John Hansmann: Sarah, thank you very much, and welcome everybody to our third rendition of our webinar or webcast for Capacity Planning Tool. Today, we're going to be talking about a couple new features that we've added in since the last time that we spoke, primarily Empirical Data Modeling, as you can see on the screen. Jason, if you want to flip to the next slide, as I'm talking here.

John Hansmann: And then, a couple other features that we'll bring into the discussion. We're going to run this session very similar to how we've done the last two, where we're going to have a couple minutes of two slides actually, and I'll review of the planning tool itself. And then, the new features that you can see on here, the empirical model length of stay for ICU admissions.

John Hansmann: And then, we'll actually get into the demo of the application or the Capacity Planning Tool, and then open up the time for question and answers. Before we get to that, Jason, if you want to flip over while you're changing the screen, let us introduce ourselves. So, my name is John Hansmann. I'm a senior vice president at Health Catalyst, and I've been at Catalyst for almost five years now.

John Hansmann: I've spent over 30 years in health care industry working with operations, and operational tools, labor or management staffing, supply chain, patient flow, and that's what I support at Health Catalyst that fits all well into the Capacity Planning Tool that we're going to talk today. Jason, please introduce yourself.

Jason Jones: Thanks, John. Jason Jones, I'm responsible for data science at Health Catalyst. I've been here for a couple of years. It's been really great to work on this Capacity Planning Tool, and see people use data science in different ways. Previous to this, I was lucky enough to work at Kaiser Permanente and Intermountain Healthcare, and a few other places. But those stick out as lucky points for me in my career.

John Hansmann: Thank you, Jason. So, we've been on a journey for the last six or eight weeks in developing this Capacity Planning Tool. If any of you have had the opportunity to come to either one of the two previous webcasts, we talked about the tool itself.

John Hansmann: And we got into this nine weeks, or eight weeks or so ago trying to create, and develop a tool that will allow you as hospital operators, the understanding of your capacity problems or potential capacity problems that you may run into if your demand of COVID patients exceeded the number of beds that you have available in your organization.

John Hansmann: We were taking national regional data that were available at the time, and then comparing it to your individual bed capacity, and then identifying sometime out in the future, whether it was days or weeks when you were going to run out of beds so you can make that determination looking at your individual capacity when you are going to run out of beds.

John Hansmann: And then, start your planning process or actually kick in you're planning process of where are you going to get the extra beds, and the extra capacity. We saw in New York and some other cities in the country, when they surged, they use beds, and convention centers, and other places, in-house clinic space, and ambulatory surgery space, and PACU space, and things like that.

John Hansmann: So, the purpose of the tool was to give you, or build in time for you to develop those planning phases to deal with the surge, and then start to address what is it you're going to do, and put those plans into place. Then as we evolved the tool, we added into it the ability to bring in existing data, we brought in capacity from a, or demand side from staffing and PPE.

John Hansmann: We got down into different levels of staffing, whether it was a nurse or a physician. You'll see some more of this today as we get into the tool itself. Also, on PPE side, gloves, gowns, shields, et cetera. And all with the importance of providing information to your COVID task force, your incident command centers, your planners, your C-suite folks to have the ability to understand when you were going to run out of beds, when your surge was going to occur, and then allow you to put in your surge capacity plans that you identified. Next slide, Jason.

John Hansmann: So, now, since the last time we met, we included a couple new tools, and a couple new features into the tool itself, the empirical model length of stay component to it. Up until a few weeks ago, we stayed true to the Penn Med model. That's the basis of the demand side of the curve. And thanks again to the Penn folks for putting together the tool that we built our capacity component off of.

John Hansmann: But we knew at some point in time, we were going to have to deviate from Penn, and this is that time. Basically, with a number of cities, and states, and counties within the country, have experienced enough of covered patients coming into their organizations and into their hospitals. We got a request and many requests from people like yourself on the phone of when can we start using our own data to projected demand curve.

