet. But instead, I'm going to say we can look at designing high performance teams. But the next part I want to focus on is now that we know that we can take digital trace data, and we see that it's a fairly good proxy for survey data, not great, but a fairly good proxy for survey data, what can we do with that? This is an example of a study, we were trying to see to what extent we can understand how self assembled teams and self designed teams are modified by giving them a recommender system. Sometimes we have a dream team that looks like this. More often, we have a nightmare team that looks like this. We'd like to see what we can do to enhance the likelihood that you'd have a dream team. And so this is what I did with my former PhD student, Marlon Twyman, who's now a faculty member at the Annenberg School for Communication and Journalism at USC, Diego, who just finished, Diego Gómez-Zará, who just finished his dissertation year at Northwestern, has just started a postdoc at the Kellogg School of Management at Northwestern and will be joining the University of Notre Dame next year as an assistant professor, and my third former student, Jackie Young, who is now a postdoc at Harvard Business School.

So we were interested in looking at what happens to team formation, when instead of just getting no information, there's random team formation here that we try to see if we can give them more information but before they form a team. And the information we were going to give them was essentially the recommendation system that I've talked about before, my dream team recommendation. You go search for people, you go invite them, and they either respond to it. And so the idea then, in a situation like this was to try to understand who people were inviting into the network. So all we were asking here was how do people decide who to invite to their team in the modern organisational landscape. So what mechanisms explained the invitation process, who invites who. This is the kind of data we've not had before because trying to capture data, but who invited who on a team would be, would require us to get data before the team was assembled. And and accepting if we would ask them retrospectively who they invited and who turned them down, we wouldn't be able to study that process. Now we have the ability to do that, because we're able to get digital trace data of who they searched for, and who they then invited, and what responses people get to that invitation.

The data that I'm going to talk about here was collected from two universities assembling project teams. So this was data where the teams were being caught on at two universities. One was a class on environmental ecology, in one university, and another class on social psychology at a second university. They were asked to work on project teams together, each team was required to have members from both universities. The goal of the project was to simulate an advertising campaign to mitigate an environmental sustainability issue. Hence the fact that you had to have team members who were majoring in Environmental Ecology as well as team members majoring in Social Psychology. They were given a week to using the My Dream Team platform that I mentioned earlier to assemble into these teams.

We had 213 participants in the first sample that we did one year and then 197 participants in the second year sample two which assembled into 31 teams. As I said, the platform we used was My Dream Team that I mentioned to you previously, that was developed here at the Science of Networks, in Communities research lab Sonic. And people responded to personal surveys, once they responded to it, then they began to go in there and state their teammates preferences, they were given results of the kind that you see here. And they looked at these results, and they could find out more about the person. And if they wanted, they could then invite that person, the invitation would go on, and by email to that person, and that person could decide whether you were invited, whether you will accept the invitation or not.

Right now, all I'm going to talk about is the invitation network, who invited whom and why. And so the dependent variable was who invited whom to a team, the independent variables was the network of invitations, were why people were inviting it. The hypothesis in the teaser that I showed you at the top of this presentation was we will control factors such as homophily and competence, which we know people, we are going to drive who you invite, we also included in the model familiarity, prior collaboration, because we asked them who in the class you have previously collaborated with. So we had that network that we could use. And we were interested in the recommendation from technology that is, if a recommendation came with top 10, were you more likely to invite that person? What did we find? We found that recommendation with the top 10 was significant in both samples we looked at, so people were paying attention to the recommendation. People were also looking at prior collaboration, if you looked at somebody, if you're collaborating with someone, previously, you were more likely to reach out to that person and invite that person to work with. But the really interesting one was the interaction here. What if somebody that you had previously worked with also showed up on the recommendations? Will you now just way more likely to invite that person or not? And what we found was quite interesting.

The blue line here refers to people you had not previously collaborated, while the red line refers to people you previously collaborated. In general, the y axis, meaning the likelihood of inviting someone is obviously going to be much higher for someone that you did previously collaborate with, as compared to somebody you didn't previously collaborate. But if that person wasn't the top 10 recommendation from the My Dream Team platform, you see something quite interesting. That spike, the increase in likelihood of someone with who was recommended with whom you had not previously collaborated with, goes up dramatically, despite if you want to call it that, of the person who you had previously collaborated with. When that shows up on the top 10 list is very small by comparison.

