

**Paul Leonardi, UC Santa Barbara**

*Keywords: modelling, predictive policing, constructivism, performativity, organization of work, stochasticity.*

Good morning, or good afternoon, or good evening – wherever you are.

Like the other panelists said, it is a great pleasure for me to be here and to speak with you today.



I have been a member of OCIS Community since I was a first-year doctoral student, and as all the panelists have mentioned it has been an extremely welcoming community. It's a community that is friendly and open to ideas, but also quite rigorous and will challenge you. I have never been on a Panel or made a presentation at the Academy Annual Meeting where my ideas have not been challenged and pushed forward. And

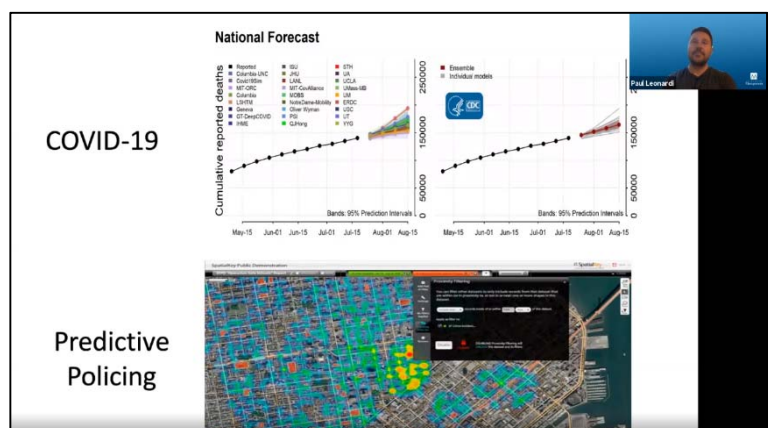
frankly that is one of the big reasons why I continue to submit to OCIS. I feel like our Community really engages with ideas, and it makes for an exciting scholarly experience.

Many of my fellow panelists have echoed some of the themes that I want to mention today. We talk about inclusivity of our membership, about the diversity of research interests, and the different levels of analysis we span. All of these things are emblematic of what it means to be a member of the OCIS Community. And as a last panelist I really took the charge of thinking about *what kind of ideas and themes we should be considering as scholars in Communication and Information Systems* as we move into the next several years. I couldn't think of a better way to be inspired to answer this question than thinking through some of the issues that we have been dealing with in the current global crisis.

What I want to do in the next couple of minutes is to use the research I have been focusing on, to try to talk through several themes that I think are important for the OCIS Community, and what these themes actually mean for our scholarship as we move forward.

Obviously two of the major crises that we have been facing as the global community in the last several months that have really come to the fore are the *Coronavirus* and also, perhaps slightly more an US issue than elsewhere at the moment, *predictive policing* and the way it is affecting our communities.

At the core of these two very different crises is a very similar issue: Modeling. Computer simulation modeling is, of course, nothing new: we have been doing this for decades and decades, across various occupations and professions, but the language of modeling and *what it means to represent something mathematically*, has really moved into the public consciousness in the last several months. So you can see here on the

