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1 P R O C E E D I N G S

2 (9:30 a.m.)

3 DR. MCGIVERN: It is 9, it's after 9:30.

4 Good morning and welcome to today's session on
5 emerging and reemerging diseases. I'm David
6 McGivern from FDA's Office of Blood Research and
7 Review, and I'll be chairing this session with my
8 colleague, Dr. Ranadhir Dey.

9 Our first speaker is Dr. Charles Chiu.
10 Dr. Chiu is Professor of Laboratory Medicine, and
11 Professor of Medicine in the division of
12 Infectious Diseases at University of California,
13 San Francisco, and director of the UCSF Clinical
14 Microbiology Laboratory.

15 He leads a translational research
16 laboratory focused on the development and clinical
17 validation of metagenomic next generation
18 sequencing and host profiling assays for the
19 diagnosis of infections, outbreak, investigation,
20 and pathogen discovery. Please join me in
21 welcoming Dr. Charles Chiu.

22 DR. CHIU: Thank you. And I'd also like

1 to begin by thanking the FDA for inviting me to
2 speak with you today. The title of my talk
3 actually has been a little abbreviated. It should
4 be actually Metagenomics and Host Profiling for
5 Diagnosis of Infectious Diseases. And so the
6 motivation of doing so is that we face many
7 challenges in infectious disease diagnosis,
8 especially for emerging infections.

9 One is that we know that conventional
10 microbiologic tests have poor diagnostic yield.
11 In fact, approximately 50 percent of the time,
12 we're unable to identify the cause of
13 meningoencephalitis in patients admitted to
14 intensive care units despite extensive testing.

15 For pneumonia, it's anywhere from 15 to
16 62 percent depending on the study that you look
17 at. And even for sepsis, approximately 20 percent
18 of these cases remain undiagnosed.

19 In addition, the typical infectious
20 disease patient undergoes multiple tests without a
21 diagnosis as a result. And available tests may be
22 limited in both sensitivity and/or scope. This

1 contributes to a long diagnostic odyssey for many
2 patients, especially patients who are affected
3 with emerging infections, which contributes to
4 prolong hospitalization, progressively invasive
5 tests, and unnecessary treatments.

6 In addition, the need for doing this
7 testing and the lack of assays contributes to very
8 high costs or high cost of burden of patients who
9 have infections or potential infections. For
10 instance, meningoencephalitis patients in
11 intensive care units typically incur around 50 to
12 100K. And then pneumonia and sepsis can incur up
13 to \$8.1 billion in costs per year.

14 So my interest has been in developing
15 kind of clinical metagenomic sequencing for
16 diagnosis of meningoencephalitis, and meningitis,
17 and encephalitis. And the general idea is the use
18 of essentially rapid pathogen detection. So what
19 we've done here is the goal is to take a research
20 based assay to do metagenomic sequencing and be
21 able to, in a single assay, be able to diagnose
22 the full range of infections that may affect

1 patients.

2 So this has been clinically validated at
3 UC San Francisco since 2016. We've been running
4 spinal fluid metagenomic assays in our diagnostic
5 laboratory here. And we've also have developed
6 respiratory, and plasma based metagenomic assays.
7 And the principle of this has been demonstrated in
8 several papers that have come from my laboratory.
9 One includes a paper in the New England Journal of
10 Medicine titled Clinical Metagenomic Sequencing
11 for Diagnosis of Meningitis and Encephalitis.

12 The general principle of clinical
13 metagenomic sequencing is it's essentially shotgun
14 sequencing of DNA and RNA, because bacteria,
15 viruses, fungi, and parasites, they're inherently
16 DNA RNA based, there's no reason that with a
17 single sample, we can in principle be able to
18 diagnose the full spectrum of infectious diseases.

19 In addition, we've been able to show
20 that this technique is universal in the sense that
21 you can actually apply this across a wide variety
22 of different body fluids. So what makes us quite

1 attractive for the purposes of emerging infections
2 is that you don't need to add targets as new
3 targets arise.

4 So to give you a good example, many of
5 the respiratory virus panels that were available
6 at the time when the COVID pandemic happened,
7 really, it was very challenging for manufacturers
8 because they had to ensure that by adding a new
9 target, in this case SARS- CoV-2, would not affect
10 the performance of their assay. And so what we
11 really want to do is we want to develop methods
12 where we don't have to rely on constantly updating
13 the composition of our panels, depending on the
14 current epidemiology of the disease at the time.

15 And metagenomic next generation
16 sequencing, because it doesn't apply any primers
17 or probes to target any individual pathogens, is
18 very attractive for broad based diagnosis of
19 infections.

20 I want to move now into kind of where I
21 see though the next generation. I mean,
22 traditional microbiology has always been based on

1 detecting the pathogen. So we're always
2 interested in either culturing the organism,
3 detecting antigens from the origin. Example would
4 be the spike protein on the SARS-CoV-2 viral
5 particle.

6 PCR testing, or nucleic acid testing, or
7 perhaps the most broad based testing, nucleic acid
8 testing, which would be DNA and RNA sequencing of
9 pathogen genome. These are all essentially direct
10 detection methods, meaning that you're looking for
11 the pathogen.

12 Now we do have in infectious diseases
13 other ways to diagnose infection. So one would be
14 serology, which had been used for now more than a
15 century looking for antibodies that may be
16 specific to a certain type of infection. In
17 infectious diseases, we can also identify like
18 cell profiles, such as from spinal fluid, cell
19 counts and differentials, to be able to
20 distinguish, potentially distinguish between, for
21 instance, bacterial infections, which cause
22 bacterial meningitis, versus other organisms that

1 cause meningitis, such as aseptic meningitis,
2 including viruses, and parasites, and fungi.

3 And then we've also developed protein
4 biomarkers. A good example would be
5 procalcitonin, as a way to distinguish potentially
6 between bacterial and viral infection. Now,
7 however, one thing that you should note is that
8 really we lack assays, abundant assays, on the
9 host side. And my interest has been in
10 potentially leveraging metagenomic sequencing as a
11 way to not only look for the pathogen, but also
12 look for host response signatures.

13 But we do know that disease itself, that
14 infectious diseases, is really highly dependent on
15 an interplay between the pathogen and the host. A
16 great example of COVID-19 where you can have the
17 spectrum of disease ranges from asymptomatic
18 infection to critical illness.

19 Okay. I want to give you an example of
20 potentially how we can do host based diagnosis of
21 emerging infections. So a good example are
22 diseases where there's both an acute and a chronic

1 component. So a great example was Lyme disease,
2 where you have, now this is a disease that has
3 various stages. In early Lyme disease, or acute
4 Lyme disease, for instance, you potentially can
5 identify the organism by directly looking for
6 *Borrelia burgdorferi* in the blood.

7 Or you can look for antibody testing.
8 In fact, the gold standard testing is actually 2
9 tiered antibody testing. However, there is also
10 kind of a later phase of Lyme disease. So either
11 chronic complications of Lyme disease, including
12 arthritis. You can have a condition called post
13 treatment Lyme Disease syndrome, which is where
14 it's a poorly characterized syndrome, where
15 patients continue to have symptoms, neurologic
16 symptoms, and signs despite successive, presumably
17 successful treatment for acute Lyme.

18 And for these, for chronic
19 manifestations of Lyme disease, we really have no
20 tests. We sort of lack accurate tests for either
21 diagnosing the disease in the chronic stage, or
22 for monitoring the disease. And ideally, we would

1 want to have targeted tests for different stages
2 of a disease.

3 Another good example is long COVID and
4 acute COVID, where we now have new methods of
5 treating, new treatments, or vaccines for
6 addressing kind of acute COVID. But we really
7 have nothing for long COVID. And part of the
8 reason is that we don't really understand the
9 pathogenesis, which almost certainly involves the
10 host response.

11 Okay. So my interest now that has been
12 moving towards, can we expand potentially for
13 addressing acute infections, can we expand beyond
14 simply looking at for diagnosing acute cases of
15 disease to where we can better understand not only
16 the infection itself, but also the host response
17 to the infection.

18 And so the general idea here is we want
19 to employ a technique which is part of metagenomic
20 sequencing called RNA sequencing or host
21 profiling. And the general idea is, with
22 metagenomic sequencing, you sequence all of the

1 DNA and RNA in the cell or in clinical samples.

2 But however, most of what you end up
3 sequencing is actually not from the pathogen. The
4 goal of metagenomic sequencing is the needle in a
5 haystack approach. I'm interested in looking for
6 specific fragments of DNA or RNA that may
7 correspond to pathogens.

8 On the other hand, most of what you end
9 up sequencing is actually the human host. So what
10 you're actually sequencing is, with RNA
11 sequencing, for instance, you're actually doing an
12 RNA sequencing experiment. You're actually
13 sequencing the host transcriptome.

14 Similarly, by doing DNA sequencing,
15 you're, I mean, technically you're sequencing the
16 host genome and in principle depending on your
17 coverage, you may be able to even assemble the
18 genome or identify genomic markers. I'm going to
19 focus in this talk on the RNA side because my
20 feeling is that by looking at the transcriptome,
21 the idea is can we actually simultaneously compare
22 not only looking for the pathogen with sequencing,

1 but also characterizing the host response profile.

2 And we've been able to do so from spinal
3 fluids. So this is actually an LDA plot, linear
4 discriminate analysis plot, which is analogous to
5 a PCA plot, for those that are about principal
6 component analysis plot. And you can see what
7 I've done here is I've actually taken a wide
8 variety of different infectious and noninfectious
9 conditions and essentially plotting them to look
10 for what are the similarities in the host
11 response, and the RNA, patterns of RNA gene
12 expression among these different conditions.

13 And in principle you might be able to
14 look at this and say, well, if I had an unknown
15 sample of a patient that had, say, an unknown
16 meningitis encephalitis, could I essentially place
17 it on this plot to identify, potentially be able
18 to identify does the patient have a bacterial
19 viral fungal parasitic infection, or even a
20 noninfectious etiology, such as malignancy, or
21 vasculitis, or autoantibody syndromes.

22 And so that's the general concept that

1 we want to do with host profiling with
2 metagenomics. Now, we've been able to show that
3 this actually does work. So for certain types of
4 emerging infections, so one is actually
5 enterovirus associate acute flaccid myelitis.

6 So my group was actually initially
7 involved in some, essentially a worldwide effort
8 to try to identify the cause of acute flaccid
9 myelitis in children. And it seemed that the we
10 identified enterovirus, and others as well
11 identified enterovirus D strains as sort of
12 implicated in acute flaccid myelitis.

13 But one of the things that's made
14 analysis of this very challenging is that you have
15 children that present with the acute flaccid
16 myelitis syndrome, and yet, we almost never can
17 detect the actual virus in spinal fluid. I think
18 the yield from the CDC was roughly two out of 500
19 patients actually ended up having detectable
20 enteroviral RNA from the virus.

21 Now they were able to make the diagnosis
22 because we were able to look at other sample types

1 like respiratory secretions for instance. Many of
2 these patients presented with essentially an acute
3 febrile illness, a self limited viral illness that
4 came back several weeks later, or a few weeks
5 later with acute flaccid myelitis.

6 And so one idea is can we leverage, for
7 instance, the host response to better develop
8 diagnostics for this kind of condition. So the
9 general idea here is, well, why don't we leverage
10 the tools of precision medicine, and the idea here
11 is we want to leverage the diagnostics that have
12 transformed, for instance, cancer or rare disease
13 genetics. But we want to use this for infection.

14 And so essentially the idea here is that
15 we want to identify RNA gene biomarkers and using
16 AI and machine learning actually develop models
17 that can help us predict responses to infection
18 and be able to use to either diagnose or to
19 predict infections. And so this is a technique.
20 It's a very standard technique in the research
21 world, which is called RNA SEQ or RNA sequencing.

22 But the general idea is since we're

1 already doing metagenomic sequencing to identify
2 RNA viruses, why not leverage the sequencing data
3 to now look at host responses simultaneously. And
4 we can do so in using machine learning, using a
5 machine learning based analysis workflow, we can
6 actually identify, for instance, features that can
7 help us kind of predict types of infection.

8 So this is how Google Image, for
9 instance, works in that I could, for instance,
10 feed the algorithm, say thousands of cars, for
11 instance, in this case. And the general idea is
12 by identifying cardinal features, you can then
13 train the model to identify not only the cars that
14 were used in the model, but also potentially new,
15 essentially new brands, new models of cars.

16 So this is the idea is that with machine
17 learning, you traditionally take your dataset
18 divided into 80/20 percent. 80 percent is used to
19 train the model, and 20 percent is used to
20 actually test the model. And so this has been
21 done in the machine learning analysis workflow.
22 And essentially the idea is can we develop now a

1 classifier for actually differentially diagnosing
2 neurologic illness.

3 Now you might expect this would be very
4 important, for instance, for emerging infections,
5 because emerging infections, as I said before, all
6 of our tests are really highly targeted. Right.
7 So if you have a new, say, a new coronavirus,
8 there's no guarantee that existing assays are
9 going to pick up that coronavirus.

10 So if you have a new Bunya virus that's
11 causing an emerging infection, there's no
12 guarantee again that your assays will be able to
13 pick it up, because there's no genome
14 representation in the database.

15 And the same is true as well for fungi
16 and even fungi and bacterial strains. And so the
17 general idea here is can we leverage host response
18 to be able to diagnose disease. So instead of
19 taking just the non-human reads, looking for
20 aligning those to identify paths, why not take the
21 human RNA reads and generate the host response.

22 And so we've developed, in fact, the

1 classifier. This is a very complicated slide, but
2 in short, the general idea is we're using machine
3 learning and cross validation to be able to
4 identify essentially factors or models,
5 classification models that can predict disease.

6 So I'm going to kind of go quickly
7 through this. But the general idea is, let me
8 kind of skip through this. The general idea is
9 now we've actually developed models, and this is
10 based on spinal fluid RNA sequencing, where we can
11 distinguish, for instance, potentially between
12 autoimmune disease, bacterial, viral, and fungal
13 infection.

14 And indeed, many of the genes that we
15 identify that appear to be associated with these
16 makes sense. So if you look, for instance, here
17 like with bacterial infection versus everything
18 else, one of the genes is PI3, which is a well
19 known antimicrobial peptide. For viral infection,
20 the top gene is actually, as you might expect, an
21 interferon associated gene.

22 And autoimmune noninfectious diseases

1 like auto AINI, which includes, for instance,
2 cancer, malignancy, vasculitis, autoantibody
3 syndromes. There are a number of
4 neurodegenerative autoinflammatory genes that are
5 represented kind of in that set.

6 And so what we can essentially do here
7 is we can actually develop essentially a use the
8 training set, 80 percent of your data, generate a
9 fairly accurate model, and then apply that to the
10 test sets to be able to diagnose infections.

11 What's also quite important is, and
12 what's interesting here, is that if you actually
13 classify a priori, let's say you take, in this
14 case I took 1,000 infections, and I took spinal
15 fluid data. We did clinical metadata in a blinded
16 fashion. Look to see what was the clinical score.
17 In other words, what was our clinical confidence
18 in the diagnosis.

19 Did I know for sure that this was a
20 viral infection, did I know for sure this is a
21 bacterial infection. What you can do here is you
22 can actually show based on the clinical confidence

1 score that the accuracy of the model depends on a
2 priori, how confident you were.

3 And in fact, if you actually decrease
4 the confidence level, the score here varies from 1
5 to 4. You can see that the accuracy actually
6 decreases. And what that suggests to me is it's
7 not that the model is being less accurate, it's
8 more likely that the clinical diagnosis was
9 actually not accurate at the time.

10 And so this highlights potentially the
11 utility of this as an adjunct to aid in clinical
12 decision making. Okay. I also want to state that
13 this is not only for general categories. So
14 traditionally, host response has been like
15 bacterial versus viral infection. Can we
16 distinguish between that.

17 Now, that's important for certain
18 applications. For instance, like if you want to
19 do a workup of sepsis. And there's a lot of
20 interest, several companies have developed tests
21 that can distinguish between viral and bacterial
22 infections, for instance.

1 I'm actually a little more ambitious.
2 I'm interested here in potentially being able to
3 use host response to identify specific types of
4 infections. Now, for many of these infections,
5 though, they happen to be rare or uncommon, you
6 may not have a good many examples of them. So
7 we're using essentially what we call a leave one
8 out algorithm.

9 And the idea behind it is imagine I want
10 to validate a test for, say, mycobacterium
11 tuberculosis infection. Well, if I only have 10
12 cases, what I do is I take one of the cases out,
13 and the remaining 9 cases in all the other samples
14 generate a model, and then see how well does that
15 model predict that one case, and then you go on,
16 so on and so forth, for the remaining cases.

17 So that's called the leave one out
18 method of validation. And essentially we did this
19 for several categories. And you can see here
20 that, in fact, we're able to develop essentially
21 host response classifiers for a variety of
22 different types of infections, parasitic

1 infections, herpesvirus infections, coxy and
2 histo, which are emerging, dimorphic fungal
3 infections, enterovirus, associated acute flaccid
4 myelitis, D68 and A71, MTB, and cryptococcus.

5 And this gives you an idea of how
6 specific you can, these are what we call ROC
7 curves or receiver operate characteristic curves.
8 And you can see that the performance actually is
9 quite good for cases of acute flaccid myelitis,
10 but not as good overall, interesting enough, for
11 like more general cases of enterovirus meningitis.

12 And my interpretation of this data is
13 that the AFM or acute flaccid myelitis happens to
14 be a very specific type of syndrome, so it's more
15 easily distinguishable than more of a generic
16 enteroviral meningitis.

17 But what's interesting is also that the
18 more distinct syndromes are actually the syndromes
19 that we're interested in developing better
20 diagnostics for. I want to give you another
21 example. This is an example of a very specific
22 classifier that can be used potentially to

1 identify neuroborreliosis from spinal fluid or
2 Lyme disease.

3 And if you look here, these are
4 essentially what the model predicts are the 10 top
5 genes associated with Lyme disease, at least in
6 the neuroborreliosis, neurologic Lyme disease.
7 And you can see here what's interesting is also
8 post priori, we actually found out that what I
9 have highlighted there in asterisks are actually
10 the, those are actually genes that have been
11 reported in the literature.

12 So you can see the vast majority of
13 genes have actually been already reported, which
14 helps to kind of validate the model in the first
15 place, even though the model itself was developed
16 in an entirely unbiased fashion.

17 Okay. I want to end by actually talking
18 a little bit about how we can actually apply this
19 in practice. So what we're going to see, and this
20 is if you happen to have, say, an unknown
21 outbreak. The idea here is that we not only want
22 to be able to identify the organism, potentially

1 using metagenomic sequencing, but can we
2 simultaneously look at host response.

3 And these are actually an example.
4 These are 5 cases, again, spinal fluid from 5
5 cases of meningitis and encephalitis that were
6 essentially unknown. So like the first example is
7 the case of MTB. That was negative by sequencing.
8 It was culture negative as well.

9 You can see here clearly a bacterial
10 infection. A case of GABA receptor (inaudible)
11 encephalitis. This is an auto antibody syndrome
12 that was read as a noninfectious condition. If
13 you look on the bottom, a case of Zika virus that
14 was read as a clear viral meningitis.