John Hansmann: And so, what we built into, and then Jason will go into the method from the empirical model perspective. But now, we're using actual live data, real data coming from New York Times, and infected patients around the country, and then also, census data, and having those data elements built into the tool. Identifying four different forecasting methods of how to then predict where that demand curve is going to go.

John Hansmann: And we'll show you all that as we get into it. In addition to the empirical model, we also modified a length of stay component on the ICU-admitted patients based upon the original Penn model also. Original Penn model, effectively, they used when a patient came into the ICU, they stayed in there for the entire length of their stay in the hospital, and then they left the building in the model from ICU.

John Hansmann: We know that in most cases, patients go from an ICU to a step down or to a med surg floor. So, we built in that capacity to now separate between for an ICU-admitted patient. The ICU length of stay and then also, in the non-ICU length of stay. Jason, you want to get into the model? I think we're at a point where we can start showing what we built over the last few weeks, and give a preview of what was there prior.

Jason Jones: Absolutely. And just in case anyone ever forgets how to get to it, I'll just briefly show you how to get to the model in first place. So, if you forget, there is a direct URL, but let's just go to the healthcatalyst.com site, we're not ever going to charge for this model, so don't worry about that. And then if you click on the COVID-19 solutions right here, then at the top, you'll see the Capacity Planning Tool.

Jason Jones: And if you click on that Capacity Planning Tool, it will then take you in, and you can use it. And for those of you who haven't participated before, please know that you can also get to... maybe I'll just show you those quickly as well. If you want to see the past versions of our presentation so that you have an understanding of where we've been in the past, and how to use those.

Jason Jones: You can go to the Knowledge Center, and then webinars, and just look at the last webcasts that we've had, and replay those if ever you'd like to do that. This one will also be posted, as Sarah mentioned earlier. So, when we get in here, so far, it looks fairly familiar from what you've seen before. Once again, there's a left-hand pane, which is where you do most of the controlling for how the application works.

Jason Jones: And then, there's a right-hand pane where for the most part, you're seeing the results of whatever changes you make on the left-hand side, including as john mentioned. How it is that infections are going to progress, information about admissions, and census, and how that relates then to needs for things like personal protective equipment, staff, and alike.

Jason Jones: So, the main thing is right at the top here in terms of the first change, and to make it easy for us, I'm going to immediately load a scenario for us to work with. And you can see on my screen on the right-hand side, I've saved this scenario. And if you don't know how to save a scenario, please look at the prior webcast, but I'm just going to take the scenario, and drag it on top so that we can immediately look at what John was mentioning in terms of how it is that things play out, again, through infections, and admissions by type.

Jason Jones: So, total admissions to the hospital, non-ICU admissions, admissions to critical care, and the need for ventilators. We go through, and from admissions to census, and then from census to how that maps to your capacity in terms of beds, and ventilators. And then, we'll skip over personal protective equipment for the moment. If you want to see it, you can just check the box.

Jason Jones: And we'll go right to the impact on staffing because the first thing that we'll cover before we get into the forecasting is how it is that changes in length of stay get shown or reflected in the nurse activity. So, right now, as John mentioned, you previously could not split out for a patient admitted to the ICU, the number of days that they spent in the ICU versus the number of days that they spent outside of the ICU.

Jason Jones: So, effectively, if we had a total length of stay of 18 days, the way that the Penn model worked in the past was assuming that all 18 of those days were in critical care. And now, we can change that so that you can say no, the first 14 days you're in critical care, and then the four days after that are outside of critical care. And john, how would you like to change this to illustrate how people could playlist it?

John Hansmann: So, what we wanted to show here is Jason is going to change the number of length of stay for the ICU and outside the ICU, just going to flip the numbers. And so, why don't you put four in the ICU frame. And then, let's just put that at 14. So, we'll keep the total length of stay at 18. And if you notice the chart, and we'll go back to the old view here in a second, that the orange line or the gold colored line is the number of nurses required for our critical care area.