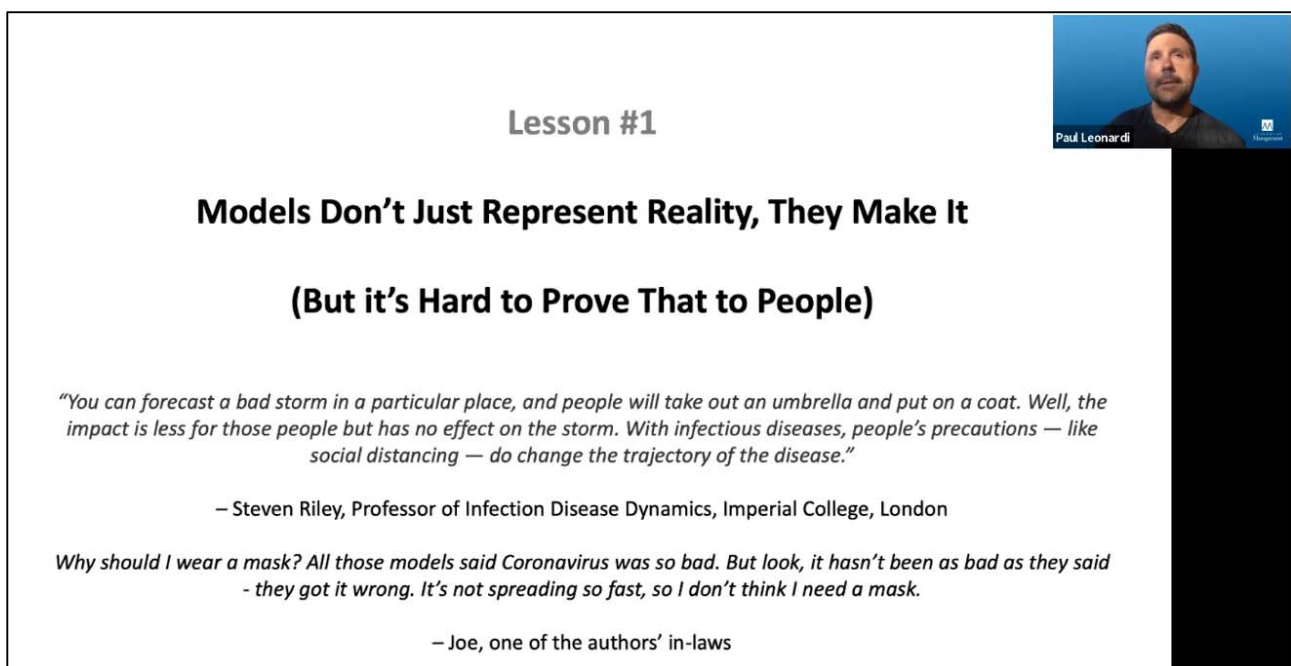


screen visual results of two different models. The top is an assembled model from the [Center for](#)

[the Disease Control and Prevention](#) in the US, looking at a number of different predictions of COVID-19 infection and mortality rates. And the bottom is a screen shows a screenshot of a predictive policing application that tries to identify where crime hot spots are. And you can see them visualized.

Computer models lie at the center of each of these kinds of predictive apparatuses. My colleagues, DJ Woo at Rutgers University and Will Barley who is at the University of Illinois, and I have been studying modeling for about a decade across three different occupations: in the Automotive engineering, in Atmospheric Weather Science, and in Urban Planning.

What I want to do is to take **several lessons** that we have learned from studying modeling and to describe how our studies of these models begins to point to some areas *where OCIS may go and may need to go, given the expertise that we currently have, to make the kind of societal and policy impact that we have mentioned before*. I want to briefly touch on these five lessons.



**Lesson #1**

**Models Don't Just Represent Reality, They Make It**  
**(But it's Hard to Prove That to People)**

*"You can forecast a bad storm in a particular place, and people will take out an umbrella and put on a coat. Well, the impact is less for those people but has no effect on the storm. With infectious diseases, people's precautions — like social distancing — do change the trajectory of the disease."*

— Steven Riley, Professor of Infection Disease Dynamics, Imperial College, London

*Why should I wear a mask? All those models said Coronavirus was so bad. But look, it hasn't been as bad as they said - they got it wrong. It's not spreading so fast, so I don't think I need a mask.*