15 And that's actually quite interesting
16 given that Zika virus was actually not represented
17 on the original model. So it gives you, perhaps,
18 the hope that should we identify, say, a novel
19 viral pathogen in the next, say, 10 to 15 years,
20 which we may indeed do, this type of approach
21 would have ability to detect it without actually
22 having a specific diagnostic test targeting the

1 genome or the pathogen itself.

2 And this is currently what we're
3 envisioning would be the results report, is not
4 only would you get a metagenomic result. So this
5 is a case of Lyme disease, again neuroborreliosis.
6 So not only can you detect in principle the
7 *Borrelia burgdorferi* bacterium, but the idea is
8 could we couple that with the host response to be
9 able to characterize not only the infection itself
10 but also the patients host response to the
11 infection.

12 Okay. I wanted to give one last example
13 on terms of how we've actually been able to apply
14 this to an outbreak. So in October of 2021, four
15 recipients of organs from a common deceased donor
16 in the United States, developed of febrile illness
17 and encephalitis 2 to 6 weeks after
18 transplantation.

19 Essentially, the blood donor provided
20 blood to the tissue organ donor and the deceased
21 donor then donated organs to various recipients.
22 And unfortunately, two of the recipients ended up

1 dying from this because they developed essentially
2 post transplant encephalitis.

3 And so the key question was, you know,
4 what is this. And we actually identified this as
5 a case of yellow fever virus. And actually, the
6 way it was identified was a detection of a single
7 read in a patient who, in an infected patient, and
8 it was this detection of a single read that
9 precipitated a CDC investigation, wherein they
10 found out that the blood donor had actually
11 received the live yellow fever virus vaccine 3
12 weeks prior to donation.

13 And it had turned out that the blood
14 donor had then donated to the deceased organ
15 donor, and then had 2 of the 4 recipients
16 developed a fatal encephalitis. And eventually,
17 this was actually proven by antibody testing, and
18 unfortunately, autopsy testing of the brain.

19 But one thing to note, though, is that
20 we detected a single read out of 15 million reads.
21 Now we could have easily missed this by
22 metagenomic sequencing. But what are we going to

1 do in the future? Well, what we can do is we can,
2 again, now do kind of the host response analysis.
3 And this data is now published where you can see
4 that all of the affected recipients, and these are
5 the recipients that receive organs other than the
6 cornea, the cornea recipient had no symptoms. But
7 the other recipients who were affected and were
8 symptomatic all had a very strong viral signature.

9 And what's quite interesting as well is
10 in the viral signature, again, I've highlighted
11 with the asterisk there. Those are actually genes
12 that have been linked to association with either
13 yellow fever, vaccination or infection.

14 So in hindsight, let's say that we had
15 not detected with metagenomic sequencing. Well,
16 we actually have another shot at potentially being
17 able to identify the cause of this outbreak by
18 host response analysis.

19 So I'd like to end by thanking the
20 members of my lab who were involved in this work,
21 funding from the NIH, BARDA, the CDC, the Delve
22 Bio, and the Steven and Alexander Cohen Foundation

1 for their Lyme disease support. My website is
2 there and thank you for listening.

3 DR. MCGIVERN: Thank you, Dr. Chiu, for
4 your informative presentation. We're open for
5 questions, but while people are thinking of
6 questions, I'd like to ask a question myself.
7 What's the timing of the results and the analysis,
8 and are they fast enough for clinicians to make
9 decisions based on the result?

10 DR. CHIU: That's a great question, and
11 I didn't get into that. So metagenomic
12 sequencing, at least the metagenomic sequencing
13 that we run on lumina instruments in the clinical
14 lab, has a turn around time that varies from 24 to
15 72 hours. And that's an interlaboratory turn
16 around time.

17 The actual, and we actually have a paper
18 which is shortly to be published in Nature of
19 Medicine that goes over our seven-year experience.
20 But in short, the actual turn around time ends up
21 being somewhere on the order of like 4, 3 to 4
22 days. And that's primarily because there's also

1 time incurred upon having the sample sent to the
2 lab, the need to batch samples.

3 So unfortunately, it becomes there is a
4 delay in kind of the turn around time. And as you
5 know for infectious diseases, you really want to
6 minimize that turn around time. We are indeed
7 trying to develop methods using, for instance,
8 nanopore sequencing that will help us get same day
9 turn around time.

10 But with respect to the host response
11 though, or metagenomic profiling, we're also very
12 interested in developing sort of leveraging this
13 information. For instance, I'm interested in
14 transferring these models over to a very rapid
15 testing model. So we're currently working with
16 Thermo Fisher on TaqMan array card, which is
17 essentially a multiplex RTPCR type of platform,
18 where we can get the same sort of results within 2
19 hours.

20 But currently with sequencing itself, we
21 have been able to do same day sequencing using a
22 nanopore sequencing platform. Thanks.

1 MR. KUMAR: Yeah. Hi. This is Sanjay
2 Kumar from Office of Blood at CBER. Charles,
3 excellent as always. So my question here, I think
4 more extension to something you answered. Do you
5 have a pattern emerging from pathogen specific
6 immune response, then you can associate with acute
7 disease, to help (inaudible) management, and also
8 long-term disease, chronic infection.

9 You know the turn around time, the early
10 most is very rapidly 2 or 3 days. I mean patient
11 is dead really. So can you pinpoint the immune
12 responses that can really aid in clinical
13 diagnosis? And I would listen.

14 DR. CHIU: Yeah. I think you have like
15 two excellent points there. So the first question
16 is, you know, is it useful to have a test that's
17 like just a few days. Now, actually, you'll
18 actually see in our paper, it was useful.

19 So part of the reason it may also be the
20 clinical syndrome. So for instance, encephalitis,
21 I mean, these patients are in the hospital for
22 weeks and in some cases months. So there is, and

1 many of them as I said, more than 50 percent of
2 them actually end up being discharged from the
3 hospital without a diagnosis.

4 I mean, they're empirically treated with
5 antimicrobial agents or autoimmune, and
6 immunomodulatory agents. And yet we still don't
7 have a definitive diagnosis. And so my feeling is
8 that metagenomic sequencing by itself even having
9 a turn around time of say 2 days, or 1 to 2 days,
10 is still going to be clinically useful.

11 We've been able to show that actually.
12 That need for diagnostic yield. You know, that
13 being said, it's always better to actually be able
14 to kind of get results in a more rapid fashion,
15 and that's why my interest has been in potentially
16 moving these onto portable platforms, either
17 highly multiplexed, you know, RTPCR or PCR
18 platforms that will allow us to get kind of the 2
19 hour turn around time. Or at least the same day
20 turn around time that you really need for acute
21 infections.

22 On the other hand, for chronic diseases,

1 so you introduced another important point in that
2 we found that the host response differs for, for
3 instance, chronic manifestations of acute diseases
4 versus acute disease themselves.

5 So for instance, a good example is the
6 host response to COVID-19 infection is quite
7 different than that in long COVID patients. And
8 so what I really feel is that we would need to
9 develop assays that target both the acute stage
10 and the chronic stage of these diseases.

11 And so a related study that we're
12 currently doing, for instance, we're identifying,
13 again, using RNA sequencing as well as cytokine
14 profiling, we're identifying biomarkers that can
15 distinguish between long COVID, chronic Lyme
16 disease, and myalgic encephalomyelitis chronic
17 fatigue syndrome.

18 So we are trying to address that as
19 well. But it seems to me that it's very likely
20 the signatures are going to be different.

21 MS. ELKINS: Anybody else in the room, I
22 have quite the list coming in from online, so I'll

1 try to do them justice. First, how do you avoid
2 bias in MGS because the genome copy number of the
3 pathogen of interest is very low.

4 DR. CHIU: Okay. Yeah. So yeah, it
5 really has, to date, it's primarily been developed
6 as a qualitative test. Meaning it's either that
7 you detect it or not. So the idea is that you
8 have to set certain thresholds. And so these are
9 obtained empirically. We essentially use ROC
10 curve analysis to identify what is the optimal
11 threshold where we call something positive or not.

12 We have not been using this in a
13 quantitative fashion, which is what the questioner
14 might be asking about. But we are actually
15 working on that, and it does appear that it may be
16 potentially we might be able to obtain
17 quantitative information. So in fact, not only be
18 able to detect an organism by sequencing, but also
19 be able to identify the viral load or the pathogen
20 load.

21 But we currently have developed this as
22 a qualitative tests with specific preestablished

1 thresholds.

2 MS. ELKINS: So that may relate to a
3 follow up part of that question. The host
4 response obviously overlaps in several pathogen
5 infections. So how do you avoid misinterpretation
6 or ambiguity? But if you consider it qualitative,
7 that may be part of the answer.

8 DR. CHIU: Yeah, yeah. But that one is
9 actually quite interesting, because it is true the
10 host response does overlap. But we found out that
11 you can identify differences. So a good example,
12 for instance, is one thing that we found out is we
13 tried to find a differential host response between
14 coxy infection and histo infection, both dimorphic
15 fungi that causes similar illness.

16 And we were unable to. So what we ended
17 up doing is we sort of combined it into what we
18 called dimorphic fungal infection. So I think
19 that as we get more experience with this, we'll
20 know kind of at what level resolutions to sort of
21 classify these responses.

22 But another good example would be acute

1 flaccid myelitis, which is we know it's caused
2 very likely by certain strains of enteroviruses,
3 where that appears to be very specific, it's not
4 the same as enteroviral meningitis. So I think
5 over time we'll have better, more experience in
6 terms of how to classify these types of
7 infections.

8 MS. ELKINS: Thank you. Next, have
9 metagenomic methods or analyses been applied to
10 controlled human challenge models or subjects
11 immunized with attenuated, live attenuated
12 vaccines?

13 DR. CHIU: It has been. So there have
14 been studies, for instance, done in challenge
15 models of acute infection like the, metagenomic
16 sequencing has been done, for instance, in college
17 age volunteers who were basically infected with
18 influenza, for instance.

19 So the answer is yes. And host response
20 profiles have also been done in challenge models,
21 as well as in animal models as well. I didn't
22 talk at all about the literature, but my interest

1 is, of course, is being able to kind of translate
2 that to clinical use.

3 MS. ELKINS: Next, have you considered
4 host genotype, for example, in order to determine
5 what aspects of the host response detected are
6 functions of the baseline characteristics of the
7 host versus acute response to infection?

8 DR. CHIU: Absolutely. And in fact,
9 that also raises kind of the possibility that we
10 could sort of do everything with a single test,
11 because with clinical metagenomic sequencing, we
12 sequence both DNA and RNA. I didn't talk at all
13 about the DNA side.

14 We have been able to show, for instance,
15 that we can use DNA analysis sort of a liquid
16 biopsy concept, where we can identify, for
17 instance, essentially a copy number of variants to
18 be able to, potentially be able to identify
19 leukemias or other cancers or malignancies on the
20 DNA side.

21 So certainly, there's a lot of, and
22 there's a lot of interest, for instance, in

1 looking at methylation profiles, cell and tissue
2 types of origin, as well, to be able to better
3 diagnose disease. So I think there's a lot of
4 room to mine in that area. Our focus has really
5 been on RNA to date, but we eventually want to
6 incorporate DNA information as well.

7 MS. ELKINS: So the next one is fairly
8 open-ended, and I'll warn you that I can't keep
9 up here with the influx. Would you elaborate on
10 how to achieve machine learning accuracy?

11 DR. CHIU: Yeah. With machine learning
12 accuracy, the best way to achieve accuracy is
13 actually numbers, well annotated data and more of
14 it. I can tell you when I spoke with my
15 (inaudible), when we first tried to develop it, he
16 wanted 100,000 cases of meningitis encephalitis.

17 I told him I'm not giving you without
18 100,000. So we're going to have to make do with
19 fewer cases. And my feeling is especially for
20 emerging infections, you're not going to have a
21 lot of cases to test with. But there actually
22 have been kind of advances in both, in not only in

1 diagnostic medicine, but also in AI and machine
2 learning.

3 There's a technique called GANs that
4 we're currently applying. It's called Generative
5 Adversarial Networks. And it's essentially a
6 method by which you can essentially use machine
7 learning, but it applies for very small numbers of
8 samples. So for instance, 10 to 15 samples,
9 potentially you can generate fairly good data by
10 virtually expanding it using this technique.

11 So there are some advances, so parallel
12 to some of the advances that are being made in AI
13 and machine learning, we're hoping to adopt that
14 for use in diagnostic medicine.

15 MS. ELKINS: Got it. Does your model
16 account for age-related changes in immune
17 responses to different classes of pathogens?

18 DR. CHIU: It currently does not. And
19 again, it's because we simply don't have as many
20 samples. But certainly we we'd want to do that.
21 But again, it's difficult if you don't have a lot
22 of cases to actually work with.

1 But eventually, there would be the
2 possibility that we could stratify the data as
3 well by age. We haven't done that to date. By
4 either age or sex.

5 MS. ELKINS: Next, leave out one testing
6 is still susceptible to one of the samples being
7 wrongly diagnosed. So have you challenged the
8 methods using a wrongly diagnosed sample?

9 DR. CHIU: Yeah. So what's interesting
10 about wrongly diagnosed samples is that that
11 appears to be, again, that's sort of dealt with by
12 having numbers. So for instance, in fact, I even
13 know in some of the machine learning models that
14 they're either wrongly diagnosed, or they might
15 potentially be wrongly diagnosed.

16 But it's important that you sort of
17 minimize those. And in fact, when we do actually
18 do the training set, we want to make sure that
19 that's less than 10 percent of your samples. But
20 it turns out that if the number of, quote, wrong
21 classifications that are made a priority, if it's
22 less than 10 percent, it doesn't appear to affect

1 the performance of the final model.

2 It seems to be dominated by the well
3 performing samples. But it is something you
4 definitely have to take into account, especially
5 because for many of these diseases there's no gold
6 standard.

7 MS. ELKINS: This may be partly answered
8 by the fungal example, but can the approach be
9 used to distinguish more than two genetically
10 closely related viral infections, such as
11 consecutive flavivirus infections?

12 DR. CHIU: We have tried to do that.
13 We've actually tried that. It doesn't appear to
14 work very well, probably because the flavivirus
15 responses are very much in common. So we tried,
16 for instance, for distinguishing West Nile virus
17 meningoencephalitis from Powassan virus. And we
18 were unable to do so.

19 So I mean, this is clearly a limitation.
20 If it has a similar response, similar
21 pathogenesis, it's probably going to have a
22 similar host response as well. So it's really

1 being able to identify which responses are
2 specific and which or not. And I think generating
3 more data will help us do so.

4 MS. ELKINS: Is there a risk that
5 nucleic acid sequences from a resolved infection
6 can result in a false positive?

7 DR. CHIU: No. It's more likely that
8 host responses from a resolved infection, so one
9 thing I should mention is host responses from a
10 resolved infection we found are clearly not the
11 same as from an acute untreated infection.

12 So the best time to actually do host
13 responses is as early as possible when a patient
14 is maximally symptomatic or is untreated. If you
15 have a patient that's successfully treated, we
16 find that the host response disappears very
17 quickly. At least the host response of infection.

18 There may be a host response of treated
19 infection or partially treated infection. We
20 haven't explored that. But it's more likely that
21 a resolved infection is going to yield a false
22 negative host response, rather than a false

1 positive.

2 MS. ELKINS: Now we're starting to
3 overlap. Let me see if I can combine a bit. Once
4 you identify host markers by genomics, can you use
5 them as a simple blood assay?

6 DR. CHIU: Yes, yes. In fact, we are
7 doing that. Our hope is to move it to a rapid
8 RTPSR platform. And we're working with Thermo
9 Fisher on developing a TaqMan array card platform
10 for host response assay that could be with a two
11 hour turnaround time. Yes.

12 MS. ELKINS: And what are your thoughts
13 on increasing the specificity overall?

14 DR. CHIU: Increasing specificity, I
15 think, is important, but my feeling is that to
16 some extent there's going to be a limitation in
17 that. Because again, we're limited with our
18 access to essentially gold standard samples. You
19 know, unfortunately, you know, biology happens to
20 be somewhat, just happens to be somewhat ambiguous
21 in the sense that very rarely do we get clear cut
22 cases.

1 And in fact, I would argue that it's
2 actually better to have these sort of ambiguous
3 cases. So for instance, to give you some example,
4 the host response is never, is very rarely as
5 clear as you would like it, for instance.

6 So you have a patient with a fungal
7 infection may have, for instance, the host
8 response that suggests a bacterial fungal
9 infection. We know that these host responses
10 overlap. A viral infection overlapped quite a bit
11 with autoimmune and noninfectious etiologies.

12 And so my feeling is that we want to
13 incorporate all of that data. And we don't
14 necessarily want to develop a test that has 100
15 percent specificity, because our feeling is that's
16 actually going to be much less useful. Those are
17 not the cases you encounter in real life.

18 MS. ELKINS: Can you describe a
19 threshold for the number of reads required to
20 designate a sample as positive?

21 DR. CHIU: Yeah. So that's been
22 published. And if you look in our literature,

1 we've already established thresholds, and these
2 thresholds are established in the validation. So
3 for instance, we found, for instance, that with
4 metagenomic sequencing having just 3 reads,
5 non-overlapping reads, to 3 different viral genes,
6 is sufficient to specifically identify a virus.

7 Over 7 years, and this is a paper that
8 we have published. I'll be happy to provide the
9 reference. The specificity of our metagenomic
10 assay has been 99.6 percent. So it's very, very
11 high.

12 MS. ELKINS: All right. And we have
13 already discussed age groups. So last but not
14 least, can you discuss how close you're getting to
15 finding a biomarker for long COVID?

16 DR. CHIU: That's a great question. I
17 think it's not just us, but like several groups or
18 many groups are actually working on this. I would
19 say that we're working on it. We definitely have
20 what would appear to be a cytokine profile that
21 can distinguish long COVID from other conditions.

22 My feeling is that you don't necessarily

1 want a biomarker for long COVID specifically, per
2 se, you want a biomarker that the distinguished
3 long COVID from mimic or look alike diseases,
4 including chronic fatigue syndrome and Lyme
5 disease. So we're working on that. Thank you.

6 SPEAKER: Last question, I guess, can
7 you comment on whether you went back to those
8 samples that were not diagnosed and you use your
9 models to learn whether there are some viral,
10 let's just put an example, you learned that your
11 model shows that it's a potential viral infection,
12 you went back to those samples and look for
13 potential mark or genes that will show that they
14 are viruses that were not yet identified.

15 So in other words, have you data mined
16 your samples that you were not able to track
17 traditional pathogens?

18 DR. CHIU: Yeah. We haven't done that
19 yet. Because it's sort of a chicken or egg
20 problem. Right. Because you can identify a
21 signature that may suggest a novel viral
22 infection. And yet, unless you can actually

1 culture, or no one's going to believe you, unless
2 you actually culture, are you able to identify the
3 pathogen itself.

4 One thing I can say is that we have been
5 able to identify, for instance, a viral signature
6 associated with emerging pathogens. So I don't
7 talk about it in my talk, but we identified, for
8 instance, two new bunya viruses or emerging bunya
9 viruses. One is Potosi virus and Lone Star virus.