John Hansmann: And then, a blue line is the number of nurses required for noncritical care service. If you notice that, and all of you deal with nurse staffing, understand that typical nurse patient ratio in critical care is one nurse to two patients, and med surge is one to five to one to six, which you've also entered prior to up on the left-hand side as Jason is showing right now is one of the parameters.

John Hansmann: And if you're running a one to five, we just have six in here right now. But if you're running one to five, you change that to five. But basically, because of that difference in the ratios, you need more nurses in ICU when you have more patients, obviously, because you're taking care of two patients at a time versus four or five or six in the med surge.

John Hansmann: And so, with the majority of the patients now in our example, having a four-day length of stay in the ICU, and a 14-day length of stay outside the ICU, you get the curve that we see on the right-hand side. Now, if it flips back to where we were, we'll keep the 18 days, so 14 days in ICU and now, four days post ICU, which is more typical to what you would see with your patients here.

John Hansmann: You saw the two lines flip. We went the orange line was below the blue line before, now because we have so many more days in a higher intense area, the ICU, our number of nurses now have significantly gone up. So, ICU nurses now are in the 500 range at the peak give or take, or is that 600, actually, I can't read my graph, it's almost 800 at the peak.

John Hansmann: And then, on the peak of the blue, same day is closer to the 300 range. And the actual figures are shown below in the table, where ICU peak was at 312 per shift. And then, the non-ICU peak was at 742.

Jason Jones: Okay. So, this is an example of a request that we've gotten in the past, and we've been taking your requests and trying to implement them as quickly as we can in the tool. So, thank you for those, and trying to make it as realistic, and helpful as possible. So, now, what we'll do, and again, we'll answer any questions that you may have.

Jason Jones: Now, towards the end, now what we'll do is go through and look at how it is that we've changed how we even figure out demand in the first place. I'm going to go ahead and refresh the screen. And if you're used to using this tool or the Pennsylvania Medicine model in the past and like it, you still can. You can just change the mode from empirical model to Penn model, and you'll get back an interface that hopefully looks very, very similar to you, or very familiar to you.

Jason Jones: What we have found, and what we've been asked to do is that, generally speaking, the people are starting to get enough local data, and experience that they would like to use the actual local infection spreads that they're seeing in their data, and not be purely assumption based. And that's what the empirical model does. So, instead of putting things in, like what is the regional population, and how many patients are in the hospital?

Jason Jones: And when did social distancing start as though, and what's the doubling time? So, instead of entering all of these things manually, we're now going to estimate them from the data. And one of the key things, as many of us are seeing is that this previous model is essentially allowed for a single shift in the spread of the disease. And we're not seeing that play out so much in real life as social distancing effect and this waxes and wanes in different areas, and testing rates change as well.

Jason Jones: So, we'll go back and select the empirical model, and what goes away are things like, how many patients are currently in the hospital, and what's the doubling time, and when does social distancing get put in place? And instead, the very first thing that you're going to want to do after you've selected the empirical model is to select the geography that you are in or that you care about.

Jason Jones: So, for instance, I can come in and we were using New York before in our prior example. And as soon as you have populated the state in the United States, it'll immediately pull from the US census to estimate the population, which you can override if you would like to. And then, if you would like, you can leave this at the state level. But as John and I know in the states of California and Texas, where we live, there is not a common experience across our states.

Jason Jones: It keeps changing differently in different places. And so, you can then come in and specify a county or the New York Times has actually come up with the grouping of counties and called it New York City. So, again, you can look at the level of an entire state. And you'll note, we can now see the cases pulled from the New York Times, thank you for that New York Times.

Jason Jones: So that we can easily see how many cases we're seeing on a daily basis. And you can see in New York City, or sorry, New York State, it's been fairly spiky, with peaks over 12,000 or close to 12,000. And then, more recently, thankfully, it's been going down. But you can also see there's been a fair bit of volatility in there. So, on April 21st, they were "only" because only is still very high for just about every other state in the nation.