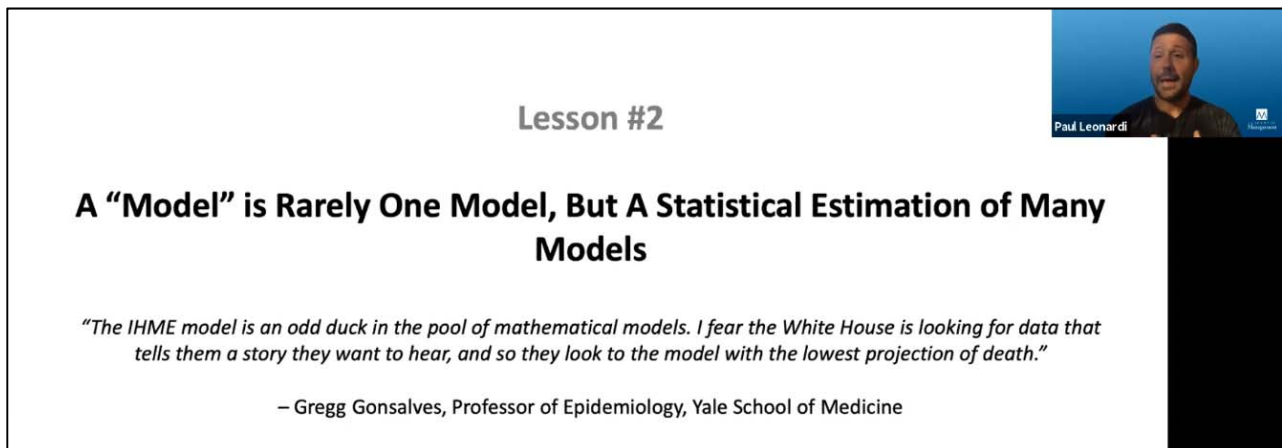
— Joe, one of the authors' in-laws

Paul Leonardi

Source: Presentation of Prof. Leonardi, keynote speech.

**The first lesson** that we have learned from our immersion into the world of modeling, is one that would not be unfamiliar to many of you in the OCIS Community. It is that models do not simply represent a reality out there, waiting to be apprehended, but rather that they *actively construct the realities they purport to describe*. As models begin to induce behavior that then aligns with the very predictions that the models make we start to see that models can have a *performative effect*. But also often *counter-performative effects*, when we predict: something is going to happen -- and then we engage the behaviors *that help enable an opposite outcomes*. So, it is very difficult to say that models and realities are two separate phenomena because models are in a sense very much constitutive of the realities in which we live. This is something I think that would be common to many OCIS-scholars who take a constructivist view of the technology. One important thing, though, is that for OCIS to really be able to branch out and to help other scholars across the Academy to understand what it means for technology to have this kind of performative effect, we need to be able to show and help to articulate the very ways that the technology does not simply mediate our interactions, or simply reflect our interactions, but is rather producing - every day - the kinds of interactions that we have. And this constructivist or performative notion is something that OCIS-scholars, I think, are very well equipped to theorize, and can also draw on lessons from other Divisions, such as Critical Management, Organizational Theory, to help explain the broader set of

institutions that to reflect the technological innovations that create the outcomes that they are supposed to predict. So, our first lesson is “**Models Don’t Just Represent Reality, They Make it**”.



Lesson #2

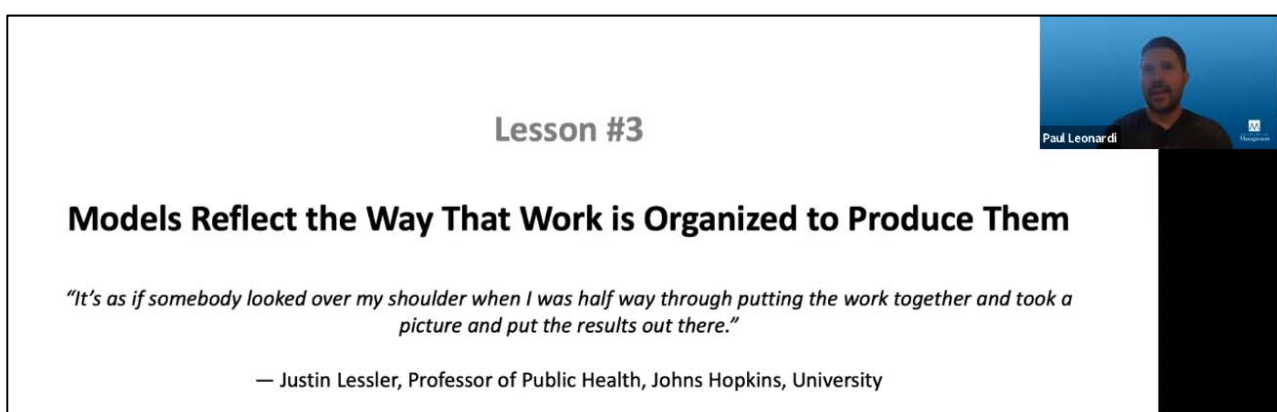
**A “Model” is Rarely One Model, But A Statistical Estimation of Many Models**