10 And those bunya viruses are interesting
11 because they have, to date, they have not been
12 associated with human infections. They were
13 identified by doing mosquito and tick sequencing.
14 And so we've actually identified them in a
15 patient, and when we looked at the host response,
16 it was very clearly a bunya viral host response.

17 So it suggests that in the future this
18 might be a useful technique for identifying new
19 viruses. Thank you very much.

20 DR. MCGIVERN: Thank you, Dr Chiu. So
21 our next speaker is, it's a pleasure to welcome
22 Dr. Shirit Einay. Dr. Einay is a physician

1 scientist in the division of infectious diseases
2 in the Department of Medicine and in the
3 Department of Microbiology and Immunology at
4 Stanford University.

5 Her research program focuses on
6 understanding the roles of virus host interactions
7 in viral infection and disease pathogenesis. Dr.
8 Einav's research program also includes
9 translational efforts to apply this knowledge for
10 the development of broad spectrum, post censored,
11 antiviral approaches to combat emerging viral
12 infections, and methods to predict their
13 progression to severe illnesses.

14 Please join me in welcoming Dr. Shirit
15 Einav.

16 DR. EINAV: Thank you, David, for the
17 introduction, and Karen for inviting me to be here
18 today.

19 MS. ELKINS: And I'm sure our AV folks
20 are good. There you go.

21 DR. EINAV: Thank you. All right. So
22 it's a pleasure to share some of our work in the

1 area of targeting cellular kinases to combat
2 multiple emerging viral infections today. So
3 there are over 200 viruses that are known to cause
4 disease in humans, and of course, the list keeps
5 growing.

6 And when you look at currently approved
7 drugs for treating viral infections, we're quite
8 limited. We're essentially targeting around 10 to
9 15 viruses, depending on how you count. So
10 clearly, there's a very large unmet need in this
11 area.

12 The prevailing antiviral approach relies
13 on targeting viral function, specifically viral
14 and schematic functions, usually. And this
15 approach has shown a tremendous utility in
16 treating chronic viral infections, such as
17 hepatitis C virus, and HIV.

18 But its utility for treating emerging
19 acute infection has been more limited. So the
20 spectrum of coverage that's typically provided by
21 this approach tends to be narrow, and this is, of
22 course, due to the high diversity of viral protein

1 structures and sequence.

2 And so it's usually in the order of few
3 viral serotypes all the way to few related viral
4 infections. We know that it takes about 8 to 12
5 years to develop a novel drug, and a cost of over
6 \$2 billion. So combined with the narrow spectrum,
7 this makes the development of such approaches
8 quite a slow and expensive process.

9 Of course, this is not scalable to meet
10 the large unmet clinical need that we are
11 observing with emerging viral infections. And if
12 you take (inaudible) here, for example, the active
13 moiety of Paxlovid, yes, there was a very rapid
14 rollout to the clinic, but this was not a new
15 chemical entity. In fact, it relied on the
16 revitalization of already existing compound that
17 Pfizer developed for the original SARS COVID.

18 And since we all know we cannot predict
19 the future threat, this approach does not provide
20 the global health protection we need and the
21 national security readiness we hope for.

22 Treating viral functions as monotherapy

1 is also often complicated by emergence of viral
2 resistance, and in the context of HCV or HIV, we
3 solved this issue by using cocktails of individual
4 drugs that target distinct functions. But again,
5 this is not a feasible approach for emerging viral
6 infections.

7 So when I was a post doctoral fellow at
8 Stanford, I was mentored by Jeffrey Glenn and
9 Stephen Quake, and I was focusing on a
10 nonstructural transmembrane protein and 4B protein
11 and hepatitis C virus. This is in the period
12 where both David and I were working in the field,
13 and there were no antivirals available at the
14 time.

15 One of my project ended up with the
16 discovery of the novel target, and DAI, direct
17 acting antivirals against these targets. So while
18 there was a lot of excitement with that came a
19 disappointment because this compound essentially
20 targets mostly genotype 4, which is not prevalent
21 in this country.

22 And treatment was associated with rapid

1 emergence of resistance. So when I established my
2 own lab around 2011, I decided to try to think a
3 little differently about targeting viral
4 infections and moved to focus more on targeting
5 host functions.

6 So as you all know, viruses replicate in
7 a host, and they rely on cellular machineries for
8 every step of the viral life cycle. So my goal
9 here was really to try to identify those cellular
10 functions that are required by multiple viruses
11 and use those as potential targets for broad
12 spectrum antivirals.

13 The hope was that this would also
14 introduce an opportunity to repurpose already
15 approved drugs that target these functions. So
16 combined with the broader spectrum, this could
17 reduce the cost and time for drug development and
18 provide readiness for future outbreaks.

19 And then since cellular functions are
20 not under direct control of the virus, genetic
21 control, this may also increase the barrier to
22 resistance. Another potential advantage is that

1 the repertoire of targets that this approach
2 provided larger than when direct acting
3 antivirals.

4 So viruses typically have anywhere from
5 10 proteins, if you take virus like dengue, all
6 the way to 200, if you take herpes viruses,
7 majority of these proteins are not enzymes. So
8 not surprisingly, current approaches rely on
9 largely targeting viral proteases, or polymerases.

10 Whereas if you move to host targeted
11 approach, now you have a repertoire of 20,000 the
12 whole human proteome. So with that comes a lot of
13 diversity and indeed, multiple groups, including
14 ourselves, have characterized very broad cellular
15 functions that could be targeted.

16 So how do you discover such host
17 targeted broad spectrum antivirals? So I'm going
18 to share two examples. This came from our work
19 and the first goes from the unification of the
20 target, then to the discovery of the drug.

21 So the approach that we've taken was to
22 focus on cellular proteins that are involved in

1 intracellular membrane trafficking. The thinking
2 behind this was that studying these virus cells
3 interactions would not only solve some
4 underexplored areas in viral infection but will
5 also potentially identify such common mechanisms
6 shared by viruses, because every virus essentially
7 has the traffic intercellularly during their life
8 cycle between various intracellular compartments.

9 So in my lab we've been focusing on
10 various cellular machineries that are involved in
11 regulating intracellular trafficking of viruses.
12 And one of our earlier projects focused on
13 interactions between viral proteins and a group of
14 adapter proteins shown here are AP-1, AP-2, and
15 (inaudible).

16 These are cargo specific adapters that
17 are involved in either clutering mediated or
18 other intercellular trafficking pathways. And
19 what we've shown is that viruses such as HCV use
20 these adaptors sort of as buses to shuttle
21 intracellularly. And what you're seeing here are
22 live cell imaging of individual viral particles

1 labeled green via tetracysteine labeling.

2 And you can see that the green goes
3 together with red, which is (inaudible) labeled
4 adaptor proteins. We then discovered that there
5 is a group of kinases called NUMB associated
6 kinases. There are 4 kinases in this family
7 listed here by (inaudible) and SDK 16. And these
8 kind of stimulate those virus source interactions.

9 So what we've observed is that they
10 could basically regulate those temporally distinct
11 stages of the viral life cycle, where these virus
12 associated interactions happened. So they could
13 almost be viewed as master regulators of viral
14 infection and perhaps attractive targets for broad
15 spectrum antivirals, because we've seen this
16 across multiple RNA viruses.

17 So this is sort of the model that we
18 proposed and then validated in a large number of
19 papers. Some are shown here. Interestingly, we
20 discovered that there are already existing kinase
21 inhibitors that are very potent suppressors of
22 these kinases, even though these kinases may not

1 be their primary target.

2 So for instance, erlotinib, anti cancer
3 drugs, erlotinib is known as an EGFR inhibitor,
4 but if you look at its kinome profile, it actually
5 targets GAK, one of the NUMB associated kinases
6 with very high potency, with KD of 3 nanomolar.

7 And indeed, we've demonstrated that this
8 is, some of these compounds essentially elicit in
9 vitro activity, again, 7 viral RNA families.
10 We've also demonstrated in vivo activity in a
11 dengue mouse model, this is data that was
12 generated in my lab, and in John Dye's lab, in an
13 Ebola mouse model. So in both models we saw
14 protection from lethality as well as separation of
15 viral replication.

16 So this data was generated right during
17 the time of the 2014 Ebola outbreak in West
18 Africa, and it was selected by the Gates
19 Foundation to be included as 2 out of 3 arms of an
20 adaptive clinical study that was planned to be
21 launched.

22 Sadly, by the time we had access to the

1 drugs and IRB approval and everything, the
2 outbreak started to resolve, which is good for the
3 outbreak, not good for the approach. But this was
4 sort of then saved as a drawer protocol. This
5 technology was also licensed by a local biopharma,
6 but raising funds by local investors didn't work
7 out, so this was never tested clinically.

8 Of course, when COVID hit, we tested
9 this against COVID selectivity, and this is for
10 SARS-CoV-2 were higher. So this was not relevant,
11 but some selective, chemically distinct NAC
12 inhibitors that we've been developing have shown
13 some promise.

14 So I'm going to focus the rest of the
15 talk on the more recent work that we've conducted
16 and here, this was early in the pandemic when like
17 everybody else, we were also very motivated to
18 identify some repurposed approach that may be able
19 to suppress the replication of this virus.

20 And Marwin and Sirie (inaudible) to the
21 lab at the time, we're spearheading this project.
22 So what we did was to approach the Stanford high

1 throughput facility and see what's available. We
2 wanted to focus on compounds with known targets,
3 and active bioactives, and FDA approved drugs.

4 And you could see the libraries that
5 were selected. We complemented this collection
6 with self assembled set of kinase inhibitors. And
7 overall we screened over 3,500 unique compounds.
8 The assay we used was based on immunofluorescence.
9 These are Vero cells that are labeled with GFP.

10 We then infect them with SARS-CoV-2 in
11 the presence of the compound, and then read the
12 GFP signal after 4 days. And what you could see
13 here is the cumulative data. So uninfected cells
14 on the left, as you can see, there's high signal,
15 because these cells are alive. Upon infection in
16 the absence of treatment, essentially there's
17 complete cell lethality.

18 And on the right, as you could see, the
19 majority of the compounds showed no effect.
20 However, outliers indicated in those colorful dots
21 show essentially rescue of cells from SARS-CoV-2
22 lethality.

1 So if you zoom on this group of
2 compounds, you could see the list here, and 7 of
3 them have shown activity in sub micromolar range
4 when it was tested via plaque assay. These
5 compounds essentially target diverse cellular
6 functions, and for the rest of the talk, I'm going
7 to focus just on one of them called lapatinib.

8 So what is the therapeutic potential of
9 lapatinib for SARS COVID 2 infection was of course
10 the first question we asked. And what you could
11 see here is that those response curves, now this
12 is the plateau stage in Vero cells on the left,
13 and in (inaudible) cells on the right.

14 The black curve demonstrates effect on
15 antiviral activity, and the blue curve shows the
16 effect of the drugs on cytotoxicity, and you could
17 see those response effect with EC50 values at .5
18 and .7 micromolar, and EC50 greater than 20
19 micromolar.

20 Lapatinib was able not only to suppress
21 viral replication, but also to rescue cells from
22 SARS- CoV-2 induce laterality in this orthogonal

1 fluorescence based assay. To study lapatinib in a
2 more biologically relevant model, we collaborated
3 with (inaudible). I'm sorry there's some
4 technical formatting issues here. Sorry.

5 So we used an organoid model that was
6 developed by the DAS Lab. These are essentially
7 stem cells derived from lung samples that are then
8 differentiated into proximal and distal lung
9 epithelial cells. They're grown in monolayers and
10 can be propagated. And what you could see in this
11 model is again those response effect with EC50s
12 that were essentially comparable to those measured
13 in the cell lines.

14 And this is how this looks via
15 immunofluorescence. You could see in the center
16 that cells infected with SARS-CoV-2 demonstrated
17 staining for the nucleocapsid labeled in green and
18 lapatinib essentially reduced this staining.

19 More recent data, in collaboration with
20 Luis Martinez at Texas BioMed, used in vivo model,
21 these are wild type mice, and they're inoculated
22 intranasally with mouse adapted SARS-CoV-2, that's

1 labeled with (inaudible). And this is done in
2 animals are treated with 200 mg per kg of
3 lapatinib given via oral lavage daily.

4 This is below the approved dose that's
5 given to patients, to cancer patients. And
6 treatment was given over a course of 4 days post
7 infection, starting a day before. So animals were
8 first subject to bioluminescence measurements.
9 And as you can see here, infected animals
10 demonstrated increased bioluminescence in their
11 lungs. And treatment with lapatinib reduced this
12 signal, particularly after 4 days of treatment.

13 And these are controlled uninfected
14 mice. Lapatinib also demonstrated an effect on
15 weight loss, as you can see on the left. And it
16 also reduced mortality in this animal model. And
17 this effect correlated with suppression of viral
18 titers measured in the lungs and in nasal
19 turbinates, as you can see 4 days, that was
20 essentially close to the lower limit of detection
21 of the assay.

22 So basically this shows that lapatinib

1 suppresses SARS-CoV-2 infection in vitro, in the
2 human lung organoid model as well as in this mouse
3 model. So we of course were curious to determine
4 what is the relevant target. Now, lapatinib
5 cancer targets are ErbB1, which is EGFR, and
6 ErbB2. But when you look at the kinase profile of
7 this compound, it also appears to bind 5
8 additional kinases.

9 One of them is ErbB4. So what are these
10 ErbB's, these are receptor tyrosine kinase,
11 they're on the cell surface, and they form
12 homodimers or heterodimers. We did confirm
13 binding of, I'm sorry, catalytic activity of
14 lapatinib against ErbB4. You could see with an
15 IC50 of 28 nanomolar in this in vitro assay, which
16 was essentially comparable to its activity on the
17 cancer target, ErbB2.

18 So we then asked which of these 7
19 candidate targets may be relevant for SARS-CoV-2
20 infection. And to start addressing this question,
21 we conducted an siRNA base screen where we
22 depleted cells for these kinases individually and

1 measured viral replication.

2 This was done initially in Vero cells,
3 and you could see that suppression of the
4 individual ErbB's reduced viral replication. This
5 was then confirmed in Calu-3 cells, and you could
6 see about lock reduction in viral replication via
7 plaque assays.

8 So it appears that ErbB's are required
9 for viral replication. To further confirm this,
10 we also studied the effect of two chemically
11 distinct pan-ErbB inhibitors, ibrutinib, which is
12 another approved kinase inhibitors, and sunitinib,
13 which is investigational. And once again, you see
14 those response curves with no toxicity in the
15 concentration range used.

16 So this shows that ErbB's are required
17 for SARS-CoV-2 infections. We validated them as
18 potential antiviral targets, both genetically and
19 pharmacologically. And this is truly a class of
20 compounds versus a single ErbB inhibitor that were
21 discovered.

22 To determine whether this antiviral

1 effect correlates with functional suppression of
2 ErbB's, we looked at the phosphorylation level of
3 the ErbB's in infected cells and treated cells,
4 and on the bottom you could see the nucleocapsid
5 staining could see that lapatinib does dependently
6 suppress the nucleocapsid expression as shown in
7 the orange curve.

8 And then lapatinib also dose dependently
9 suppressed phosphorylation of the ErbB's as
10 measured by looking at both the phosphorylated
11 form and the total protein form and measuring the
12 ratio.

13 So this shows that we're seeing target
14 engagement and modulation in this concentration
15 range. To determine whether ErbB's are targets
16 that are mediating the antiviral effects of
17 lapatinib, we conducted these rescue assays, and
18 by mistake I included the data with Venezuelan
19 equine encephalitis virus. But we showed similar
20 results with SARS-CoV-2.

21 So here we're ectopically expressing
22 wild type ErbB4, or catalytically inactive ErbB4,

1 and what you could see in the green column is that
2 wild type ErbB4 was able to rescue or reverse the
3 antiviral activity of the compound, whereas
4 catalytically inactive ErbB was unable to do so.

5 So this truly establishes the link
6 between sort of the molecular target and the
7 antiviral effect. So I've shown you that ErbB's
8 are validated antiviral and molecular targets of
9 lapatinib.

10 So what is the mechanism of antiviral
11 action? This is still a subject for ongoing work,
12 but I'm going to share some of the findings. So
13 first thing we tried to do is to pinpoint a
14 specific stage of the viral lifecycle that
15 lapatinib suppresses.

16 And to do so, we conducted time of
17 addition experiment where the components added at
18 different time points in the course of a 10 hour
19 experiment, which is equivalent to a single viral
20 replication cycle in this model. What you could
21 see here is that when the compound was present
22 throughout the 10 hours, 0 to 10, there was

1 significant suppression of viral replication as
2 measured in cell culture supernatant.

3 But by plaque assays, when the compound
4 was present in the first 2 hours, there was
5 significant suppression, suggesting that the
6 compound may be suppressing early stages of viral
7 entry. But when it was added at later stages of
8 viral replication, such as the last 5 hours, or
9 even last 2 hours, we still observed an effect
10 indicating that the compound suppresses temporally
11 distinct stages of the source copy to life cycle.

12 And this, of course, has potential
13 implications for drug resistance and so on. We
14 probed the role of ErbB's in viral entry, and
15 again just sharing some of the data we
16 demonstrated, it's difficult to see, but we're
17 tracking here individual SARS-CoV-2 particles that
18 are labeled green by staining the nucleocapsid.

19 And we're asking how are these
20 internalizing into the cells by looking at their
21 colocalization with Rab7, which is an endothermal
22 marker. SARS-CoV-2 is known to internalize into

1 this compartment. And what we could see is that
2 lapatinib suppressed the colocalization of viral
3 particles with Rab7, suggesting that it impairs
4 internalization.

5 We also looked at internalization of the
6 receptors. So if you look on the right, you could
7 see that the red arrow points to the effect of
8 SARS-CoV-2 infection on a level on the cell
9 surface measured by flow cytometry. And you can
10 see that infection causes internalization of the
11 receptor because the virus uses it to enter cells.

12 Lapatinib reverses this effect, as shown
13 with the green arrow. The same pattern we
14 observed with ErbB2. So it appears that lapatinib
15 suppresses the internalization of both receptors.
16 And then we also demonstrated binding of
17 SARS-CoV-2 spike S1 domain on 2 ErbB's via
18 coimmunoprecipitations.

19 So at least some of this shows that
20 ErbB's regulate SARS-CoV-2 internalization and
21 viral induced receptor internalization. And that
22 this effect may be mediated, at least in part, via

1 this interaction of virus source interaction.

2 So ErbB's are activated by a large
3 number of ligands, and they're known to signal in
4 pathways, including p38 map kinase, ATTM
5 (inaudible). These are pathways that were studied
6 extensively in the context of acute lung injury
7 and lung fibrosis in noninfectious models. Such
8 as neomycin, idiopathic fibrosis, and so on.

9 So to determine what is the impact of
10 SARS- CoV-2 infection and ErbB suppression on
11 these pathways, we studied the phosphorylation of
12 some of these downstream factors, and what you
13 could see is that at 1.5 hours and 24 hours post
14 infection, we see induction of phosphorylation of
15 these downstream signaling factors by infection.