Jason Jones: Only had 4,324 cases, but that was down from April 15th, with almost 12,000 cases, and also below what was experienced on April 25th, with almost 11,000 cases. So, the reality has been that we have seen a lot of change across geographies, a lot of change across time. And we've tried to make it easier for you to reflect that going forward. I'll pause on one more philosophical thing here, and what might the utility be going forward?

Jason Jones: So, we're now starting to hope that some geographies are like New York is on the downside of this curve. And the concern is, when might we see upticks either second waves, or people are talking about wavelets. And this tool should help you accommodate that quite quickly. And so, if I look for instance, at the state, where our already organization is based in Utah, we can see that this is actually continuing to rise over time.

Jason Jones: So, we're not yet at that downward slope in Utah, whereas if we look at Texas here, we'll see Texas overall. It looks like it may also be increasing. But if we focus on a particular county, like Dallas, we'll see a very different pattern where it was flat, and then it went up, and now it's flattish again.

Jason Jones: So, again, we're just not seeing a lot of consistency, across geographies and over time, and that was why we built the tool in this way initially. But also, why we hope it will continue to be useful to you going forward as we continue to see volatility going forward in time. So, that's how you can go in and select geographies that are of particular interest.

Jason Jones: And that data, again, are updated from the New York Times continuously. So, as soon as it gets updated on their Get Site, it will download the data for you, and it will be reflected. And again, we'll get the total population information as well. So, having done this, we'll go through some of the forecasting methods, but you don't have to be a forecaster at all.

Jason Jones: Meaning, a technical forecaster, to know how to use this tool. What we're trying to do here is to augment the sorts of knowledge and experience that you bring locally, like what really happened with a spike? Was this really a bunch of new people who have tested positive, and we were on the verge of catastrophe, and a spike through the roof? Or was this the availability of testing that changed?

Jason Jones: And you're much more likely to understand that than any computer model would be. So, we can bring the data to you, and we can also bring some methods, which we'll go through to you, we can bring the methods to you. But still, your ability as an expert person in your local areas will probably be able to come up with a better forecast than any computer algorithm could do on its own.

Jason Jones: So, let's go through some of the techniques that you have. And there's two things to think about, assuming that you're in the empirical model. The first is, how do you want to think about infection spread? And there are two very common measures. One is doubling time, which is the one that was baked into that you have to enter directly into the Pennsylvania Medicine model.

Jason Jones: And the other was reflected in the Pennsylvania Medicine model, although you didn't have to enter it directly. You've probably seen in publications and other places, that's the reproduction time or reproduction number. Importantly, for both of these, they're dynamic.

Jason Jones: Meaning, that we're estimating a doubling time, or a reproduction time, or number differently here than here, than here, than here, than here, and there're algorithms behind the scenes, which we'll share what those are if you're interested, that figure out how to allow the doubling time and the reproduction time to change dynamically because the reality is that's what we're seeing.

Jason Jones: So, that's concept one is, do you want to use doubling time or reproduction time as a measure of infection spread? And the second is, which forecasting technique do you want to use going forward, which is signified by what's currently a blue line here, although we'll see the color will change.

Jason Jones: And the four choices that you have there are called exponential smoothing, loess or local regression, spline regression model, or linear regression model, and you really don't have to know what any of these things mean. The part that you should be able to do is to understand how to interpret the nature of your history.

Jason Jones: And then, you can simply click through these options to see which of them reflect what you think makes the most sense, or maybe want to run a couple scenarios of what could be true going forward. So, for instance, I could change from doubling time to reproduction number, the historical data will stay exactly the same, but you will see the blue line shift as I go to reproduction number.

Jason Jones: And the algorithm looks at the nature of the spread of the infection through a different lens. And now, instead of projecting a flatline forward, but it's plateaued and perhaps slightly increasing, is now projecting a continued decrease in the estimated number of new cases each day.