*“The IHME model is an odd duck in the pool of mathematical models. I fear the White House is looking for data that tells them a story they want to hear, and so they look to the model with the lowest projection of death.”*

— Gregg Gonsalves, Professor of Epidemiology, Yale School of Medicine

Source: Presentation of Prof. Leonardi, keynote speech.

The **second lesson** we have learned very clearly is that **there is rarely one model when we talk about models, because every model that we look at is a broad statistical estimation of many-many models**. And what this means for scholars is that there are always choices that have been made about *how we are constructing algorithms that are pooling together models of different types*. We aggregate data in a variety of ways and we produce statistical analysis of this data that often is aggregated into a policy structures or predictions. And we do not really understand very well how model aggregation happens. A big part of that is because a lot of the work that has been done, to pool models together, is *quite mathematical in nature*. And much of the scholarship in the OCIS tends to focus on the social and behavioral aspects of the use of technologies. To understand the ways how the models are chosen and are aggregated together and have these kinds of effects, we will have to understand a little bit more of the mathematical and statistical work that is going on to aggregate these multiple models. I think it is a real challenge then for the scholars in the OCIS Community to think through what kinds of research methodologies we need to be developing, and how can we leverage the scholars in other disciplines, perhaps [Research Methods Division](#), that do have or are developing an understanding that help us make sense of what is happening behind the scenes mathematically, as models are getting bundled together in the ways that are producing a seemingly overarching and broadly aggregate model.



Lesson #3

**Models Reflect the Way That Work is Organized to Produce Them**

*“It’s as if somebody looked over my shoulder when I was half way through putting the work together and took a picture and put the results out there.”*

— Justin Lessler, Professor of Public Health, Johns Hopkins, University

Source: Presentation of Prof. Leonardi, keynote speech.

**The third lesson** is that “**Models really do reflect the way that work is organized**”. The way the models are produced matters a great deal based on the kinds of data inputs that they receive. And *data input from a variety of different sources depends on how work is organized*. As we start to see more of a move to open-sourced platforms, to cloud-based computing, to crowd – another forms of organization, – the typical ways that we receive data, that we check data, that we combine datasets together are changing quite dramatically. And when we start to begin to ask whether models are based on strong assumptions, whether they actually reflect baseline capabilities that are contested, these answers become difficult to get when we do not know where all the data have come from – data that are being aggregated into the model. To make sure that right kind of data sources are represented we need to have a very clear understanding of the way work is organized - - both on micro- and macro-levels. And so, lifting the gaze that many OCIS-scholars take from focusing on behaviors around technologies to much broader institutional forms is going that important to understand how and why models have the data they do and the subsequent effects they produce.