16 So if you compare the second to this
17 lane, to the lane on the first, the first lane,
18 you could see induction by the virus. And
19 importantly, suppression of ErbB reduce this
20 phosphorylation.

21 So it appears that lapatinib suppresses
22 phosphorylation of signaling pathways downstream

1 of ErbB's. And as I mentioned, these are
2 signaling pathways implicated in injury and
3 fibrosis.

4 We then looked at the effect of
5 lapatinib on cytokine production and this is again
6 done in the adult lung organoid model. You could
7 see that infection with SARS-CoV-2 increased
8 production of proinflammatory cytokines, including
9 TNF-a, IL-1B, and IL-6 as shown by multiple groups
10 before.

11 But lapatinib treatment does dependently
12 suppress production of these inflammatory
13 cytokines. Lapatinib treatment also demonstrated
14 effects on tissue injury in these adult lung
15 organoid models, as you can see that in uninfected
16 ALO's, we see very nice architecture of what we
17 call alveolar like structures, and intact membrane
18 staining of clotted-7, which is a tight junction
19 molecule.

20 Upon infection with SARS-CoV-2, we see
21 complete disruption of this architecture and
22 membrane staining, whereas lapatinib treatment

1 restored a normal phenotype. So this shows that
2 lapatinib suppresses SARS-CoV-2 induced
3 inflammation and tissue injury.

4 And what I argue is that this is not
5 only by suppressing viral replication, but also
6 via a direct effect through its activity on those
7 signaling pathways that I mentioned. And indeed,
8 a paper in idiopathic pulmonary fibrosis mouse
9 model has shown an effect on lapatinib. This is a
10 noninfectious model, of course, and you could see
11 effect on fibrosis.

12 To study the utility of lapatinib in
13 combination drug treatment, we studied its effect
14 on SARS-CoV-2 infection in combination with
15 existing direct acting antivirals. And whereas in
16 combination with molnupiravir and remdesivir, it
17 showed additivity, its combination with
18 nirmatrelvir, the data I'm showing here, showed
19 significant synergy.

20 So what you're looking here, we treated
21 cells with either compound alone or with multiple
22 combinations to create this checkerboard matrix,

1 as you can see on this Z and X axis. And what
2 you're seeing is this mountain or peak above the
3 plane of additivity. This is using a max synergy
4 algorithm, and this is consistent with synergistic
5 effect.

6 And when we quantify the volume under
7 the curve, it's in the range that is predicted to
8 be significant in vivo. And this synergistic
9 antiviral effect was not a result of synergy in
10 toxicities. You could see on the right showing
11 plane of additivity.

12 So this is quite exciting because
13 lapatinib and nirmatrelvir combinations have the
14 potential to perhaps reduce Paxlovid rebound,
15 which currently complicates about 40 percent of
16 treatment courses. It may help address resistance
17 concerns that have emerged, yet, thus far, mostly
18 in immunosuppressed patients.

19 It may allow to reduce the dose. It may
20 provide better tissue injury protection due to
21 this direct effect that I've mentioned. And since
22 lapatinib by itself is a CYP3A suppressor, it may

1 overcome the need to include ritonavir.

2 So in terms of the broad spectrum
3 potential, we have tested lapatinib against thus
4 far 5 viral families, and it has shown activity.
5 The majority of these are antiviruses with the
6 exception of pox virus, which is, of course, a DNA
7 virus.

8 Just to share some of the data. Alpha
9 viral infection model diseases, Venezuelan equine
10 encephalitis virus transmitted by a mosquito and
11 causes severe encephalitis. It's also a biothreat
12 agent since it could be aerosolized.

13 Here, we collaborated with Artin
14 Narayanan and George Mason University, and using a
15 neurovascular unit model that attempts to capture
16 the 3D blood brain barrier architecture, we
17 observed a log reduction or so of viral
18 replication. This is treating a donkey, which is
19 the wild type VV virus, both on the vascular
20 chamber and on the brain chamber across this BBB
21 like membrane.

22 Similarly to what I've shown you in the

1 SARS-CoV-2 model, here again we're seeing effect
2 on reduction of proinflammatory cytokines, as well
3 as protective effect on BBB integrity, as measured
4 here, the FITC-dextran permeability assay.

5 In a mouse model, the Narayanan lab has
6 demonstrated protection with lapatinib against the
7 V challenge. In this case, it was the vaccine
8 strain of VVTC83. Wild type mice that were
9 treated again with lapatinib had protection from
10 lethality and this effect correlated with several
11 log reduction in viral titers, both in the serum
12 and the brain.

13 So this is yet a second unrelated viral
14 disease model where we were able to show activity
15 both ex vivo and in vivo. And to determine
16 whether viruses could escape treatment with
17 lapatinib we passaged VV in the presence of
18 lapatinib, or a direct acting antiviral, ML336.
19 And what you could see in the pink curve is that
20 virus that was passaged under the DAA essentially
21 was suppressed initially.

22 But then this was followed by a rebound,

1 which coincided with the emergence of a resistant
2 mutation in the nonstructural protein that's known
3 to be suppressed by these compounds. And in
4 contrast, virus that was passaged under lapatinib
5 continued to be suppressed.

6 When we obtained the supernatants that
7 was derived after the tenth passage and used that
8 to inoculate naive astrocytes, we saw that virus
9 that was passaged under lapatinib continued to
10 show susceptibility to lapatinib, whereas the
11 virus that was passaged under ML336 essentially
12 lost its susceptibility to the direct acting
13 antiviral.

14 So this sort of shows that the genetic
15 barrier to resistance of lapatinib is higher than
16 direct acting antivirals. And this is something
17 we have seen with some of our other host targeted
18 approaches.

19 So the model that we sort of proposed
20 and have been validating is that, as I've shown
21 you, ErbB's are involved in regulating existing
22 stages of viral life cycles in the context of

1 SARS-CoV-2. I showed some of the data in viral
2 entry. We're looking at other stages right now.

3 Moreover, they regulate signaling in
4 those downstream pathways that are implicated in
5 tissue injury, acutely and chronically. So by
6 suppressing those ErbB's, we could sort of achieve
7 a triple role, not only suppressing viral
8 replication, but also the inflammatory signals, as
9 well as potentially protect from tissue injury.

10 I don't know how we're doing with time,
11 but I can -- so yeah, we're good. Okay. So what
12 is the repurposing potential of lapatinib. So it
13 is approved globally for advanced ErbB2 positive
14 breast cancer in combination drug treatment with
15 antimetabolites or antiestrogen treatment.

16 It is dosed orally once daily. And it
17 appears to be accumulated in the lung. And this
18 is something we've seen in our mouse model. In
19 terms of its safety profile, the most common side
20 effects in the first days of treatment is
21 diarrhea. And yes, there have been severe side
22 effects that were reported, including liver

1 toxicity and QT prolongation.

2 However, these were always in
3 combination with drug treatments, with
4 antimetabolites in sick metastatic breast cancer
5 patients, and not within the first month of
6 treatment. And there is some concern about drug
7 interactions. As I mentioned, it suppresses the
8 cytochrome P30A4.

9 And its synthesis can be scaled up
10 easily. It is a small molecule. So what I've
11 shared with you was a couple of proof of concept
12 for the potential utility of targeting cellular
13 kinases to combat acute emerging viral infections
14 and propose a few approved drug candidates for
15 repurposing either individually or in combination
16 drug treatments.

17 But of course, there are numerous
18 challenges. And maybe this is something I can
19 leave for the discussion. So we're far from
20 achieving the goal of having an established
21 (inaudible) portfolio for pandemic preparedness.

22 But when we think about the future,

1 perhaps a best approach would be to both develop
2 and stock host targeted broad spectrum antivirals
3 as the first line of defense. And then couple
4 that with direct acting antivirals, and ideally if
5 there was a portfolio, NIH is currently trying to
6 create where we have small molecules for each of
7 the major viral families that could accelerate
8 rollout, as we've seen with the case of
9 nirmatrelvir.

10 And I'd like to end by thanking the
11 people in my group, particularly Sirle Saul and
12 Marwah Karim, who've done the large bulk of the
13 work. Our funding agencies and collaborators.
14 And thank you again for the invitation and for
15 listening.

16 DR. MCGIVERN: It's time for questions
17 now. While people are thinking of the questions,
18 I'd like to ask a question. So how late can you
19 administer these drugs in the animal models? Can
20 they be quite symptomatic?

21 DR. EINAV: Thanks for the question,
22 David. Yeah, thus far, we've essentially studied

1 them at the prophylactic model. I mean, we
2 administered them 12 hours prior to inoculation.
3 We are currently actively doing the postinfection,
4 you know, studies. So that's definitely going to
5 be more biologically relevant for treating acute
6 infections. Yeah. Thank you.

7 DR. MCGIVERN: Thank you. Do we have a
8 question in the room?

9 SPEAKER: Thank you for that. Thank you
10 for that. It was great talk. You know, we are
11 Center of Biologics, and so we are interested in,
12 you know, protein drugs. We see combination of
13 small molecules. Has anybody tried mixing
14 monoclonals with small molecule, and whether that
15 would be beneficial?

16 And then another corollary to that, have
17 you looked into using this compound against, for
18 example, hepatitis C, where cirrhosis and fibrosis
19 is a big issue? And so this would be a well
20 suited compound for that.

21 DR. EINAV: Thank you for the question.
22 Yeah. We did not try to combine these agents with

1 antibodies. And I don't know if there have been
2 publications where that has been done. I can
3 certainly look it up. It's interesting.

4 In terms of chronic hepatitis C, I think
5 there are challenges. And again, I want to
6 emphasize that the host targeted approach is, and
7 I'm going to go back to my slide I skipped about
8 challenges. I mean, for an acute infection where
9 we are, we are looking at treatment duration of
10 days, I think that these would be safe.

11 For a chronic viral infection where you
12 need to treat over many months, I am not sure. So
13 I would take that with a grain of salt. But for
14 mechanistically, I think that there is definitely
15 potential, and as yeah, as you saw, I mean, for
16 idiopathic pulmonary fibrosis, it has been used.

17 So those pathways are really common
18 pathways for multiple injuries within infectious
19 and noninfectious etiology.

20 MS. ELKINS: Does this one work? Ah,
21 good. I have the online selection, and a couple
22 of these arrived before your challenges slide, and

1 before another discussion. But let's go over them
2 again. So with regard to repurposing drugs, what
3 do you expect in terms of dosages and change of
4 dosage, and what are the implications for safety
5 when the dosage is changed?

6 DR. EINAV: Yeah, thank you. So thus
7 far, we've been able to show an effect in vivo
8 with dosing regimens that were lower than the
9 approved doses in humans. I want to say in
10 general the safety is a concern. But a few
11 comments about that. We do treat all
12 noninfectious diseases with host targeted
13 approaches. Right.

14 So why would treating viral infections
15 be different with that respect. I mean we're
16 seeing toxicity in direct acting antivirals as
17 well. So it's not necessarily specific to host
18 targeted. It's all about finding a concentration
19 range that would be sufficiently inhibitory for a
20 viral replication, yet not toxic in a cell.

21 Again, I emphasize acute viruses as
22 opposed to chronic viral infection. So we are

1 talking about treatment durations that are in the
2 order of days. We're also seeing redundancy in
3 cellular machineries. For instance, some of the
4 NUMB-associated kinases, we see that they have
5 overlapping substrates to some extent, so you
6 inhibit one, it may be sufficient to kill a virus,
7 but not yet cause toxicity.

8 So and then the last thing I'd say about
9 that is that, ultimately, I think it's really the
10 severity of the outcome that should dictate the
11 threshold. I mean what you can tolerate for a
12 lethal infection such as Ebola would be very
13 different from what you would do for a rhinovirus.
14 Right. So it all has to be dependent on the
15 context.

16 MS. ELKINS: Thank you. Next is thanks
17 for a great presentation. You mentioned the lung
18 to plasma ratio of 2, was that total, and how
19 different was the time course in kinetics?

20 DR. EINAV: So the lung to plasma ratio
21 in terms of, I assume, lapatinib concentration.
22 So we actually, it's even greater than that. Let

1 me see if I have the slide here. Yeah, so here it
2 is.

3 So this is what we measure in our animal
4 models. After 8 hours of treatment, you could see
5 concentration of 100 micromolar in the lungs,
6 whereas in the plasma, it's essentially tenfold
7 lower at that time point, so quite significant.

8 MS. ELKINS: And returning to the safety
9 question, could you discuss further from your
10 point of view how the safety profile of broad
11 spectrum antivirals compares to that of narrow
12 spectrum antiviral therapies?

13 DR. EINAV: It's a tough question and
14 eventually, it's very dependent. It's dependent
15 on the moiety. We've seen liver toxicity from
16 decimvir. We're seeing, I mean so the profiles
17 change. It's really the mechanism of the drug
18 rather than the spectrum of coverage that it
19 provides.

20 MS. ELKINS: Others in the room?

21 DR. MCGIVERN: Thank you, Dr. Einav, for
22 an informative, thought provoking presentation.

1 DR. EINAV: Thank you.

2 DR. DEY: Good morning. And moving
3 forward, this is Ranadhir Dey. I'm from Office of
4 Blood Research and Review, and it's my pleasure to
5 introduce today's next two speakers. First one is
6 Dr. Viswanath Ragupathy, Dr. Ragupathy also works
7 in OBRR, which is Office of Blood Research and
8 Review. He's a staff scientist and he's
9 virologist with almost 20 years of experience in
10 HIV and AIDS research.

11 He has published several articles in
12 high impact scientific journals and has been
13 actively involved in international collaborative
14 research studies, including those focused on the
15 use of NG's and the IML technologies.

16 Our next speaker will be Dr. Gabriel
17 Parra. And he's a principal investigator at the
18 Office of Viral Products in the OVRP at the Food
19 and Drug Administration. And his research focus
20 on the epidemiology, genomics, evolution, and
21 immunity of viruses associated with
22 gastroenteritis.

1 So with this, I would like to please
2 welcome Dr. Ragupathy.

3 DR. RAGUPATHY: Again, come back to that
4 first one. Sorry with that technical glitch.

5 Thank you. Next presentation is unbiased
6 metagenomic exploration of transfusion transmitted
7 infections with nanopore sequencing. Early
8 morning, Charlie Chiu set the stage about this
9 matter, metagenomic sequencing, which makes my
10 life easier to make you better understand about
11 this technology.

12 So with that, the outline of my
13 presentation is I will go over the background
14 about metagenomics and the issues with the blood
15 safety and how we mitigated it, and also some
16 issues with this technology and challenges with
17 this technology. And also I'll touch upon some
18 information on regulatory insights.

19 Yesterday, Dr. Marks have highlighted
20 how scientific research supports the diagnostic,
21 the role of biologic products, and I will give you
22 some examples of our research studies supporting

1 the approval of in vitro diagnostic devices. And
2 also I'll go over a little bit on the methods used
3 and conclude with some results and discussion.

4 So blood safety has significantly
5 improved in recent years. The emergence of new
6 infectious agents that can be transmitted by blood
7 products continues to pose a significant
8 challenge. (Inaudible) currently used in blood
9 testing centers for pathogen detection are highly
10 specific to known pathogens, making them less
11 effective for identifying the uncharacterized
12 microbes.

13 Alternative approaches such as pathogen
14 reduction or inactivation, which you heard in
15 yesterday's presentation, where they have shown
16 significant improvements with these technologies.
17 These are broad and nonpathogenic specific actions
18 shows promise.

19 However, certain methods are not equally
20 effective across all the types of microbial
21 pathogens. For instance, (inaudible) viruses,
22 such as hepatitis E virus and hepatitis A virus

1 are particularly resistant to these methods. So
2 this is the world we are living in.

3 And here, I'm showing you with different
4 viruses that have been either emerging or
5 reemerging in different parts of the world. I've
6 highlighted a few parts, which are currently
7 affecting an epidemic which caused the, both the
8 economical impact, as well as morbidity and
9 mortality.

10 While I was finalizing these slides two
11 weeks ago, CDC Infectious Disease Journal
12 published a report on a patient with unknown rise
13 of liver enzymes with a negative for all the
14 hepatic agents and also some parasitic infections.

15 So when they did their metagenomic
16 sequencing they found out this human circovirus
17 which is causing, associated with hepatic failure,
18 with the association with the pathogenesis found
19 that individual, immune compromised individual.

20 So the challenges associated in blood
21 safety, I have kind of grouped them as an emerging
22 viruses. Those are hepatitis B, HCV plasmodia,

1 and CMV, and emerging viruses are HIV, COVID-19,
2 Jakob's disease, SARS, flu, transmissible
3 spongiform encephalitis, Zika, and Ebola.

4 And reemerging ones are West Nile
5 bacteria, (inaudible), malaria, and babesia. Sub
6 emerging are HGV, which I'll touch upon, and TTV,
7 I'll touch upon latter part of my presentation.
8 And SEN-V virus, and other infections.

9 NAC assays are highly accurate in
10 identifying all these infections at the acute
11 stage where you have a (inaudible). However, the
12 residual risk because of this window period, or a
13 new emerging variance is unavailable.

14 So can we ask questions, can NGOs
15 enhance the blood safety by improving the
16 detection of emerging uncharacterized pathogens.
17 The use of novel technologies, such as NGO's
18 metagenomics, allows comprehensive analysis of all
19 nucleic acids present in the blood sample,
20 providing a valuable tool for diagnosing
21 infectious disease of unknown origin.

22 This method is known as agnostic NGS and

1 does not require a prior knowledge of the genome
2 sequence to be analyzed. However, diagnostic
3 approaches faces the challenges while bacterial
4 diversity in clinical samples can be identified
5 through 16S, kind of an universal signature. No
6 such universal gene exists for viruses, which are
7 highly complex due to our error prone replication
8 process.

9 And I kind of put in here the band
10 metrics associated in characterizing some of these
11 microbes for the known pathogens. It's kind of
12 informatics is quite simple. But with unknown
13 viruses, it's highly complicated, which involves
14 more additional robust tools required to
15 characterize the genome.

16 So with that, we have some studies and
17 how that supported our regulatory approval of NGS
18 devices. So our office in OBRR is responsible for
19 regulation of HIV in vitro diagnostics, including
20 donors staining assays, which involves HIV and
21 other viruses, and some parasites. And also HIV
22 diagnostics, viral load, and drug resistance

1 monitoring.

2 So as you all know that Next Generation
3 Sequencing has been there since 2005, with the 454
4 raw sequences, and around 2012 commercialization
5 of short sequences have been rolled out. We have
6 approved two genomic based assays that uses Asana
7 technology.

8 So we envision that at some point these
9 asset sponsors will intend to use these NGS
10 technology. So around '20 time points we
11 initiated evaluating this NGS technology with
12 external collaborations on understanding the
13 complexities and applications of NGS in genomic
14 research.

15 We published three study results with
16 the multiple applications of this technology. All
17 three are development of either a proficiency
18 panel or reference materials. The first one is
19 specifically for HIV-1 drug resistance, where both
20 the industry and academia collaborated in this
21 effort.

22 At least 11 centers have participated,

1 including our laboratory, and this panel is
2 currently available in (inaudible) care for
3 commercial use.