Jason Jones: Similarly, if I go back to doubling time, I can come in here and say, "Well, rather than use this thing called exponential smoothing, how would it look if I went to local regression?" And you'll note that the color of the line changed. But fundamentally, where it was going did not change very much, or I can use nonlinear regression. Again, not much of a change, or I could use linear regression, and not much of a change.

Jason Jones: Let me show you, hopefully, how easy it is for you to be able to apply your own judgment. So, again, your interpretation of where do we expect this trend to go forward in New York City or wherever your local geography is. You could try out two different scenarios of doubling time versus reproduction time, and see that doesn't change.

Jason Jones: That it goes from either flat or declining, and then again, we went through the different forecast methods, I believe with doubling time. Now, let's see what happens if we apply local regression to this. It gives us what I think most of us would suggest as a wacky plot that we would never expect to happen in real life.

Jason Jones: So, although again, the key point here is that you don't need to be a mathematician, or a data scientist, or a professional forecaster to be able to use the tools. And you can use them to drive a single scenario like say, "Yes, I feel pretty confident that this represents how we expect new cases to develop over time in a particular geography."

Jason Jones: Or you can run multiple scenarios and save them just as you would have before. But the important thing is, you don't have to understand the math in order to understand what's happening, and we've tried to make it as transparent as possible so that you can interpret the results that you're seeing and apply the methods without that knowledge.

Jason Jones: If you do have interest in the methods, you can show the methods, click the box to show the methods, and then go and read up on how it is that we're calculating dynamic doubling time. Per usual, we've tried not to create our own methods and instead, leverage the terrific work that's been out there already.

Jason Jones: So, here's the whole 2014 publication around doubling time, and the quarry 2013 publication around reproduction rate, and we simply implemented those methods for you, and that's what's there. So, if you do have any more interest in the methods yourselves, you're welcome to look.

Jason Jones: When you check this box, the other thing that you'll be able to see is it now represents for you the data that are used to derive this number of new cases each day here. So, now, you can see how it was that the algorithm under the hood saw the dynamic doubling time changing, and also how it saw the reproduction rate changing over time.

Jason Jones: So, you can understand what's happening even with history under the hood. You can also see how each of the different forecasting methods played out with each of the different infection spread approaches. So, all of this is displayed for you if you're interested.

Jason Jones: Or again, if you don't like to look at that level of detail, you can just uncheck the box and have everything represented for you in terms of the number of new cases that you've experienced historically, as well as the projection for the new cases expected. Once you get through that, and I'll just drag on talk again, the scenario for this webcast, which loads in all of your preferences, including what geography you wanted to look at.

Jason Jones: Then importantly, everything else in the model behaves as it did before if you're with the Pennsylvania medicine model. So, if you're familiar with that, there was this concept of using a certain model, the susceptible, infected, and recovered patients in a population. And that's still what is underlying the core of everything else we're doing.

Jason Jones: What's changed is that we've allowed the infection spread measures to be dynamic, and then we're forecasting forward, how those parameters are going to be dynamic in the future. So, you can still get to your new number of admissions, both again, this vertical gray bar is today.

Jason Jones: So, here's what's happened historically, here's what your current forecast suggests is going to happen in the future. You can still see this play out in hospital census, in your capacity, and as we saw before in terms of staffing, and if we wanted to see it, we could check the box for showing PPE. And it will show you the demand for your masks, and your gowns, and everything else.

Jason Jones: So, everything behaves exactly as it did before, in terms of building on the number of infected people that we expect to be in the population, show up in the hospital, stay in the hospital, and so on and so forth. What's different is that we've allowed the spread and the number of new cases to be dynamic over time. So, hopefully, that makes some sense.

Jason Jones: And again, if we think about just note right now, I'm using the reproduction time, and the spline fit, and it's showing New York City, the number of new infections is going to decline. We see that then represented in the number of new admissions, we see that represented in the number of hospitalized patients, the census, and we see it represents in our capacity.