The moral of the story, we have a new insight. The recommendation algorithms are going to be more infusive, if you may. When it is talking about people we don't know previously, as compared to those we might have known previously, the same exact same finding was replicated in the second sample.

The next example I'm going to give you is moving to team staffing. One of the things that I've been involved in over the last five to six years, is helping NASA figure out how they're going to send the right dream team on a mission to Mars. So let's drill into that a little bit. This is work that is done with my current PhD student Brennan Antone. My former student and current colleague, Alina Lungeanu was on the Faculty at Northwestern, as well as Jackie Ng from Harvard Business School. Leslie DeChurch was my collaborator here at Northwestern, and Suzanne Bell, who is listed here at DePaul University, which is where she was, and still is somewhat, but she has now actually moved over to join NASA as a full time staff working in the astronaut office out there.

So by way of background, we all probably have heard the humans are about to become an interplanetary species and that by 2033. We are going to be on Planet Mars probably even before that. NASA has been very committed to this journey to Mars but it recognises there are some challenges. The International Space Station which orbits the Earth is 250 miles per hour, the moon is 250,000 miles. Mars, on the other hand, is 250 million miles away. With that means a distance for travel. For example, it takes about a year to get from Earth to Mars. And that's when the orbital dynamics oppositions that it's a basic swing from the Earth to Mars. But then you have to stay in that orbital dynamics till that orbital dynamics returns, which is again about a year. And then again, there's a year by which you come back, which means that you cannot really have a trip to Mars to be much shorter than three years. And what that means then, is that in addition to the distance and the duration of the mission, the distance means that as you get closer and closer to the mass you get on Mars, there is going to be as much as a 22 minute delay in the signal being travelling from Earth to Mars and back, which means that the old adage where Apollo 13 said, Houston, we have a problem is not going to be very helpful now, because Mission Control is not going to be able to do something quickly. What that means is that that the team that is out there has to work much more autonomously than it has ever done in the past.

So who on earth are you going to send on this challenging mission that's going to be three years, international meaning people from different cultures, and they have to work autonomously. This is not the first time that people on Earth have thought about these kinds of challenges. When Shackleton and others were looking to make the first expeditions to Antarctica, they faced similar challenges. And at the time Ernest Shackleton put this classified ad in the British newspapers, 'Men wanted for hazardous journey, small wages, bitter cold, long months of complete darkness, constant danger, safe return doubtful, honour and recognition in the case of success'. Wow, that's not very attractive and exciting. And sure enough, what it did was it attracted people who were those low on self-reflection, and low on emotional expressiveness. In fact, in this article in '74, it said the Antartic station had become a haven for the technically competent individuals, deficient in social skills.

Fast forward to the space station. And now all of a sudden, if you look at this diary entry by an astronaut on the space station, talking about his, about his commander, he says 'he's brilliant at knowing the perfect balance of fun with professionalism'. So all of a sudden, space is a place for the personal interpersonally gifted individuals. What are the characteristics that will predict success, will someone will be a good team player. This was a review commissioned by NASA that was led by Suzanne Bell, who I mentioned, is one of our collaborators, and now is also a member of, a staffer at NASA. And she was working on the same premise that made Captain Scott Kelly say, when he got back after his long time, duration mission on the International Space Station, he said, 'teamwork makes the dream work at NASA'.

So our goal here is how, what happens to teamwork under extended periods of isolation and confinement. Well, what happens in those situations is we have a team staffing dilemma: people we need to figure out which is the right American that we can put along with the Japanese, Indian, French, German and Russian, for example, so that they will play well together. Wouldn't it be nice to have a human petri dish where we could experiment and build models about by, by putting people into manipulating them into isolation and deprivation for hundreds of days, making them do complex boring tasks, monitoring them 24/7?