4 The next publication is there is a need
5 for highly divergent HIV variants are required for
6 artists to perform better and also for the multi
7 (inaudible) vaccine manufacturing. So again, in
8 collaboration with NIAID and Duke University, we
9 developed a highly diverse HIV reference panels.
10 And these panels are also currently available in
11 an (inaudible) with Duke University.

12 And lastly in collaboration with NIBSC,
13 we developed reference panels for advantageous
14 agents characterization where this panel is spiked
15 with the 25 viruses. And we are part of this
16 collaborative effort where both industry and
17 academia are involved in development of this panel
18 material.

19 So with the past five years, we gained
20 sufficient experience both in terms of
21 methodologies and also in bioinformatics. In
22 2017, two NGS device sponsors submitted the

1 pre-submissions seeking agency guidance on
2 appropriate regulatory pathway and the proposed
3 performance studies.

4 Just to note here, so there is no
5 predicate available at the time when the sponsor
6 submitted this application. So this is a kind of
7 novel application for us. During the interactive
8 review we provided our guidance on regulatory
9 pathway, and also we mentioned to the sponsor that
10 we asked them to submit their NGS data file in an
11 organized way, that we provided them a template
12 for an independent internal assessment.

13 And also, we provided that in our
14 guidance on how to submit these NGS, large NGS
15 data files in our secured format. And also we
16 provided the guidance and agreements for utilizing
17 external reference databases used in their
18 analysis.

19 So in 2019, Sentosa SQ HIV genotyping
20 assay for monitoring HIV drug resistance was
21 authorized via direct de nova pathway, because
22 there is no predicate exist. Special controls

1 were established to provide a safe and effective
2 use of this IVD HIV genotyping assay using NGS
3 technology for drug resistance monitoring.

4 In 2019, another device sponsored filed
5 their metagenomic sequencing application at CDRH,
6 and we were involved as a consult review for that
7 application.

8 So to better understand the complexities
9 with this evolving new NGS technologies, Multi
10 Center International Collaborative studies on, and
11 use platform was performed in our lab to evaluate
12 the assist assay performance.

13 Specifically this one is use of nanopore
14 sequencing platform for characterizing the
15 advantageous agent. This effort was actually put
16 forth by Dr. Eficon in another office at CBER, in
17 collaboration with both industry and academia.
18 And this study is almost now complete, and we'll
19 be expecting this publication very soon.

20 So with that, the goal of today's
21 presentation is unbiased characterization of
22 transfusion transmitted diseases, where we

1 specifically focus on cataloging both the known
2 and unknown viruses with this use of unbiased
3 sequencing approach. And also using the nanopore
4 platform.

5 And also to develop bioinformatic tools
6 to identify the microbial diversity of bacteria,
7 viruses, and fungus in biological specimens. So
8 these tools we try to implement them in our CBER
9 hive, so that in future applications, we could be
10 able to use those tools for our independent
11 assessments.

12 So it's kind of, that slide is kind of
13 mixed. Okay. So our methodologies or two parts.
14 One is an experimental and a bioinformatics. And
15 for our experimental part, we have analyzed some
16 clinical samples which are sourced commercially.

17 And also virus panels are prepared at
18 different viral thresholds, lowest is 1,000
19 copies, and highest is 100,000 copies. And total
20 nucleic acids are extracted from 200 microliter of
21 the samples. Something is missing there. The
22 panels are also prepared, evaluated individually

1 as HIV, HCV, and HBV.

2 Kind of representative viruses for our
3 transfusion transmitted diseases. And we also
4 mixed all these viruses as a virus cocktail and
5 evaluated them. So nucleic acids are extracted
6 using Zymo kit, which extracts total nucleic
7 acids, and cDNA is synthesized.

8 And we didn't use any gene specific
9 primers here. And so samples are purified using
10 (inaudible) system, and laboratory preparation, of
11 course, we followed the manufacturers instructions
12 provided in the nanopore sequencing platform.

13 This nanopore is kind of a quite rapidly
14 evolving method. So when we started this work, we
15 used R-9 full fill, and by the time we completed,
16 that kind of evolved with an R-10 full fill. So
17 that's what I'm going to show. I have results
18 from both R-9 and R-10 platforms.

19 For bioinformatics, we use the half
20 model, and we profiled all the reads above quality
21 seven. And for adapter trimming, we used a tool
22 called Porechop. And for the quality control, we

1 filtered out all the reads that are less than 200
2 in this pack. But also filtered out all the reads
3 that have a quality score below 7.

4 And we also removed the host because we
5 used the clinical material from a host human. So
6 more than 95 percentage of the genome is host
7 genome. So that needs to be removed for better
8 evaluations. And for the alignment, we used
9 Minimap. Also we included multiple databases.
10 I'll touch upon why we have included multiple
11 databases. And for samples, Mega 11 are used for
12 statistics and phylogenetic analysis.

13 So here is our clinical samples
14 metagenomic profiling. This heat map shows you
15 again these are all known viruses we wanted to
16 catalog and whether to see whether these viruses
17 can be metagenomically or without using any gene
18 specific primer, we can able to detect these
19 viruses.

20 What you see in the first one is HIV,
21 and you can see we do see a high hit for HIV. And
22 the second one is hep-C. You see it's high for

1 hep-C. And third one is hep-B, and you'll see
2 it's high it's for hepatitis B. And last one is
3 GBC virus which is also infecting with HCV
4 individuals. I'll show you the additional data on
5 that.

6 So once we've got this, it's the next
7 step is to characterize that genome in depth. So
8 what we did is we kind of derived our consensus
9 sequence from these viruses and then build a
10 phylogenetic tree using that. So with HIV
11 clinical sample, we were able to find out it
12 belongs to the (inaudible) B, and for HCV it is
13 genotype 40A. And for hep-B it is genotype C.

14 And for all these three genomes, we were
15 able to obtain near full length of the genome,
16 which is indicated in a kind of linear color
17 coding at the bottom of this phylogenetic tree.

18 For our West Nile virus, we were not
19 able to get a full length of the genome. Per our
20 investigation, we found out that it's due to a
21 sample integrity issue. However, with a small
22 fragment, what we received, what we observed when

1 we did an phylogenetic analysis, we were able to
2 see that closely kind of clustering with lineage
3 1A.

4 So a little bit on pegivirus. So the
5 pegivirus is the one which we identified with an
6 HCV infected individuals, and once we got an each
7 for this pegivirus, we derived our consensus
8 sequence and generated a phylogenetic tree.

9 And you can see from this phylogenetic
10 tree greater than 90 percent nucleated (inaudible)
11 was observed with pegivirus genotype 2. So what
12 are these pegiviruses? They belong to the family,
13 Flaviviridae family and it's a single negative
14 strand RNA virus with 9 times 4 kilobase genome in
15 size. The pegivirus genus includes 11 species,
16 pegi A2K, with the pegi C infecting the humans.
17 Historically, the pegiviruses are called as a GBV
18 virus or hepatitis G virus, and currently it's
19 called as an hepatitis pegivirus 1.

20 So today there are only two known
21 pegiviruses are identified. That is pegivirus 1
22 and pegivirus 2. Although not linked to the liver

1 disease, this pegivirus infection with HIV or HCV
2 can slow the disease progression by immune
3 modulating. Specifically, in HIV, these
4 pegiviruses kind of down model at CCR4 and CCR5
5 receptors.

6 So in studies of general population and
7 healthy donors, the prevalence of the pegivirus is
8 found to be 0.8 to 44.6 percentage. Through
9 agnostic approach, we were able to identify the
10 full length of this genotype to pegivirus.

11 On the cartoon below is to show you how
12 closely these pegiviruses are associated with HCV.
13 So HCV genomically has a single polyprotein, and
14 both the pegiviruses also you see a single
15 polyprotein, both structural and nonstructural
16 elements are quite similar, except the
17 untranslated regions on both five prime and three
18 prime, you'll see some differences with this
19 pegiviruses.

20 So next virus, which we identified as
21 the anellovirus. In our first standardized
22 protocol, we were not able to identify these

1 viruses. So we slightly modified our protocol
2 introducing rolling circle amplification at the
3 stage of cDNA synthesis.

4 And by doing the so we were able to kind
5 of profile the hepatitis B and this anelloviruses.
6 So you can see from this profile and also
7 phylogenetic analysis indicate that the Toscano
8 virus is closely associated with our clinical
9 samples, which are sequenced, which is BB9.

10 So anelloviruses are our single negative
11 strand circular DNA belonging to the family of
12 (inaudible), with a genome size of 2 to 3.9 KB and
13 encodes 4 overlapping fragments, which is
14 indicated in the cartoon below. The most studied
15 genus of anelloviruses, in fact, humans, is the
16 Toscano viruses.

17 And there are 29 species of this virus
18 identified today. High prevalence in human
19 population at greater than 90 percent of the
20 individuals are infected with this anelloviruses,
21 both HCV and non HCV infected individuals.

22 They are considered commensal and have

1 not been associated with any specific diseases
2 just by their ubiquity in the human population.
3 Recent studies have revealed the structure of
4 analog virus particles, which include unique spike
5 domains, that may help the virus to evade the
6 immune system by exposing diverse epitopes as
7 immunological decoys.

8 Through an agnostic approach, we were
9 able to also identify the full length of this
10 virus. We have deposited both this pegivirus and
11 anellovirus in an SRA NCBI database, which will be
12 released to the public at the end of this year
13 because the publication is still due.

14 So this is general statistics for
15 combined evaluation of HIV, HCV, and hep-B in
16 different virus thresholds. So on the X axis you
17 see different virus thresholds, and kind of the
18 first row indicates the total number of reads.
19 The ones with the red and orange are HIV reads.
20 The ones with the green and blue or hepatitis B
21 virus. And one with the lavender are HCV reads.

22 So the first row indicates the total

1 number of the reads. So these number of what
2 you'll see there is the number of reads mapped to
3 the virus decreases as far as the virus dilution
4 is increased. So this is expected.

5 And also the number of days is also,
6 (inaudible) also decreases with the virus
7 dilutions. So these two are quite important for,
8 you know, getting the establishing the limit of
9 detection or improving the accuracy of these
10 assays.

11 And for the read quality, when we
12 profiled this HIV, HPV together, we were able to
13 see a greater than 10 for the quality of the
14 reads. And of course, the read length is always
15 greater than 1,000, enable for the comprehensive
16 genome coverage.

17 So next is we wanted to measure how low
18 this virus can be measured. So we kind of diluted
19 the virus with the human background as more than
20 around 100,000 viruses or 10,000 genome copying
21 equivalence, or 1,000 base pairs.

22 So what we have found out is at about

1 10,000 genome copy equivalents, we were able to
2 consistently detect these viruses. And also we
3 could able to characterize the full length of this
4 genome. At 1,000 copies, we do see the hits, but
5 some of the replicates missed detection of these
6 representative HIV or HPV, RA, CD.

7 So we kind of stick to a 10,000 genome
8 copy as a limit of detection. And when we ran the
9 replicates of, three replicates, three independent
10 replicates of this at that viral load, and we were
11 able to consistently profile these viruses.

12 So this slide also shows you the
13 repeatability of HIV, HPV sequencing at 10,000
14 genome copy in sequence. And what you'll see is
15 all these replicates, there is not much
16 variations. And for our reliable virus detection,
17 at least 20 reads are required. I think that that
18 is one of the questions early morning with Charlie
19 Chiu's presentation.

20 So for our reliability detection, we
21 found that 10,000 genome copies at 20 reads is
22 sufficient. And also the base count of 10,000

1 bases with the read lengths greater than 1,000.
2 And also we noted the quality scores of these
3 reads are greater than 15.

4 So in our previous experiments, we kind
5 of analyzed these three representative viruses
6 individually. In our next experiment, we mixed
7 all these viruses together and we kind of wanted
8 to profile them to find out whether we could able
9 to get that same inference at the 10,000 genome
10 copy equivalents.

11 So this heat map indicates the three
12 different replicates of our cocktail, and you can
13 see all three replicates, we were able to detect
14 the expected HIV, HPV, HCV. And also here we have
15 included multiple databases. So the use of these
16 databases for taxonomy profiling enhances the
17 accuracy and comprehensiveness.

18 And this is also another question came
19 today morning about the bias of this. So this use
20 of these multiple databases kind substantially
21 mimic those biases. For blood metagenomics, most
22 of the viral database produce consistent results.

1 This again, it's some general statistics
2 for the virus cocktail. And what you'll see shown
3 above, there is no significant difference with the
4 replicates measured. And N50 read length remains
5 constant for all the replicates tested, which is
6 important for differentiating from viral targets
7 and from non viral targets.

8 And finally, we have also evaluated, so
9 this nanopore sequencing as leveraged as to kind
10 of start and restart approach. So where we can
11 run this sequencing for up to a certain time point
12 and then you can stop it, watch it, rerun it.

13 So we wanted to profile it and see how
14 early we could able to detect the virus and how
15 early we could able to detect entire genome of the
16 virus where the coverage is equal to just one
17 read.

18 So what we noted is in less than 5
19 minutes, we were able to see detecting all HIV,
20 HPV, HCV when the viral threshold is around that
21 10,000 copies. At about close to half an hour, we
22 were able to get the full length of this genome.

1 that is ability to detect a wide range of
2 pathogens, significantly enhances the blood safety
3 by providing a comprehensive insights into the
4 microbial communities present.

5 With that, I would like to acknowledge
6 my supervisor and their ability to provide a
7 constant support of my both research and
8 regulatory activities, and Karen is our fellow in
9 our lab who performed all the replicates, and the
10 validation experiments, and other members of our
11 HIV team.

12 I also wanted to thank CBER-hive, who
13 are continuously provided that support, Louise,
14 Ilya, and Sean Smith. Whenever I approached them
15 to implement these tools or in any future
16 applications are filed, we have all these tools
17 implemented for our informatic analysis of our
18 independent assessment. I'll stop here and thank
19 you for your attention.

20 DR. DEY: Thank you. Thank you. Thank
21 you, Dr. Ragupathy. Thank you. Please hold your
22 questions, because we'll move to next speaker.

1 Our next speaker is Dr. Gabriel Parra, please.

2 DR. PARRA: Well, thank you to the
3 organizers to give us, to give me the opportunity
4 to present some of the work that my group has been
5 doing for the past few years. And thank you all
6 of you for being present here. And those that are
7 virtual also. Also, thank you for your interest
8 in hearing our research.

9 Okay. Today I'm going to be talking
10 about some work that we've been doing to
11 understand norovirus antigenic evolution and
12 vaccines, at this time. And before I get moving,
13 let me give it a try. Okay, here. Antigenic
14 evolution and vaccine design.

15 Probably some of you already
16 experienced, but just let me put everybody in the
17 same context here. But norovirus is a major cause
18 of gastroenteritis worldwide. As I say, some of
19 you might experience it, and you know exactly what
20 I'm talking about, the norovirus disease is
21 characterized by explosive, uncontrolled diarrhea
22 and vomiting.

1 The symptoms usually self resolve in
2 healthy individuals within 1 or 2 days. But the
3 imprinting is there. You will never forget that
4 you had norovirus, right. But the in vulnerable
5 populations, they can develop severe disease, like
6 malnourished children in the third world
7 countries, the elderly, and immunocompromised
8 individuals.

9 And there is no vaccine or specific
10 treatment for norovirus. Norovirus is an RNA
11 virus. So it changed a lot. The capsid is quite
12 simple. It's a nonenveloped virus. The capsid
13 is, hang on one second, the capsid is icosahedral
14 capsid. This whole capsid is formed by one single
15 protein. There are in general, not always, but in
16 general there are 180 molecules of VP1 arranged in
17 this icosahedral particle.

18 VP1's usually form dimer and trimers to
19 make this particle. This is shown here, a dimer
20 of VP1. You can see this is the axis. So the one
21 monomer is here. The other one is here. And what
22 is interesting about this protein is they have a

1 very unique structural confirmation, which is only
2 shown in caliciviruses.

3 The VP1 has two structural domains, the
4 shell domain which is shown here in blue. And
5 this domain forms the scaffold for the capsid to
6 make this array. And there is an extension of
7 these from this shell domain, which is the
8 protruding domain, and this structure has been
9 only seen in caliciviruses.

10 And it's quite interesting because this
11 is a part of the virus that interacts with the
12 host. And one interesting fact about this is full
13 loops. So there is a lot of potential for
14 variation in that particular part of the capsule.
15 And I'll discuss that later.

16 A few things. We don't have a cell
17 culture system or robust cell culture system, so
18 obtaining viruses is quite difficult for us. We
19 rely sometimes in stool samples and
20 epidemiological data. That's the reason now my
21 lab is actually quite interested in genomics and
22 the technology, so we can capture information.

1 carbohydrates, different carbohydrates.

2 So the virus needs to use different
3 strategies to attach. These are carbohydrates
4 from the histo-blood antigen, or we call them for
5 short ABGA. These are not the receptor, but what
6 we know that they facilitate infection.

7 Once an individual is infected, this is
8 a classical immunology from book, right. Immunity
9 or immune response from book, I meant to say. The
10 individual will develop, two weeks later, very
11 strong in homotypical responses for antibodies.
12 And these antibodies will wane after the infection
13 occurs.

14 This antibody seems to protect amount
15 between 2 to 5 years, depending on what kind of
16 data you look at. So reinfection can occur. But
17 despite that many people have high antibody titers
18 in the population, reinfections occur very often.

19 And those that had norovirus before,
20 multiple times, you know exactly what I'm talking
21 about. So how can high titers not protect you
22 from infection. So one of the things that we know

1 is that not all antibodies are actually
2 protective. And I'm setting the stage. We have
3 no clue what the other antibodies are. The ones
4 that do not protect.

5 But basically, what has happened here is
6 using control experimental challenge volunteer
7 studies, what we have learned from these studies
8 is that individuals that were challenged with the
9 virus and they developed disease. Sorry and they
10 did not develop disease after challenge.

11 What was found is that this individual
12 have very high titers of HBJ blocking antibody.
13 So if you have high titers of this, that blocks
14 interaction of the virus with these carbohydrate,
15 you more likely will be protected. While those
16 that do not have those type of antibodies, you
17 will be not protected.

18 So what I told you so far is a complex
19 interaction of waning immunity potential, or
20 motific immunity. I haven't talked about this,
21 but the virus actually changed, and I told you
22 that there are multiple different HBGA's that that

1 people can express. So virus can change and
2 attach stronger to certain carbohydrates. So and
3 also an enhance of viral replication based on this
4 difference on attachment.

5 But one of the things that happened with
6 the virus actually changes generated viral
7 antigenic diversity. And that's exactly what my
8 lab is exploring and trying to understand. Human
9 noroviruses, there are more than 40 different
10 genotypes. What are genotypes. Genotypes are
11 viruses that cluster together in a phylogenetic
12 tree, and they are defined by changes in the VP1.

13 Just to give you an example, the
14 different viruses from genome group 1 and genome
15 group 2 can be classified based on 50 percent of
16 difference in the capsid protein. So we're
17 talking about more than 250 mutations just in
18 between these two viruses.