Jason Jones: But if I come in, and go back, and change this to doubling time, which you might remember, let's just go back, when I change this to doubling time, then instead of continuing to have fewer cases each day, I'm going to flatline it. Let's see how that plays out in our census. And so, here's our census. Here's our bed capacity based on the assumptions. And now again, I'm going to change it to doubling time, which is going to flatline the number of new cases.

Jason Jones: And we'll see that the census flatlines, and our capacity flatlines, and we struggle to make it out of being short on beds. So, I think I should probably pause there. And Sarah, John, is there anyone that's asked for just a clarifying question that we could cover quickly before we move on to broader questions?

John Hansmann: No. All the questions will take a little bit of time to answer. So, Sarah, why don't you interject at this point, and then we'll continue after you're done?

Sarah Stokes: Okay. Sounds good. All right, everyone. We just wanted to launch this one quick closing poll question because we know some of you are going to have to drop before we dive into those questions. And in this poll, we'd like to know, would you like to have additional live demonstrations sharing other COVID best practices and solutions?

Sarah Stokes: And I'll give you just a few moments here to submit your responses. And this is also a great time, if you haven't submitted questions, and there's anything top of mind, we encourage you to submit that now because we will be diving into those next. And if you do have to drop off right now, I do just want to let you know that the recording will have the Q&A included.

Sarah Stokes: So, if you're unable to stay and hear the answer to your question, no worries, still submit it, and we'll be sure that it gets posted with recording. Okay. Just one more second here. I'll give you a three, two, one, and we're going to go ahead, and close that poll. All right, back to you, John.

John Hansmann: Right. So, Jason, we have four questions so far to answer. So, let's hit the first one. Can the same tool be used to predict a second wave? And if yes, how do you determine if an increase we see is just noise, or the actual patient surge?

Jason Jones: Yes. That is a great question, and one we've done a fair bit of thinking and simulation around. So, the good thing is, is that this basic approach, which takes the best infection data that we have at the moment on a daily basis, and treats it as though the infection can be dynamic, that approach will respond well to a second wave.

Jason Jones: So, let's just see, and we really hope this doesn't happen, that New York starts to see an actual increase, then the model will respond accordingly, and show you how that second wave will play out. Now, what we haven't been able to do, and it's not for lack of trying, it's why it took us a couple of weeks to come up with an approach that might work.

Jason Jones: What we have not been able to do is to come up with an algorithm that works across even the entire United States, let alone the entire world. Every time there isn't a single best answer about whether we're better off using doubling time or reproduction time, there isn't a single best answer about which forecasting method to use going forward.

Jason Jones: And that's why we've tried to make it as simple as possible for you to use your local knowledge, and experience, and expertise to guide the computer. So, you don't have to fetch the data, you don't have to understand the math, but you do still need to provide your judgement about what is reasonable.

Jason Jones: And we've seen lots of reasons why that might be the case. I've mentioned earlier about, was this truly an event that happened where some group of people all of a sudden infects a lot of other people that wouldn't have otherwise been affected, or was it a change in the testing, or even the data anomaly, which we've seen plenty of.

Jason Jones: So, those are the kinds of things that are difficult for us to be able to integrate directly, adequate granularity across the whole country in each of your geographies. So, instead, again, what we've done is provided transparent methods that you can simply apply, and then pick the one that works best. But the short answer is, yes, the approaches will pick up on changes, including second waves.

John Hansmann: So, a continuation of that question is how does the calculated number of admissions measures compared to actual empirical data?

Jason Jones: Yeah. This is another one actually, our hope when we started to switch to the empirical model was that we could use hospital data, local hospital data, to do a good job of predicting the future. And now here, we were only able to do this with Health Catalyst clients. What we found is that there were other dynamics playing out in geographies that made that pretty... it didn't work very well.

Jason Jones: So, you can still upload your own local data. At the bottom of these inputs, there's a section where you can drag and drop your actual admissions and census. But what we found is that hospitals were getting different market share. So, here, we have a hospital market share. They were getting different hospital market share in the COVID-19 age, and that that was evolving over time.