Well, all of this might make you think of Zimbardo's dream or of a nightmare based on the Stanford Prison experiments, for example. But in fact, that's exactly what we do. And we're doing it at places like the United... like NASA's human exploration research analogue Hera, which is at the Johnson Space Centre, we're not the only ones doing it, but they put people into confined spaces for 45 days at a time. And we get to psychologically and physiologically poke and prod them, and they put them into communication delays, they put them into sleep deprivation, we do the same thing. The Chinese do the same thing at a place that euphemistically referred to as the, as the Lunar Palace, the Russians put people in there, we are collaborating with them.

I've been to this facility where they put people in for 300 plus days at a time, we collected data from them for 120 day mission and studying them about a month, we're going to launch a 240 day mission where we are collecting data in this space, the Japanese have their own, so do the European Space agencies and many other private foundations. So here's the kind of data we get from them. We ask them who, with whom do you work effectively. And you see the green arrows say these people seem to get a long way. But we also asked them who makes tasks difficult to complete. And notice here something very interesting. The person here at the bottom is become the target of everyone thinking that this person makes tasks difficult to complete, this person that not only doesn't think that other people make tasks difficult to complete, but really enjoys working with them. Challenges could be predicted, who was seen as a hindrance in this context, before the entire mission began.

We built an integrated theoretical model where we looked at a lot of different factors that might predict crew relations, if you may, we use that to build an agent based model to guide the crew composition, we then parameterize the model by actually collecting data in error and using that to estimate the value of each, of each model parameter. We use that to build an agent based model and see if this might work. Oh, we have an error. It would require me to oh, there we go. It is working. And you can see how that simulation is playing out within this context. This is actual data being modelled by the empirically infused agent based model that we use with the data was calibrated and parameterized using real empirical data. We found interesting findings such as self-monitoring, being an important positive impact and task effect, which means if somebody is high on self-monitoring, they were very likely to be seen as somebody who was, who other people enjoyed working with. And, and were less likely to be seen as a hindrance, for example. There were other examples of how workload will impact somebody's ability to be seen

as a positive data. We checked, tested this in terms of training data, and then we tested this in terms of performance data. As you can see our F1 scores, the combination, the harmonic mean of precision recall is pretty high. We got the sense that we are actually doing a pretty good job of being able to predict what is the extent to which somebody is getting along with others or not. I'm going to end very quickly with two examples. One in terms of team performance, this also relies on space. And in this particular case, I'm sorry, it doesn't rely on space. This one relies in terms of competition. And we are trying to predict team competition in the area of sports.

For some of you, may know that the Americans in general are not that crazy about cricket but growing up in India, I was. In fact, my namesake was a former captain of the Indian cricket team, Nari Contractor and my dad's first cousin, Farokh Engineer, was the whicket keeper for India and played county cricket in the UK for a long time. Satyam the first author, an Indian came to me one day as a postdoc here at Northwestern and said, No one seems to understand what I'm talking about. I really want to see if I can predict who would win a cricket competition'. And by virtue of me having those credentials that I said, he reached out to me to study the Indian Premier League. He was particularly interested in a puzzle, that one team in the Indian Premier League, the Kolkata Knight Riders in the left had two players from India, and the rest were all star players from round world, Australia, South Africa, New Zealand. And yet if you look at their record and compare it to the Chennai Super Kings, who had six players, all from India, not necessarily all star, he came across a puzzle. The team from Kolkata with all the stars didn't really do very well, they twice made championships, but most of the time, they didn't lead the league stage. On the other hand, if you look at the Chennai that had no superstars, they were champions twice, they were in the playoff strike twice. And they made it out the league stage, into the runners up every other year.

So why is it that the team of all stars was not doing as well? So basically, what this was doing was we looked at the data for two years, we got all the individual stats of the players and we tried to balance it with the stats of the players in the opposing teams. And what we found was quite interesting: that if you looked at the stats find themselves you were not able to really predict which team would beat the other team. But if you added to it, which players had previously worked together on a winning enterprise, whether it was on that team or another team, so just playing for their country, or India, for example, all of a sudden, you were able to do a much better job of predicting that. This was quite an interesting finding.

And we then began to see if it applied in other cases. We looked at data for the National Basketball Association, from the English Premier League, from the Major League Baseball as well as from a computer game called Dota 2. And we found that in all cases, the teams where people had prior interactions were much more important than team skills, when it came time to predict which team was going to beat the other team. So I'm just going, I'm not going to go into details here. But as you can see, the difference in between the two teams, in which team had more players who previously played together and shared successes was significantly more likely to predict which team is going to win in all of the different sports that we looked at here.