19 Just to give you a perspective that
20 these are very, very, very different viruses.
21 Then each of these genome groups can actually have
22 multiple clusters of viruses that I'm just showing

1 you here. And those are the genotypes. And we
2 have more than 40 of those that can infect.

3 So you can imagine that in the lifetime
4 of a person, if these are very distinct viruses,
5 you can be reinfected with multiple of these
6 viruses. And as I showed you, as I told you
7 before, the immunity is somehow homotypic.

8 So there are multiple chances that the
9 individual can be reinfected during the lifetime.
10 But one interesting thing happened in norovirus
11 and I'm not going to go into much details about
12 why that, but one interesting thing happened is
13 that there are 40 different genotypes, or more
14 than 40 different genotypes that can infect
15 humans.

16 One single one, G24, is the most
17 predominant worldwide. And it can account for
18 more than 50 percent of the infections worldwide.
19 And in some cases, can be up to 80 or 90 percent.
20 And that's true for all the years, or most of the
21 years that we've been looking in the literature.

22 So why is that. The reason of that is

1 this particular genotype actually presents the
2 chronological emergent and replacement of
3 variants, very similar to influenza H3 and 2, or
4 SARS-CoV-2, as we have seen in recent years.

5 But basically what happens is that one
6 cluster of viruses, I'm just giving you an example
7 and the first one I've been able to see here,
8 Farmington Hills virus, emerged into the
9 population, have multiple changes. It spread
10 through the population very rapidly, it spread
11 through worldwide very rapidly. Caused large
12 outbreaks, and a few years later will be replaced
13 by the next one just because we'll exhaust most of
14 the population.

15 What is interesting, and as you can see
16 here, there are multiple viruses that emerged in
17 the last 25 years. Two things to consider here.
18 And I'm going to go into detail, although my lab
19 is very interested on those patterns, is the
20 chronological emergence is not linear in terms of
21 the phylogenetic tree.

22 So you can have viruses from 2007

1 circulating very close to 1995, and so on, right.
2 So there's no linear or linear evolution on these
3 viruses. One thing. The second thing is that not
4 all these viruses actually cause pandemics. So
5 only 7 out of more than 10 that emerge, the other
6 ones are just locally distributed.

7 So we don't know exactly why. But one
8 of the things that we know or what we saw, our
9 working model was that this virus emerged with
10 changes in the capsid, and that's how they escape
11 the immune population, or herd immunity.

12 When I, when we started looking at this
13 data, we actually didn't have enough data to
14 support that hypothesis. So one of the things
15 that my lab did is we, using genomics, and I'm
16 going to go in detail, we selected 25 viruses that
17 we may (inaudible) out of more than 3,000
18 sequences that will look, we selected these, we
19 selected this representative for each of these
20 clusters.

21 We make an antisera for each of these,
22 each of these columns is a mouse immunized. And

1 we tested blocking assay for all of these. And
2 what we have found is that, yes, indeed there is a
3 lot of homotypic responses, and there are some
4 instances of cross activity.

5 But for the most part, early on, the
6 viruses are quite unique. And later on, the virus
7 that emerged around 2006, there are some cross
8 activities. And I'll go back to that later on.
9 But one of the things that we were able to use, to
10 do with this data is we were able to perform
11 cartography, cartography mapping.

12 We were able to use that categorization
13 mapping to determine the antigenic distance and
14 using the antigenic distance, we can actually
15 correlate with genetic, with, here. With
16 antigenic differences. So as you can see here
17 that we have a correlation a pair of viruses that
18 have X amount of distance with X amount amino acid
19 differences.

20 So just to give an example here, Sydney
21 virus from 2012 with (inaudible) virus, 2018, have
22 the most antigenic distance, and one of the most

1 genetic distance. And so on, right. And using
2 this information we were able to quantify the
3 amount of amino acids changes that you might
4 require to change this.

5 I know that is not perfect, but this is
6 the best correlation we have. I'm going to go
7 back into some of these data later on. But what
8 we have been able to define is that 18 residues
9 are most likely the threshold for these antigenic
10 difference among these viruses.

11 And one thing that I want to mention is
12 that what we have found is also that some of these
13 amino acid changes occur in synchrony. So they
14 are coevolving. And I'm just not going to show
15 you that right now. But we have all this data.

16 So using that information, we asked the
17 question what are the antigenic determinants of
18 viral antigens and how many antigenic sites or
19 epitopes are actually involved in these viral
20 antigen evolution. Using genomics structural
21 information with the experimental research, and
22 I'm just summarizing multiple years of work here,

1 but what we have found is that the 38 residues
2 which are shown here in different colors, are the
3 ones that are changing as the variants emerge.

4 Most of these changes occur here close
5 to the ABGA binding site of the protruding domain.
6 This is a protruding domain. Each of these
7 changes or clusters which we call antigenic sites,
8 each antigen site most likely contains multiple
9 epitopes. These are variable. The antigenic
10 sites are all surrounded by, surrounded the ABGA
11 binding site, which makes sense, right.

12 So the antiviral are targeting this
13 area. These epitopes are, or these antigenic
14 sites are changing, and that's the way that the
15 virus escaped these ABGA blocking antibodies.

16 Like I say, I'm summarizing. Almost
17 every slide is a lot of word here, but I just want
18 to bring the point that most of this data, when we
19 did these experiments were done with mice. With
20 mice, monoclonal antibodies just for because it
21 was simpler. It was easy to do the experiments.
22 It was cleaner to trying to understand.

1 But all these, many of these epitopes
2 lower in fields have been confirmed using very
3 complicated cell culture system which used stem
4 cell derived enteroids. She was able to show that
5 these epitopes are actually involved in viral
6 neutralization or dissenting any size in viral
7 neutralization.

8 And also with collaboration, in
9 collaboration with Vanderbilt, we and others have
10 shown that this variable and antigenic sites are
11 represented in the human repertoire for antibody
12 responses.

13 So what we have found in mice is
14 actually reproducible to humans. So then the
15 question is, okay, we have all these viruses are
16 changes. Can we actually elicit a cross-reactive
17 protective responses to different, for norovirus.
18 And I'm not going, I'm not even going into
19 different genotypes.

20 Let's just focus on (inaudible) for now,
21 right. And we have a dilemma here, right.
22 Because what we have found is a beautiful word

1 that another person in my lab can tell, is we,
2 using different approaches, we determined that the
3 most immunodominant of all these sites are A, G,
4 and C.

5 But A, G, and C actually map very close
6 to the ABGA, but they are one of the ones that are
7 more variable sites of all of these variable
8 sites. So what I'm showing you here is just all
9 the patterns, amino acid patterns that are
10 represented in at least three viruses, in more
11 than 25 years of evolutionary virus.

12 So we're talking about 47 different
13 patterns in one residue, in one antigen inside,
14 and then close to 45 patterns in another, and so
15 on. Right. So this is just a tremendous
16 variability that we're dealing with.

17 So we asked the question, maybe the
18 antibody responses needs to go to more conserved
19 area. Everybody showed good results. I'm not
20 going to show you bad results, but I can tell you
21 we spent multiple years here trying to elicit
22 cross reactive responses to very highly conserved

1 regions of the capsid.

2 And we for the most part, failed. I'm
3 not going to go into much detail on that. So then
4 the answer is well, we need to, we need to try to
5 elicit immune responses to this immunodominant
6 site.

7 Serendipity or no, when we were trying
8 to characterize these human monoclonal antibodies
9 that we been working with in collaboration with
10 Gene Crow from Vanderbilt, what we have found is
11 that antibodies that target epitope A,
12 antigenicity A, or antigenicity C, they actually
13 have different degrees of reactivity.

14 Some of them were quite specific. Some
15 of them had some reactivities, some of them have a
16 unique reactivity patterns. But one of them, one
17 norovirus Noro 123, was able to cross block, cross
18 neutralize and cross react with viruses from 25
19 years. So there is some hope then, right.

20 So if this actually targets these
21 residues and is refractory to the virus evolution,
22 there might be. So we asked a simple question.

1 How many of these antibodies are in the human
2 population. Because when we test sera, they seem
3 to be quite (inaudible).

4 But how you test that without the fact
5 that individuals might have been infected with
6 that particular virus already. So we went back in
7 time, right. So Chelsea Belinski in my in my
8 group took a, trying to address this question.
9 And she took advantage of sera samples that we
10 have from individuals that were infected in 1971.

11 These individuals were residents from a
12 hospital here in Maryland. The individuals were
13 infected in January 1971, with one, there was one
14 particular norovirus. With modern techniques more
15 than 40 years later, we were able to determine
16 that this is a G22 virus.

17 In December 1971, these individuals were
18 infected with G26 virus. So two things. We have,
19 and we have sera after the second infection, so
20 two things. People were infected. People were,
21 people never saw virus that were able to test for,
22 right.

1 Because these are sera from people,
2 that's on in '79, and we start testing viruses
3 from the 80s and in the future. And what we have
4 seen and I'm not going to go into much detail on
5 data, we have a sera sample from 24 of these
6 individuals.

7 This is a collaboration we have with my
8 former mentor, we brought those samples here and
9 what we have found is 3 out of 24 individuals have
10 very strong cross blocking responses to virus, to
11 future viruses, right?

12 That these people never saw. So we
13 asked, so we don't have samples from these. But
14 we, is there any way that we can actually
15 determine where that cross reactivity is coming
16 from. And what we have done is design a new ASI
17 that we call Haka, like the New Zealand dance for
18 the rugby.

19 But this stands for HBGA blocking
20 antigenic competition assay. It's very simple.
21 The name is more complicated on the ASI actually.
22 So this is very simple. So in HBGA binding,

1 blocking ASI, what we do is we have the VLP's, we
2 have the sera. If the sera can block this
3 interaction that is going to be bound to the
4 carbohydrate, the sera is able to block the VLP
5 binding, right.

6 But in the Haka, in the Haka ASI, what
7 we do is we include a competitor, a recombinant
8 protein that has two features. One feature is
9 that the recombinant protein should not be able to
10 bind to the carbohydrate, so it doesn't affect the
11 binding of our testing material, right.

12 And the other feature is that we can
13 modify it, we can actually deplete the epitopes
14 from this particular protein that we want to
15 study. So in other words, this competitor will
16 suck all the antibodies except for those that the
17 epitope that we modify.

18 So for instance, we can use this protein
19 to modify the antigenic site A, or antigenic site
20 G, so then we should be able to sort all the
21 antibodies that are non A or non G. And we did,
22 of course, a lot of testing. And basically what

1 happened is if you put recombinant protein that is
2 only the domain, the domain will not affect the
3 antibodies that are blocking antibody, so you will
4 have a perfect or ideal blocking assay.

5 If you put the whole P without any
6 modification except for the binding, the P will
7 reduce your titer of antibody. If you put virus
8 like particles that have mutated sites, then you
9 will be able to determine how much of that site
10 actually is involved in blocking the site.

11 And the long story short is what we have
12 found is that 2 out of 3 of these individuals are
13 actually, their crucial activity to future viruses
14 linked to antibodies that target ANG.

15 So the next question is okay, can we
16 actually learn how to elicit these antibodies. So
17 we went back to the drawing board again. This is
18 the last slide, the drawing board. And we grabbed
19 multiple monoclonal antibodies that we have from
20 mice. And we tested the reactivity patterns.

21 And what we have found is that these
22 reactivity pattern is very dependent on the

1 strain. So for instance, mouse that were
2 immunized with viruses from 2004 has almost no
3 cross reactivity. Very specific. Viruses that
4 were immunized with 2012 have some level of cross
5 reactivity.

6 And now we're trying to understand why
7 is that, why the antibodies are refractory to
8 this. But one thing I can tell you is that it's
9 not black and white. So it's not that one
10 antibody lose binding for one single amino acid or
11 is resistant to multiple. The answer is some
12 antibodies can be very, very affected by one or
13 two mutations, while other ones can have up to
14 five mutations and is still binding.

15 So we're looking now, we're doing two
16 things. We're doing machine learning, the model
17 we're building, machine models, to try to
18 understand why these patterns occur. And we're
19 also sequencing with the rhabdo B cell repertoire
20 analysis trying to understand this pattern of
21 cross reactivity, and hopefully we'll learn how to
22 better immunize.

1 This is work from Michael Landiver. The
2 people in my group have posters, so if you are
3 more interested in this research, please visit
4 their posters. And this is just a summary.

5 And I need to acknowledge people.
6 Lauren, Kentaro, Joe, Kelsey, Michael, amazing
7 people. They are always working. I try to
8 describe many years of work here in only a few
9 slides, so please go to their posters. Of course,
10 a lot of collaboration and not to forget funding
11 that supports our research. Thank you.

12 DR. DEY: Thank you, Dr. Parra, thank
13 you. Very exciting seminar. Now, Dr. Ragupathy,
14 could you please come to the stage? And now you
15 can, we can have questions here for both the
16 speakers.

17 DR. PARRA: I don't know if I can answer
18 questions, I guess. I told them everything I
19 know.

20 DR. MCGIVERN: Do we have questions in
21 the room?

22 MR. KUMAR: While others thinking, I

1 have a quick question for Dr. Parra. Is this
2 norovirus is foodborne or waterborne?

3 DR. PARRA: Both.

4 MR. KUMAR: Oh, it's both.

5 DR. PARRA: Yeah.

6 MR. KUMAR: Okay.

7 DR. PARRA: It's actually all of the
8 above. So you can find it in water, contaminated
9 water, in food. It's also person to person
10 transmitted. So yes.

11 MR. KUMAR: Okay. Thank you. Thank
12 you.

13 MS. ELKINS: And while we do the online
14 questions, anybody who is doing a flash talk,
15 please cluster over on the righthand side, and it
16 will help if you can get yourselves in order of
17 the talks because your slides will come up in
18 order.

19 Now back to the most immediate. Online
20 questions, I think, this is for Vishi. Can you
21 share what software was used to remove the host
22 genome?

1 DR. RAGUPATHY: So we used our internal
2 CLC genomics workbench to deplete the host genome.

3 MS. ELKINS: Next, I think rolling
4 circle amplification forms are very long single
5 stranded DNA strands. Is that an issue, or can
6 you convert it to double stranded for sequencing?

7 DR. RAGUPATHY: So the approach here is
8 kind of unbiased and also the threshold what we
9 are handling is with a very, very low (inaudible)
10 of our target of interest, with a high background
11 of human sequences. So introducing this rolling
12 circle kind of enhances the detection of these
13 pathogens.

14 MS. ELKINS: Thank you. Let's see,
15 norovirus. Could delivery of neutralizing
16 antibodies to target norovirus drive selective
17 pressure forcing them to evolve more rapidly or
18 making subsequent vaccinations more difficult?

19 DR. PARRA: Yes. That's the reason
20 we're trying to understand.

21 MS. ELKINS: Kind of the point.

22 DR. PARRA: Yes.

1 MS. ELKINS: Next, have you studied
2 whether or not the antigenic sites are
3 coordinately expressed on the surface of the
4 variant among variable genotypes, and whether this
5 impacts the differential coverage of specific sets
6 of antibodies?

7 DR. PARRA: The answer is yes. We're
8 looking into that. I don't have an answer for
9 that yet.

10 MS. ELKINS: Let's see. Sera prevalence
11 of animal noroviruses in humans is known. Do you
12 think there's a contribution of animal noroviruses
13 adding variants?

14 DR. PARRA: The answer is I believe it's
15 not. I believe these are human pathogens and
16 that's one of the reasons that it was quite
17 difficult for us to develop an animal model for
18 human noroviruses. There are some people that
19 have found sequences of viruses in animals in
20 people. But we don't have true proof that those
21 are interspecies transmission. In fact, the
22 phylogeny suggests that these are extremely host

1 specific virus.

2 MS. ELKINS: And finally, in a big
3 picture question, in your opinion, how far away
4 are we from developing a norovirus vaccine?

5 DR. PARRA: I will not answer that
6 question just because of my regulatory role. So
7 well, the only thing that I can say is that there
8 are multiple companies very interested in
9 developing these vaccines. So at this point it's
10 just a race. But I'm hopeful that at some point,
11 we will have a vaccine.

12 MS. ELKINS: And that covers the online
13 list. Others in the room.

14 DR. MCGIVERN: So I had one more
15 question for Vishi. So what do you see as
16 important obstacles to the routine use of
17 metagenomic MGS in clinical diagnostics?

18 DR. RAGUPATHY: So I would say there is
19 no obstacle. We can, we can, now the technologies
20 are evolving with rapid turn around times, which
21 will be one of the key question here with the
22 advent of this nanopore sequencing technology.

1 And also I've shown that as quick as less than two
2 hours or three hours, we could able to get the
3 information.

4 DR. MCGIVERN: Thank you. I think we
5 have one more question here.

6 DR. KANAI: This is for Dr. Parra. I
7 just wonder if you found anything else interesting
8 in terms of the synonymous variations.

9 DR. PARRA: In terms of what?

10 DR. KANAI: Synonymous, the so-called
11 signing.

12 DR. PARRA: Yes. But it might require a
13 few minutes to answer that. But we can pull out
14 that. In fact, it's one thing that I can say,
15 though, it's remarkable how the known G24
16 noroviruses, mostly explore synonymous mutations
17 to evolve, while the non G25 noroviruses use the
18 opposite, right. And that's the reason that the
19 non G24 norovirus actually accumulate mutations
20 over time. Yeah.

21 SPEAKER: I have a quick question for
22 Vishi. So you have used the 1-2 platform, right,

1 and you have extracted the total nucleic acids, if
2 I understand correctly. So my question is if you
3 have just used the RNA and did your assay, what
4 would be the average read length for the 1-2
5 platform?

6 DR. RAGUPATHY: Could you repeat your
7 question? I didn't get your first part.

8 SPEAKER: So if you have, if you have
9 used just the RNA for making the libraries, the
10 way you have proceeded your, processed the
11 samples.

12 DR. RAGUPATHY: Mm-hm.

13 SPEAKER: And use the 1-2 platform, what
14 would be the average read length if you have just
15 used RNA?

16 DR. RAGUPATHY: So RNA cannot be
17 directly sequenced, which you know. So we need at
18 some point conversion into the cDNA. So what we
19 observed is mostly around 1,000, 2,300 base pairs
20 with the use of whether it's a DNA virus or an RNA
21 virus, that's what we see with the representative
22 samples evaluated.

1 SPEAKER: Okay. Okay. Thank you.

2 SPEAKER: At some point I guess there
3 used to be a lot of work on the (inaudible) cell,
4 also saccharides and the connection with the
5 norovirus. What happened to that research? I
6 didn't see anything anymore. So is it not a
7 receptor or anything?

8 DR. PARRA: No. It definitely is not a
9 receptor. So we know that when we express some
10 genes that will facilitate the expression of those
11 carbohydrates in cells, they are not. They do,
12 they do act as attachment factors that facilitate.
13 The main problem with this is, the saws in the
14 field is this might be proteinase receptor that
15 the HBGA's facilitate binding.

16 They approach and this is probably a
17 multi step entry process. The main problem we
18 have is that we don't have a traditional cell
19 culture system to the classical receptor, viral
20 receptor studies. In norovirus, the in murine
21 norovirus, the receptor is a protein, is CD300.
22 So yeah. So we feel that it may be, yeah.