Jason Jones: Sometimes that had to do with whether there happened to be a very nearby skilled nursing facility that got hit particularly badly. Sometimes it was not known to the hospital why it was that patients were flowing the way that they were, and it kept changing over time. So, we found that projecting off of actual hospital data didn't work very well that performed typically performed very poorly.

Jason Jones: So, we could do a much better job modeling still off of infections, and then allowing you to overlay, and upload your local data to see how well it was fitting in terms of admissions and census.

John Hansmann: Hopefully that answers the question. Thank you. So, I think you partially answered this one or actually mostly answered this one, but let's see if you have any other commentary to it. Could we use this tool to calculate a realistic situation during COVID-19?

Jason Jones: Well, we hope so. Crazy as these admissions look, jagged as they look, the hospitals that we have spoken with have found that this is actually commonly what they're experiencing. They go from few admissions in a day to a lot of admissions the next, and another day, a lot of admissions, and then all of a sudden, it seems to calm down a little bit, and then it comes back.

Jason Jones: So, at least, the folks we've been speaking with have confirmed that it has felt like a fairly chaotic process. And that this tool is perhaps not modeling what we would wish, but perhaps doing well with respect to the reality that they're experiencing. So, that it seems to be not perfect, but perhaps, a useful model going forward to reflect reality and changes in that reality, which seem, again, to be happening frequently at a local level and over time, differently.

John Hansmann: And that's important to talk about, if I can add to your message, Jason, is the whole local knowledge, and understanding what's going on in your own communities, as Jason mentioned before, I live in the Dallas, Texas area. And my wife works for one of the big downtown medical centers in Dallas, and their organization has been experiencing when I look at the Dallas numbers on the screen that Jason showed before.

John Hansmann: We were plateauing, we spiked up a week or so ago. And then now, we're plateauing again at a higher rate. And we're starting to see the census numbers in the hospitals here start to increase. And so, are we on an increasing pattern? Probably. Are we on a plateauing pattern? Probably.

John Hansmann: Hopefully, we're going to get to that declining pretty soon. But the commentary or the gist of the conversation is with your understanding of local knowledge, you can then start to have a better feel for what the numbers are really showing you.

Jason Jones: Yeah. My keyboard broke in an unfortunate time, but there we go. Here's what John has been talking about with Dallas. And truthfully, from all of the geographies that we've looked at, we have not seen another geography with the step function in it. So, that's John's point about needing that local knowledge to understand what's going on.

John Hansmann: So, we have two more questions, and then anybody else who wants to submit, please do, but let's hit these two. One is what are the differences between the Penn model and the empirical model now that we're showing? Which one has been working better?

Jason Jones: So, that's a great question. The Penn model is again, it's a generic epidemic spread model surge, suspected infected and recovered people in the population. And we're still using it under the hood to some degree because we're still populating how many people are susceptible to infection, how many people have actually got infected, how many people have recovered now.

Jason Jones: So, that's still under the hood. But what's changed again, as that we're allowing the spread to be dynamic over time. Again, as social distancing, waxes and wanes, or for other reasons. And so, what we have found is that by allowing the spread to change over time, we're able to come up with much more accurate reflections both of where we've been, but also where we're going.

Jason Jones: And so, it's not that we've thrown away certain models, it's that we've changed how the certain model works to allow for an ever changing dynamic. I'm just curious now, I didn't go in and look at Dallas over time, but this pattern of how it's doubling, or this pattern of the reproduction number is fundamentally different from what we were seeing in New York. And, John, do you happen to know what county Houston is in?

John Hansmann: Harris.

Jason Jones: Harris. Okay. So, by the way, you can add multiple counties. So, let's just add Harris. Even if we take another large county like Harris, the pattern is different when we put the two together. And when we separate out, Houston, it looks different yet again, and admittedly, Texas is a big place. Houston and Dallas are both big cities. But the take home here is that we're seeing really different patterns across counties.