So to close here, I'm going to touch on the last one which is predicting team conflict. For this we're going to go back into space. And here what we're going to show this is what I've done with my collaborator, former postdoc, Michael Schultz, who's now a professor at... of Sociology at Indiana University. Here, I looked at, where we said we wanted to look at performance and behavioural health. And what it did is it looked at the ways in which we wanted to see if we could predict conflict before it actually happened. Well, one case where in space we saw conflict actually happening and I am just gonna skip slides in in the interest of time was actually in the area Skylab. Some of you may have heard of Skylab, it was the first National Space Station by the United States. And it happened between the Apollo missions and the space shuttles. It goes back a while, so many of you were too young to probably or not even born to remember it. They were the first space station and this was in 1973. The second crew members they were three crew members on the space station. They were three of these manned missions, each had a commander, a pilot and a scientist pilot. The first one worked for 28 days in space and did okay, the second one, Skylab 2 worked for 59 days in space and did okay the interesting one was the third one which was an 84 days in space. But about two thirds into the system, into their mission, all of a sudden they had a strike, they literally went on strike and shut down all communication with ground control. And this came to be known as the... the went on strike in space, we.. and the commander said, 'We would never work 16 hours a day for 84 straight days on the ground. And we should not be expected to do that in space.

There's this Wikipedia entry you can look at called 'Skylab Mutiny'. And there's a Harvard Business School case study called 'Striking Space'. Our goal was to see, could we predict this conflict happening in space by just looking at all the digital trace data of the text, of all the conversations that happened between these three astronauts that have all been recorded, as well as their conversations with ground control? So Michael took the two channels of air to ground communication and onboard voice transcriptions, 15,000 pages 3800 days, identify time, speaker and the verbatim utterance and began to then do topic modelling where you take each actor's utterances, associate the topics based on those with each actor, build mental models, where we now have links between actors based upon common terms and common topics that they use. I'm sorry, this was a mental model within a single actor, what were the topics that they used together. So these were linked amongst the topics within a single actor.

And then we build shared mental models by looking at the network between one astronaut and the second astronaut, seeing the overlap in the mental model networks, and then using that to index their shared mental model. And to do the same thing with the crew on ground control, which is called CC4 CapCommand. And what we basically found was a number of topics that were identified. And most importantly, we could see that when it came to Skylab1, there was a lot of similarity amongst the crew members, mental models, as well as the mental model between the crew member and the CapCom or Ground Control, that's the y axis. So it's pretty high on both the x axis and the y axis. But if you look at Skylab three, that's where you see that the mental model similarity amongst the crew as well as between crew and ground control was diminishing a lot. And this was a sign of a problem. If you look at it temporarily, you begin to see that on day 15, you didn't see much of a problem in the differences between the... what has happening on SkyLab3, and what happened on 1 and 2. But when you get to day 35, 11 days before the mutiny, you see that SkyLab3 is looking way complicated, with differences in their mental model as compared to what you see there, a leading indicator of a conflict that was about to come.

And so again, I just wanted to sign off by saying that a lot of what I've talked about here today has to do with these different ideas of how we can use computational social science. Obviously, there are concerns that we have to be looking at, whether it is as we witness the emergence of algorithmically infused societies, we have to be concerned about what happens in terms of identifying, quantifying, and rectifying the consequences of measurements. None of these measurements are perfect. And we need to be thinking hard in the field of computational social science, certainly in the area of ... in terms of methods, about how... what our measurements are actually measuring. And so these future directions are continuing to be important as we think about quality measurement models, which right now, frankly, we don't have in this area. And we need to be able to, to triangulate and look at both the consequences of mismeasurement, but in terms of ethics, in terms of privacy, in terms of transparency. And so in all we have to therefore develop these limits and recognise the limits of social theories, as well as try to build more normative ways of looking at computational social science methods that we... that we haven't been able to do so far. And that we do need to be able to look at these challenges. I will stop with that and acknowledge the various funders that have supported the research that I talked with you about today. Thank you all very much, and I'm sorry for going a little over time. I look forward to your questions and answers now.