1 SPEAKER: Yeah. Because I remember
2 those times they used to do that.

3 DR. PARRA: Correct.

4 SPEAKER: Depends on your blood type,
5 maybe.

6 DR. PARRA: Correct.

7 SPEAKER: Maybe your ear infection.

8 DR. PARRA: Correct.

9 SPEAKER: Will be, you know, yeah.

10 DR. PARRA: That type of research is
11 still ongoing and there is certain, there is
12 certain some correlation of people that express
13 certain carbohydrates in their saliva or in their
14 epithelial cells are more prone to get infected.
15 But that's not the sole requirement, right. So
16 then, and we have more than 10 different
17 carbohydrates, more than 40 different strains.
18 Even we know that even one mutation changed that
19 pattern, right. So yeah, it's a, it's a
20 complicated story.

21 SPEAKER: Thank you.

22 DR. MCGIVERN: Do we have anymore

1 questions online or in the room?

2 SPEAKER: This is a question for Vishi.
3 One of that, there are several issues involving
4 metagenomics, and so the argument could be made
5 that like 10,000 copies is not sufficient really
6 for molecular diagnostics. I mean, we know that
7 PCR has this sensitivity down to less than 100, or
8 even like 1 to 10 copies for certain assays.

9 And so, and it probably is not
10 sufficient for blood transfusion screening if
11 you're going to use it as a way to rule out
12 infection, because then if you don't have that
13 sensitivity. So that's my first question. How
14 are you going to deal with this complaint about
15 low sensitivity? Are there ways to actually
16 increase sensitivity to be equivalent to PCR?

17 The second question I had is and there's
18 a big complaint is that the implementing in the
19 clinical lab, because I run a clinical lab that
20 runs clinical metagenomics, you really need kind
21 of the simple to answer system and it doesn't
22 exist. There are a huge amount of manual steps,

1 as you know, that are involved.

2 DR. RAGUPATHY: Yes.

3 SPEAKER: And their points basically a
4 failure, and essentially like our clinical
5 metagenomic assay has 300 steps. It takes our
6 CLS, they need to be, our clinical laboratory
7 scientists need to be trained for three months
8 before they're proficient at running this assay.

9 So it's not like putting the sample in
10 an instrument and getting a result, which is
11 ideally what you would want. And then the last
12 question I had is, you know, clinical metagenomic
13 assays are plagued by contamination, and it may
14 not be as true for viruses, but certainly for
15 bacteria. Many of the commercial companies that
16 are running clinical metagenomic assays, we detect
17 bacteria that are simply part of contaminants of
18 the reagents flora introduced.

19 And the question I always get is how do
20 you interpret this with respect to a patient.
21 It's pretty clear that we identify, you know,
22 organisms that may be pathogens but are also

1 potentially colonizers or commensals.

2 And you know, having a clinician, you
3 know, I'm an infectious disease physician. Having
4 a clinician actually try to interpret that is a
5 big mess. And so the way we've dealt with it is
6 we've actually done selective reporting where
7 we're only reporting what we think are pathogens.

8 And so being able to put findings in
9 clinical context is also a big challenge with
10 metagenomics. So maybe if you could address those
11 three questions.

12 DR. RAGUPATHY: That's a great three
13 questions. I'll try to address one at a time. So
14 for the last two parts of your question, it
15 involves good laboratory practice. So with a well
16 trained laboratory setting, and structurally
17 followed protocols.

18 And the question of contamination and
19 even with the issues of multiple manual can be
20 substantially minimized. However, that said, we
21 always recommend a fully closed automated system
22 so that can kind of eliminate source of errors.

1 So wherever possible, automation always helps to
2 minimize the error.

3 The one device which we kind of approved
4 in 2019, that one is very, very minimal user
5 involvement other than moving the plates from the
6 thermocycler to the automated sample handling
7 systems. So that's all the user involvement, all
8 the rest is all automated.

9 And regarding your question on
10 sensitivity, yes, metagenomic suffers with our
11 sensitivity unless we introduce a small enrichment
12 step. Or if there isn't some type of small
13 enrichment is incorporated. I agree with you that
14 we can still push this sensitivity. Without doing
15 any enrichment like limited piece cycles, which is
16 in the case of alumina experiments, pushing the
17 sensitivities too hard with this nanopore
18 platform.

19 DR. MCGIVERN: Thank you.

20 MS. ELKINS: And we do have one final
21 question online. There are some data, this is for
22 Gabriel on noroviruses. There are data on

1 commensal bacteria that regulate norovirus
2 infection and immune responses. Do you have
3 thoughts on how that impacts the development of
4 neutralizing antibodies?

5 DR. PARRA: And the answer is yes.
6 There is some literature out there as far as I
7 remember. Most of that literature has been build
8 with murine norovirus in control experimental
9 settings. I'm not quite sure we have enough
10 information at the real live human infection.

11 So I prefer to refrain to give a comment
12 on that. But it's probably very likely. It's
13 very unlikely that it might affect neutralizing
14 antiviral, but everything is possible, I guess.

15 DR. MCGIVERN: We'd like to thank, since
16 there are no more questions. I would like to
17 thank all of the speakers from this morning for
18 their presentations and the attendees for joining
19 session 3. And next up are the flash talks
20 followed by the poster presentations. Dr.
21 Colon-Moran.

22 DR. COLON-MORAN: Good afternoon. I'm

1 Winston Colon-Moran. I'm an OTP in Dr. Nirja
2 Bhattarai's lab. The issue we're working with is
3 on immunogenicity of viral vectors, which is a
4 significant problem and, okay, there we go. And
5 so it's a major challenge for in vivo gene
6 therapy. And that's because AAV, which is
7 existing in nature, it infects the general
8 populations.

9 There is preexisting immunity and there
10 are responses against the viral vectors once
11 they're introduced. So the host immune response
12 can impact both the safety and the efficacy of
13 gene therapy products.

14 And so there are a number of strategies
15 that have been developed to deal with this issue.
16 One of those strategies is to reduce the vector
17 dose. Unfortunately, this can render the vector
18 susceptible to low levels of neutralizing
19 antibodies and reduce efficacy.

20 Another way to deal with this is to
21 modify the capsid and the capsid is the most
22 immunogenic part of the AAV vector. You can do

1 that by eliminating immunogenic T cell epitopes.
2 The leading CPG regions from the vector genome,
3 the standard of care is actually immunosuppressive
4 drugs. But these have their own problems.

5 There's patient variability. There are
6 side effects, interference with gene therapy
7 delivery, and you can still develop an immune
8 response after removing the drugs. So our
9 strategy is to learn from nature. We look at
10 viruses, and we look at the mechanisms they use to
11 persist. They have evolved, obviously over
12 millions of years, to inhibit their immune
13 response.

14 So we're looking to identify some
15 regions within viruses that do that, and we have
16 recently identified an 11 amino acid peptide from
17 the human hepatitis B virus, E antigen. And that
18 potently inhibits the T cell response.

19 So we are working on engineering that
20 into the vector in order to test it for safety and
21 efficacy in the future. So that's everything I
22 have on the poster 19. So if you have anymore

1 questions, please come visit. Thank you.

2 DR. MCGIVERN: Thank you. Thank you.

3 Dr. Alan Baer.

4 DR. BAER: Hi, everyone. My name is
5 Alan Baer, and I'll be presenting our group's work
6 in developing a novel and simple manufacturing
7 platform for adeno associated viral vectors in
8 gene therapy.

9 So viral vectors are commonly used, or
10 commonly produced using cell lines. Jumping
11 around here. And the vector market is currently
12 estimated at 6.47 billion and is projected to rise
13 to 9.5 billion by 2026. At issue, however, is
14 that viral vector manufacturing process is
15 complex, labor intensive, and expensive.

16 And this is a bottleneck, and it
17 contributes to delays in product development, and
18 increases therapeutic cost, and accessibility.
19 Viral vectors are commonly produced using cell
20 lines. And manufacturing is generally divided
21 into upstream and downstream processes.

22 Our group is looking to simplify a

1 critical segment of the upstream manufacturing
2 process involving the cell expansion and vector
3 production step. Currently, cumbersome flasks and
4 bioreactors are used for growing cells to generate
5 viral vectors.

6 We're looking to develop a simplified,
7 scalable, and low cost static gas permeable cell
8 cultivation system called G-Rex. So we're looking
9 to condense the manufacturing process. G-Rex is
10 currently used for production of T and NK cell
11 therapy products. And our group is looking to
12 adapt tech 293 cells for AB vector production.

13 And with this system, we'll be capable
14 of expanding 5 million cells to 20 billion cells
15 using two plasticware sets. And our data suggests
16 the G-Rex system can be used to manufacture AV
17 comparable to conventional systems, as shown on
18 the figure on the right, where we're comparing a
19 traditional Erlenmeyer flask system to the G-Rex,
20 looking at viral titers.

21 And our ultimate goal is to improve AV
22 vector manufacturing by reducing cost and

1 handling. Thank you.

2 DR. DEY: Thank you. Dr. Robert
3 Dorosky.

4 DR. DOROSKY: Hello. My name is RJ
5 Dorosky and I'm a research biologist in the
6 Stibitz lab. And today I'm going to talk about my
7 work on live biotherapeutic product purity assays.
8 So LBP's are biological products that contain live
9 organisms, such as lactobacillus. And they're
10 intended for use as drugs.

11 LBP purity is an important safety
12 parameter and typically involves demonstrating
13 that the product is free of contaminating
14 organisms. Traditionally, this is done by plating
15 the product onto a nonselective medium. But one
16 major challenge that sponsors often run into is
17 that the product organisms will, their growth will
18 interfere with detection of contaminants.

19 So our approach to address this
20 challenge is to use antibacterial approach,
21 specific antibacterial proteins to selectively
22 inhibit the product organisms, to reveal the

1 presence of the contaminants.

2 To that end, we evaluated the
3 antibacterial activity of four bacteriocins and we
4 found that plantaricin S exhibited broad activity
5 against lactobacillus and non-lactobacillus
6 strains that we tested.

7 But importantly, we found that the
8 lactobacillus tested were far more sensitive to
9 these bacterias and plantaricin S in particular,
10 than the non lactobacillus. And so that suggested
11 that we may be able to use these bacteriocins in a
12 purity assay.

13 And so to test that, we ran several mock
14 purity experiments with a lactobacillus
15 delbrueckii strain. And so for these experiments,
16 we took this preparation of lactobacillus
17 delbrueckii lab preparation and spiked it with
18 known contaminants and plated them on M11, or M11
19 that's supplemented with the bacterias and
20 plantaricin S.

21 And as you can see, *L. delbrueckii* was
22 completely inhibited by the plantaricin S, and

1 this allowed for the detection and enumeration of
2 both of the contaminants. And importantly, the
3 assay worked well enough to meet the system
4 suitability criteria for USP 61, which is
5 typically employed for aerobic contamination
6 detection of LBP's.

7 And so I'll be at poster 39 if anyone
8 else wants to talk more about this. Thank you.

9 DR. MCGIVERN: Dr. Byung Woo Kim.

10 DR. KIM: Hello. My name is Byung Wu
11 Kim and I'm a postdoctoral fellow working in the
12 laboratory of Dr. Zhaohui Yes in the division of
13 gene therapy. Moving on to the slides, I'm pretty
14 sure many of you who are familiar with cell
15 biology are aware of some known functions of human
16 serum albumin in cell culture and differentiation.

17 And these functions include stabilizing
18 proteins and growth factors serving as a carrier
19 for nutrients including lipids, fatty acids,
20 hormones, and other hydrophobic molecules. It can
21 also function as an antioxidant. And lastly,
22 promoting cell adhesion and attachment.

1 However, from a manufacturing and
2 regulatory perspective, there are several
3 challenges associated with the use of albumen.
4 First of all, lot to lot inconsistency. Issues
5 like impurities, contaminants, or unintended
6 posttranslational modifications can affect
7 cellular microenvironment and lead to produce a
8 reproducibility issue.

9 Qualification requirements may vary
10 between countries and regions, which can raise
11 these safety issues. And lastly, the high cost,
12 manufacturing cost is another hurdle.

13 In order to address these challenges, we
14 have been searching for a suitable replacement for
15 HSA and we finally found this chemical compound
16 called Soluplus. And using this Soluplus in place
17 of HSA, we differentiated, we successfully
18 differentiated pluripotent stem cells into
19 hematopoietic cells.

20 And the bottom panel of the slide is
21 just showing some of my slides relevant to this
22 work, which I'll be presenting in the poster

1 session. So if you're interested in it, please
2 visit poster number 41. Again 41. Thank you.

3 DR. MCGIVERN: Dr. Stepan Surov.

4 DR. SUROV: Okay. Yeah. Hi. My name
5 is Stepan, and my presentation is dedicated to
6 reversal of direct factors and inhibitor activity
7 by factor Xa variants. Oral anticoagulants
8 targeting calculation factors Xa are used to
9 prevent and treat thrombotic disorders. However,
10 they carry their risk of uncontrolled bleeding.

11 So a rapid, effective, and safe reversal
12 agent remains on medical needs. Several
13 genetically modified calculation factors and
14 variants were proposed to achieve this reversal.
15 And properties of these variants often compared to
16 currently approved drug, which requires high doses
17 and is associated with thrombosis.

18 Using computational design, we
19 engineered novel factor Xa, whereas that retain
20 enzymatic function, and we aim to test the ability
21 to reverse the action of factors Xa inhibitor
22 drugs. So in our published study, we have shown

1 that our variants demonstrated effective reversal
2 of apixaban and used bleeding in the mouse tail
3 clipping model, at doses lower than those for
4 Andexanet alfa.

5 And as a continuation of the study, we
6 are showing that in thrombin generation assay in
7 the presence of all factors Xa inhibitors at low
8 and high concentrations, both variants are more
9 efficient than Andexanet alfa in restoring their
10 inhibited calculation to physiological levels.

11 So in conclusion, our factor Xa
12 constructs can evade the effect of factor Xa
13 inhibitors, apixaban rivaroxaban, edoxaban, at
14 considerably lower concentrations at both low and
15 high doses of factor Xa inhibitors than Andexanet
16 alfa. The only specific reversal therapy
17 currently approved.

18 Thank you for your attention. Please
19 feel free to stop by my poster or email me in case
20 if you have any questions. Thank you.

21 DR. DEY: Dr. Tapan Kanai.

22 DR. KANAI: All right. Okay. Good

1 afternoon, everyone. And myself, Tapan Kanai, I
2 work on Dr. Gorman lab. The title of my talk is
3 defining the epitope of influenza HA vaccine
4 elicited monoclonal antibody using cryo-electron
5 microscopy.

6 As you know that current vaccine is more
7 stem specific, and immune response of and directed
8 toward the more (inaudible) region, there is more
9 variables. Therefore our current clinical trial
10 focused at targeting the immune response to the
11 more (inaudible) stem region.

12 That resulted in a series of antibody
13 binding the similar epitope. The goal of this
14 project to use the structural biology to define
15 the critical epitope feature for distinguishing
16 the broad and potent antibodies which are binding
17 to the stem from the others.

18 And I'll talk about the two antibodies
19 that are isolated from the stem clinical trial.
20 That is 1G01 and 1V06, and (inaudible). 1G01 is
21 more potent than the 1V06. And here is the, we
22 develop a cryo- intensity map for the complex of

1 HN1, 1G01, and view the atomic model and which
2 confirms that both antibodies binding to the lower
3 stem regions, and source (inaudible) to epitopes,
4 overlapping epitope features of the distinct
5 orientations, and binding to the timer.

6 Then we realize that what is the special
7 orientation that these two have. Then we overlap
8 this to our atomic model aligned with (inaudible)
9 and found that both have a different approach
10 angle to the viral membrane.

11 Upon comparing these two epitopes of
12 these two (inaudible), we found that there is
13 three distinct binding region found for the 1G01,
14 as compared to 1G06. And one is the overlapping
15 region with the 1G01, where both heavy chain and
16 light chain interacting with the HA timer, HA2 of
17 the timer.

18 And the other two nonoverlapping regions
19 that is found for the 1G01 that is either heavy
20 chain or light chain interact in the C terminal
21 end of the HA1, or the N terminal of the HA2. And
22 I do believe that the C terminal and the HA1

1 involving the viral obligation while the N
2 terminal of the HA2 involved in the viral fusions.

3 And the tables so the detailed
4 quantification of the different parameter that
5 have been contributed by the (inaudible). Though
6 these analysis shows that the 1G01 is more potent
7 than the 1G 06, we speculate, or we suspect that
8 the angle of approach of this (inaudible) to the
9 viral membrane may have some role.

10 Therefore we did the docking of this two
11 atomic model to the membrane bound HA. And
12 surprisingly, we observed that the angle of
13 approach for the 1G01 historically unhindered
14 approach while 1G06 may be occluded by the viral
15 membrane.

16 Therefore, from the study, we conclude
17 that higher BSA, additional hydrogen bonding, and
18 sterically unhindered approach may altogether
19 contribute to the more potent or the greater
20 breadth for 1G01, it's competitor, 1G06.

21 And during our analysis we found that
22 there is no specific difference in the sequence

1 has been observed. Our future study will be
2 confirmed the difference in binding affinity of
3 these two (inaudible) to the soluble versus the
4 membrane bound HA.

5 And if you're interested about the
6 (inaudible), please stop by the poster number 53,
7 and thank you very much for listening this brief
8 presentations.

9 DR. DEY: Thank you. Thank you. Thank
10 you, Dr Kanai. Dr. Sabarinath Neerukonda.

11 DR. NEERUKONDA: I'm Sabarinath. I'm a
12 staff fellow in Brennan Ellsworth Lab in office of
13 blood. So we compared four different cell lines
14 for their ability to support anaplasma
15 phagocytophilum infections. And these cell links
16 include HL60, which is widely used to propagate
17 anaplasma in vitro, as well as a monocytic cell
18 lines U937 and K5622. U937 and PHP1.

19 And finally we also looked at a
20 multipotent progenitor cell line, K5622. So we
21 infected all these four cell lines with cell free
22 anaplasma and we spun down the cells onto glass

1 lights. In addition, we also isolated DNA to
2 quantify the number of bacterial genomes.

3 And finally, we looked at the expression
4 levels of the receptor p-selectin glycoprotein
5 ligand-1 by testing blood. Here you can see that,
6 you can see that the bacteria replicates in HL60
7 cell line, which is widely used to propagate
8 anaplasma.

9 And the cells that are marked with
10 asterisks has the bacteria containing vacuoles,
11 whereas both U937 and the THP1 cell lines did not
12 support bacterial replication.

13 In addition, we also found a novel cell
14 line, K5622, to support bacterial replication.
15 And here on this graph you can see the number of
16 bacterial genomes quantified by qPCR. Both HL60
17 and K5622 supported bacterial application, whereas
18 monocytic cell line C937 and PHP1 failed to
19 support bacterial replication.

20 And finally, we also looked at the
21 expression levels of receptor, PSGL1, in all four
22 cell lines. As you can see, all four cell lines

1 express PSGL1 at variable levels, suggesting that
2 the ability to support replication is not due to
3 the receptor expression levels but at a post entry
4 host factor level.