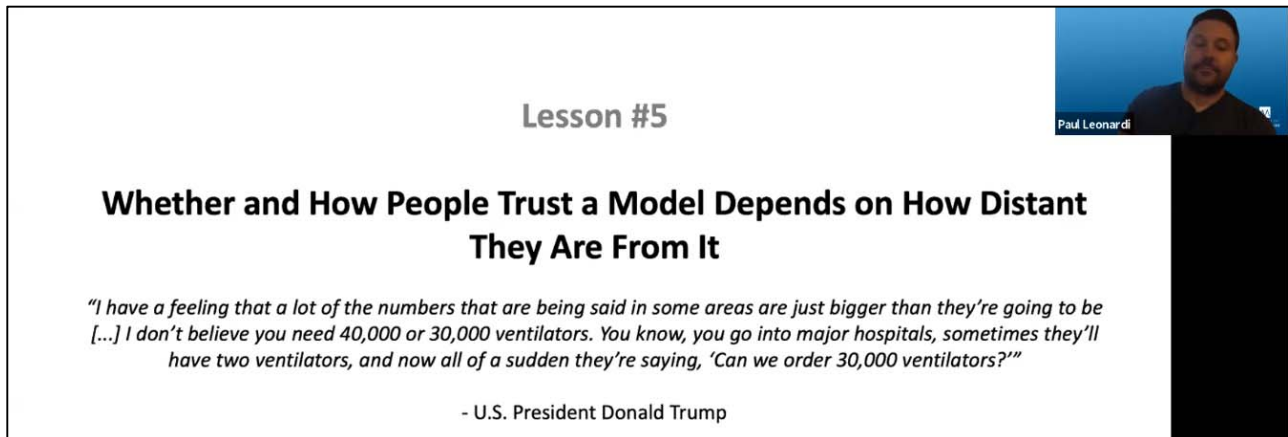
The image shows a presentation slide with a white background and a black border. In the top right corner, there is a small video feed of Paul Leonardi, a man with a beard wearing a dark shirt, with his name 'Paul Leonardi' written below it. The main text on the slide is centered and reads: 'Lesson #4' in a large, bold, black font, followed by 'Models are Stochastic, But People are Determinists' in a slightly smaller, bold, black font. Below this is a quote in italics: 'Don't obsess about the numbers because they will change... All models lie, but some are more useful than others.' At the bottom, it says '— Ross E.G. Upshur, Professor of Public Health, University of Toronto'.

Source: Presentation of Prof. Leonardi, keynote speech.

**The fourth lesson** that I want to point out is that **whereas models are stochastic**, - meaning that there is always randomness that is injected into them - **people tend to be deterministic**. That is, we tend to look at models as trying to tell us what is going to happen in very causal ways. Yet, most models are not setup to make any kinds of causal predictions. If you look at a lot of discourse around today's mathematical models, we can see that they are discussed as if they are making very deterministic kinds of predictions about the future, which in some way enables them to become performative and counter-performative. So, what this lesson teaches us that there is a whole host of rhetorical and communicative strategies that we need to deploy to make sure that we can discuss models' *stochasticity rather than the determinism* of models. It is also important that we look at how, rhetorically, models, that are inherently stochastic, are often positioned as though they were deterministic, in ways that are influencing public choice, opinion, and all the deliberative processes.

**The fifth and final lesson** I want to discuss, is that **how we can help people learn to trust or distrust models, really depends on the distances they have from understanding what the modeling enterprise is all about and how the models operate**. And we have seen this time, again and again. People bring up models for predictive policing, for Covid-19, and try to discuss what the models are doing, whether their predictions are accurate, -- and we understand that *some models feel trustworthy while others do not*. How we come to trust models depends a lot on understanding the dynamics that are being modelled; how the technologies are working; whether the algorithms that have been put together are being used in ways that are representative and unbiased. And we need to have a better understanding of *how we begin to develop trust and skepticism* towards the way

the models are developed and deployed. And doing this as OCIS-scholars may encourage us to chat with other Divisions such as Organizational Behavior, who are focused a lot on trust *to understand how we develop trust around sets of mathematical models* that does not operate the same way as the trust operates when we are looking at the personal relationships.



**Lesson #5**

**Whether and How People Trust a Model Depends on How Distant They Are From It**

*"I have a feeling that a lot of the numbers that are being said in some areas are just bigger than they're going to be [...] I don't believe you need 40,000 or 30,000 ventilators. You know, you go into major hospitals, sometimes they'll have two ventilators, and now all of a sudden they're saying, 'Can we order 30,000 ventilators?'"*

- U.S. President Donald Trump

Paul Leonardi

Source: Presentation of Prof. Leonardi, keynote speech.

So, I bring up these five lessons that we have learned from our studies of simulation models because I think *they speak to a number of areas that will be very important for OCIS-scholars* as we begin to think through tackling these broad issues affecting the society at large.

I think it is a great place for me to end, and thank you again for allowing me to be a panelist this morning.