Jason Jones: And by allowing you to leverage those data directly, what we believe we've done is provided a more accurate method of coming up with what the future looks like. So, here again, remember, we had that step function for Dallas where they were stable, and then stable. And then, they went up, and they were stable again. At the higher level, Houston has had a very different experience.

John Hansmann: Thanks, Jason. So, our last question, and this is one that you, and I have had, and our team has had a lot of conversations about. And so, it's coming from an individual who's giving us a compliment initially, thanks for the continued work on this excellent tool. With hospitals now looking at how to balance resuming electives versus managing delays and COVID throughput into the post-acute, will you be adding a post-acute planning module feature to the tool?

Jason Jones: That is a great question. And we've gotten it a couple of times. And I guess one thing we could do, I'm curious, John, how you're feeling about this now, but just like we have hospital capacity, we could add a post-acute capacity. And I'd love to have a conversation with people who thought that that would actually help.

Jason Jones: We'd have to also add probably, the amount of time that somebody would spend there, and probably wouldn't want to add something like whether they're willing to accept COVID-19 patients, which I guess is they're not. What thoughts do you have, John?

John Hansmann: So, some of the things that as we've talked before, If we go to the post-acute capacity, then do we need to differentiate what that capacity or where that capacity is? A skilled nursing facility versus a hotel concept, or dorm type concept, where patients would go that are still infected and can't go home, but do not require the acute care levels any longer.

John Hansmann: There're many different options. And as we've talked this through, we're trying to figure out if we just provided a post-acute number, does that really get us to what you would be looking for, you would be needing because there's so much variability and so many variables of where those patients could go.

John Hansmann: And so, we'd love to hear some comments from any of you on the phone on this because quite honestly, we're not really sure where to go, or how valuable that single number would be that, yeah, then you've got all this post-acute now, what do you do with? Or do we need to get into more differentiation of where they potentially go? It's a tough question, Jason, that's why we've been wrestling with it for a while.

John Hansmann: Do we do anything? Can we take the model as it exists? And somewhat jury rigged that, "to do the same thing," run a different scenario, and then have our post-acute now has 200 beds and run scenario, call it scenario ex-post-acute as an example, and then look at any search components or issues that are coming on the post-acute side.

John Hansmann: But obviously, the demand curve would be the inputs that would be coming from this, but because we're using real data, those patients have to go someplace. So, they're either going to leave the organization, or leave the hospital in some way, shape or form.

Jason Jones: Yeah. There's a lot have additional input that we would need. I'm just reloading the New York data here. So, we would need to know what we're seeing or hearing about is the length of stay is longer than it needs to be because there's nowhere for patients to go. So, we have to allow people as well to change the length of stay parameters so that we have a clinically able to leave versus physically able to leave.

Jason Jones: Yeah. I think we would need a roundtable discussion from all the different approaches people have suggested to help us figure out how best to help people here. It didn't feel very straightforward at all.

John Hansmann: Yeah. And then, I think at that point in time, you have to start to get into the expiration rate, or death rates, and all those other variables so it brings in a whole new set of parameters of how sophisticated you want this to get for it to be real. Again, we could put a number out there, but how real is that and how valuable is that? Well, we are out of questions in our list.

Jason Jones: Okay.

John Hansmann: So, any last thoughts from you?

Jason Jones: Not from me, except that we should once again, thank the people who've done the work of putting this together on the left-hand side here, Evan, and Haider, and Josh, and Larry, Max, and Mike for putting this together, and we hope you find it useful.

John Hansmann: And I'll just add my thank you's, and everything to these folks on the left-hand side, they put a lot of time and effort into this. Hopefully, this is valuable to you. If you have any other comments or suggestions, please write us at our email address that we have on the right-hand side.

John Hansmann: Then again, the tool website, or the tool link is shown on the screen as well. So, with that, I think we will wrap up the call, Sarah, and end the conversation for today. Everybody, thank you very much for attendance, and thanks for helping us out building this thing, and be safe.

Sarah Stokes: All right. Thanks, everyone.