5 We also looked at whether the entry into
6 K5622 cell line is sialic acid dependent. For
7 this, we either treated or not with neuraminidase
8 which cleaves off a cell surface sialic acids, and
9 then we infected the cells with anaplasma.

10 As you can see, when the cells are
11 treated with neuraminidase, the cells fail to
12 support bacterial entry and replication. And here
13 on the bar graph on the lower right, you can see
14 that when the cells are treated with
15 neuraminidase, we found no bacterial application
16 by QPCR. Thank you.

17 DR. MCGIVERN: Dr. Atul Rawal.

18 DR. RAWAL: Okay. Good morning. My
19 name is Atul Rawal, and I'm a postdoc with Dr.
20 Dumisana's (phonetic) lab. And today we're
21 presenting our work on using machine learning to
22 identify HLA variants for either symptomatic or

1 asymptomatic COVID-19 disease.

2 Okay. So the HLA has been known to play
3 a crucial role in the human body's immune response
4 to different diseases. Literature has shown a
5 possible role that HLA could play for COVID-19 as
6 well. So to investigate this, we took a machine
7 learning approach on applying different machine
8 learning models on HLA data to see whether we can
9 first predict a patient will have symptomatic or
10 asymptomatic disease, and then identify specific
11 HLA alleles that are more probable for symptomatic
12 versus asymptomatic disease.

13 The chart here shows the, the chart on
14 the left shows the different machine learning
15 approaches we took. And then we chose the top
16 performing model to apply explainable AI to
17 generate the feature. Oh. Sorry.

18 The feature relevance part to highlight
19 the alleles that play the most important role or
20 the most impact versus the lowest impact. So
21 based on these charts, especially the lower chart
22 right here, we're able to identify specific HLA-B

1 alleles, which will either be asymptomatic for
2 COVID-19 disease, or symptomatic for COVID-19
3 disease.

4 Based on our results, we share that HLA-
5 B4001 has the highest association with
6 asymptomatic disease, and HLA5101 has the highest
7 association with the symptomatic disease. So
8 HLA4001 will be protective against COVID. And
9 then 5101 is addressed for COVID.

10 These results show that AIBS analysis
11 can help physicians in clinic to provide better
12 personalized treatments for patients based on
13 their HLA and their clinical outcomes. Thank you.

14 DR. MCGIVERN: Thank you. Dr. Erica
15 Silberstein.

16 DR. SILBERSTEIN: Hi. My name is Erica
17 Silberstein. I am a staff scientist at the
18 Laboratory of Emerging Pathogens, Office of Blood
19 Research and Review. And the title of my poster,
20 which is number 49 is single cell transcriptomics
21 reveals the immune landscape of the mouse colon
22 during chronic *Trypanosoma cruzi* infection.

1 Chagas disease is transmitted by *T.*
2 *cruzi*, which could be transmitted by triatomine
3 bags, blood transfusion, organ transplantation,
4 and from mother to baby. So 30 percent of the, 20
5 to 30 percent of the infected individuals will
6 develop chronic Chagas disease in the chronic
7 phase.

8 The parasites persist in three main
9 sites, the heart, the GI tract, and in the
10 skeletal muscle. The goal of this research was to
11 study the immune cell landscape of the chronically
12 infected mouse colon. And also to determine the
13 mechanisms associated with parasite persistence
14 and pathogenesis.

15 And to do that, we infected mice. We
16 waited three months until they became chronic. We
17 then inspected the colon tissues. We prepared
18 single cell suspension. Then performed cell
19 capture and library preparation using the VB
20 Rhapsody system. And after sequencing, we
21 conducted the biostatistics analysis,
22 bioinformatics analysis.

1 So and we found 18 cell populations.
2 And in the infected colon, we observe the
3 expansion of TNNK cells, and also B cells.
4 Further, sub clustering of the TNNK cells
5 population revealed the different T cell subtypes,
6 including T helper cells, T regulatory cells, T
7 cytotoxic cells, and T follicular helper cells.

8 Using this chart communication analysis,
9 we predicted that the CCL signaling pathway
10 network is activated in T cells and macrophages
11 with the CCL5, CCR5 ligand receptor, they're
12 representing the highest contribution to the CCL
13 communication network.

14 Also, we conducted some flow cytometry
15 experiments. And we were able to identify a
16 higher percentage of CDA positive and CCR5
17 positive cells in infected animals.

18 In conclusion, we observe recruitment of
19 T, NK, and B cells to the colon of chronically
20 infected mice, and we also found that the CCL
21 signaling pathway could potentially be implicated
22 in cell recruitment and control of parasite

1 growth. Thank you.

2 DR. DEY: Dr. Emily Smith.

3 DR. SMITH: All right. Hi, everyone.

4 My name is Emily Smith. I'm a postdoc fellow in
5 Paul Carlson's lab in OBRR. And today I'm going
6 to talk to you a little bit about the
7 investigation of novel phage resistance mechanisms
8 in vancomycin resistant enterococcus, or VRE.

9 So antibiotic resistance is a critical
10 public health concern and vancomycin resistant
11 enterococcus, or VRE, is a multidrug resistant
12 bacteria that causes severe disease in humans when
13 it impacts the urinary tract, the bloodstream, and
14 the heart, for example.

15 This can lead to hospitalization and
16 sometimes death. The species that cause the most
17 severe disease in humans are enterococcus faecalis
18 and faecium. Now, as an alternative to
19 antibiotics, we can use bacteriophage or phage
20 therapy to treat VRE infection.

21 And phages are viruses that kill
22 bacteria. And phages can use a variety of

1 different ways to infect and kill bacteria, and in
2 turn, bacteria have developed mechanisms to resist
3 phage killing.

4 So the two main questions of my project
5 are, one, what resistance mechanisms could
6 interfere with phage therapy to treat VRE
7 infection, and how can we design an effective
8 phage cocktail to combat these very resistant
9 mechanisms.

10 And so we used an unbiased method called
11 transposon mutagenesis to create a collection of
12 mutants in two faecalis, or two faecium and one
13 faecalis strain using a Nisin inducible
14 transposase and a Mariner transposon contained on
15 the plasma shown here.

16 We were able to create a collection of
17 mutants to test these questions. And so we grew
18 these transposon libraries in either BHI broth or
19 auger with and without the presence of Nisin in
20 order to induce the transposase and collected
21 bacterial pellets for DNA extraction.

22 And we plan to use transposon sequencing

1 with these samples. And so we're in the beginning
2 of this work. Our future plans are to use these
3 transposon libraries in phage infection
4 experiments and compare before and after phage
5 infection to ultimately identify specific genes
6 that are responsible for phage resistance in VRE.

7 Then we plan to make specific mutants in
8 VRE, and test these in vivo using a newly
9 developed mouse model for urinary tract
10 infections. The ultimate goal is to use this data
11 to inform future phage therapies and combat this
12 resistance that we see in the clinic. Thank you.

13 DR. MCGIVERN: The last flash talk
14 speaker is unable to join us today. So this
15 concludes the flash talk session. Now it's time
16 for the poster presentations and lunch. The odd
17 numbered posters are going to be manned and so
18 please go and visit the posters, enjoy the poster
19 session, and join us back here at 2:00 p.m. for
20 session 4. Thank you and thanks to all the
21 speakers.

22 (Recess.)

1 DR. FRIEDBERG: Hello. Welcome back,
2 for people who've been here. Welcome to the room
3 for people who have not. My name is Daron
4 Friedberg. I'm cochair for this session. And
5 this is my cochair.

6 DR. RODRIGUEZ: Hi. I'm Marisabel
7 Rodriguez.

8 DR. FRIEDBERG: The first session, I'm
9 sorry, the session is divided into 2 parts. The
10 first 2 speakers are external, and we'll take
11 questions and answers after they speak. And the
12 last 3 speakers are from CBER, and we'll have a
13 panel on that for questions.

14 So hold your questions for those and
15 we'll introduce them. It's my pleasure to
16 introduce our first speaker, Rommie Amaro from UC
17 San Diego. She's a professor of molecular
18 biology, and today she's going to be, oh, I should
19 say one more thing. She did a calculation of the
20 spike protein on SARS-CoV-2, which now has made
21 the cover of the Essentials of Glycobiology. So
22 that's a claim to fame.

1 Okay. So Rommie will be speaking on
2 computational microscopy of viruses. Take it
3 away, Rommie.

4 DR. AMARO: Thank you. Thank you very
5 much. All right. So I'll just go ahead and get
6 started. Thanks for having me today and thanks
7 for that nice introduction. Okay. So what I am
8 going to tell you all about today are the methods
9 that we're using, which are pretty much entirely
10 computational, in order to understand the
11 structure, and dynamics, and mechanisms of viruses
12 and viral infection, as well as how antibodies and
13 other molecules, you know, can interact with the
14 different components on, you know, in viruses.

15 And so the methods that we use,
16 primarily what I'm going to tell you about is a
17 technique called molecular dynamic simulations.
18 And I like to think of it as a computational
19 microscope because that's exactly how we use it.
20 So nowadays, you know, biological data is very
21 diverse and in order to answer any biological
22 question in a meaningful way, I think that most of

1 us appreciate that you really need to use multiple
2 types of experiment, right, to interrogate a
3 particular question.

4 And so biology is multiscale. It
5 requires multimodal experiments, and that doesn't,
6 you know, I think that really holds across most
7 questions. So nowadays when we're trying to
8 investigate viruses, it's common for us to use
9 these computational techniques as a way to
10 integrate many diverse sources of experimental
11 datasets.

12 And then extend these datasets with
13 physics based simulations. And so what we can do
14 is take different types of, for example,
15 structural biology data, which can be acquired now
16 using different instruments at different
17 resolutions.

18 So for example, we can combine high
19 resolution x-ray crystallographic information
20 together with single particle cryo-EM data
21 together also with things like cryo-electron,
22 methods like cryo-electron tomography to really

1 sort of understand structure from the molecular to
2 subcellular scale.

3 And then beyond just the structural
4 data, we can further augment that those datasets
5 with data coming from mass spectrometry and other
6 types of methods. For example, glycomics,
7 lipidomics, and genomics.

8 And so we can now what we do is we take
9 all of these different experimental datasets, and
10 we bring them together to build a highly detailed
11 3 dimensional model of a biological system. And
12 then what we do is we approximate that system down
13 to its many atoms. All right.

14 So we basically assume that each atom is
15 sort of like a hard sphere and then we define this
16 potential function. And I promise this is the
17 only equation that I'll show you. I work really
18 hard to take the equations out of my talk. But so
19 this equation basically just, this potential
20 function basically just describes the interaction
21 that each atom has with all of the other atoms in
22 the system.

1 And then we, all we're basically doing
2 is we're integrating Newton's equation of motion
3 over time. So we start with some particular
4 configuration which we build based on experiment.
5 We then integrate one time step. We get a new
6 structure, we integrate again, we get another
7 structure.

8 And we do this numerical integration
9 millions and billions, and now trillions of times.
10 And what that allows us to do is build up sort of
11 a dynamical movie or what we call a trajectory
12 that describes the systems motion over time.

13 Okay. And this is sort of, this allows
14 us to get sort of new views into the structure,
15 and dynamics, and systems that is currently
16 inaccessible with direct experimental techniques.

17 And so the other thing I'll just mention
18 here is that these methods have become ever more
19 powerful due to a real just huge growth in compute
20 architectures that have taken place over the past
21 couple of decades. Most notably, the development
22 of graphical processing units made by companies

1 like NVIDIA, were really sort of game changers.

2 And you know, now it's really common to
3 think about, you know, and there's a huge focus,
4 of course, on machine learning and artificial
5 intelligence. Our field has been using these same
6 architectures now for, you know, almost 2 decades
7 or 15 years or so, thanks to the gaming industry.

8 So the same types of chips that they
9 used to make really cool, you know, graphics for
10 these video games actually are highly amenable to
11 the types of scientific computations that we carry
12 out.

13 Okay. So in today's talk, I know I
14 don't have too much time, but I wanted to sort of
15 just touch on the methods, generally, and give you
16 some examples of how we've used these types of
17 simulations to inform on structural dynamics of
18 viral targets, on cryptic epitopes, which are
19 important for biologics evaluation, as well as for
20 vaccine design.

21 So in the first part, I'll talk about
22 the structural dynamics. So I think most of you,

1 everyone in here by now is probably very familiar
2 with the SARS- CoV-2 virus. It looks like a golf
3 ball with spikes sticking out of it. And in fact,
4 those spikes are called the spike protein.

5 They're very important. They sit on the
6 outside of the virus. And so they're the first
7 point of contact that the virus has with human
8 cells. So they play a really key role in
9 infection. On top of that, they're also highly
10 immunogenic molecules. So they play a very
11 important role in all of the approved vaccines
12 that we currently have for COVID-19.

13 And so, you know, experimental
14 structural biology provided very quickly at the
15 start of the pandemic, provided really key
16 information about what this spike protein looked
17 like. There was a wonderful paper by Jason
18 McLellan and colleagues at the National Institutes
19 of Health that was put into the bio archive,
20 actually, on Valentine's Day of 2020, and
21 published in Science about one month later. And
22 now has been cited, I think, over 15,000 times.

1 It basically, this paper basically
2 provided the first high resolution structure of
3 the SARS-CoV-2 spike protein. They had resolved
4 it in what's called a one up confirmation, where
5 part of the spike protein had one of its domains,
6 the receptor binding domain, in the up
7 confirmation.

8 And this was really important data. A
9 couple of weeks later, another fantastic
10 structural biology group, the Group of David
11 Geisler at the University of Washington, published
12 a second study that largely recapitulated the
13 findings of Jason's group. But they also used
14 symmetry to create a model of the of the closed
15 spike, where all this, the RBD, the receptor
16 binding domain, and the spike were in the down
17 confirmation.

18 And this RBD plays a really key role in
19 the infection process because it's actually the
20 first, it's the part of the spike protein that
21 makes contact with the receptor on the host cell
22 called ACE-2, or angiotensin converting enzyme 2.

1 So you know, we and others are really
2 interested to understand how, you know, how this
3 interaction was taking place. So one of the
4 limitations to the experimental structural biology
5 is that if parts of the structure are highly
6 dynamic or flexible, then they're very difficult,
7 if not impossible, to actually structurally
8 resolve.

9 And so when you look back at these
10 structures, immediately you'll notice that there
11 are missing loops and other sort of entire domains
12 of the protein that are just missing. So we use
13 computational methods to basically rebuild these
14 or to sort of complete these models and provide
15 these missing loops, et cetera.

16 And we could do that using a number of
17 different computational structural biology
18 techniques. Beyond the head part of the spike,
19 which is where, you know, a lot of interesting
20 things take place, it also is connected or
21 tethered to the viral membrane by a stalk domain,
22 which also is very flexible and therefore, it was

1 not present in the experimental structural
2 dataset.

3 So we used computational methods. At
4 the time we were using Ispasir layer and another
5 program called Modeler, that actually predated
6 Alpha Poll, believe it or not. But if you repeat
7 these experiments with Alpha Poll, you find
8 largely the same structures.

9 So we basically, we predicted what these
10 other domains that were, that they couldn't
11 resolve experimentally what they would look like.
12 Beyond just the protein itself, another angle or
13 aspect of these viral glycoproteins that's really
14 important to understand are N and O linked
15 glycans.

16 And N and O linked glycans are a very
17 important post translational modification. They
18 help proteins fold, they help with trafficking,
19 they do a lot of different things. But they are
20 really highly dynamic. And again, what that means
21 is that the structures that, the (inaudible)
22 structures that became available, they actually

1 didn't have these glycans actually on them,
2 because they move too much.

3 But so what we could do is link to
4 glycomics data, and again, this is some of that
5 mass spec data that I was talking about. The
6 group of Max Crispen, again early on in the
7 pandemic, I think by April, provided this paper
8 along with Parastoo Azadi, at the University of
9 Georgia, there were several papers that basically
10 use glycomics methods to determine at each of
11 these different N-linked glycan sites.

12 And there's 30 some odd N-linked glycans
13 on each of the chains of this trimeric spike
14 protein. They could actually determine sort of
15 the molecular recipe of these glycans. And we
16 could rebuild them. So these are some of the
17 different oligosaccharides that they, you know,
18 that they find here in this.

19 The mapping corresponds, the colors
20 correspond to the images on the right. We could
21 actually rebuild these into the structure. And
22 then so we have this complete model that we've

1 built that has all of the domains, all the missing
2 loops, the correct protonation states, et cetera.

3 And then the end link glycans, and we
4 then are, we then simulate the structure to try to
5 enumerate the sort of, you know, the dynamic and
6 what it looks like. And I'll just say, so what
7 you can see, what I hope sort of jumps out at you
8 is these, so the glycans are those colorful bits
9 on the structure that looks sort of like ornaments
10 on a Christmas tree.

11 You can really see how they're moving
12 around quite a bit. We also have solvent and
13 water that has ions, and that's sort of like a
14 buffer condition. I don't show you that. We sort
15 of stripped that out of this movie so that you can
16 actually see the protein.

17 But the other thing I just want to say
18 is, you know, they're, you know, when you see
19 this, when people see this, you know, it strikes
20 them, it's a beautiful image, you know, it's a
21 pretty picture. But it's more than just a pretty
22 picture.

1 What we actually are doing here are
2 showing the time dependent dynamics as predicted
3 by these molecular dynamic simulations. And why
4 that's important is because these molecular
5 dynamic simulations are actually numerical
6 statistical mechanics.

7 And so they are computed, these
8 different positions are computed in accordance
9 with the laws of statistical mechanics. And so
10 what that means is that we can link microscopic,
11 time averaged microscopic properties that we've
12 computed in the simulation, directly to
13 experimentally testable macroscopic observables.

14 So we can compute from these
15 simulations, we can compute things like free
16 energies of binding, entropies, heat capacities.
17 There's all these things that actually are, that
18 can be directly, again, sort of correlated to or
19 compared to experiment.

20 And so these speculations are expensive,
21 but they are also very useful in actually
22 informing on sort of mechanism and dynamics of

1 these proteins. And so okay.

2 So what did we learn. So one of the
3 things that was sort of, of course, high interest
4 was that we were able to show the world what the
5 spike protein actually really looks like. So on
6 the left, in light blue, is essentially what the
7 structural biologists see.

8 They basically are able to see the
9 protein, just the protein. On the right is what,
10 though, is what the (inaudible) would see if they
11 could see the glycans. And so now we're actually
12 showing the glycans here in these blue, are the
13 positions of the end link glycans.

14 These sort of puffs that you see
15 actually represents a composite image of all the
16 different snapshots that are sampled from one end
17 glycan over about a microsecond of dynamics. So
18 what you see is that these glycans are basically
19 moving around very rapidly on the surface of the
20 structure of the spike protein, and creating a
21 very good shield that basically hides the spike
22 protein from the human immune system.

1 The other thing that these simulations
2 showed was why this spike actually adopts these
3 different conformations with the one up
4 confirmation of the RBD and all down. And so on
5 the left, I'm showing the slow spike, and what you
6 see is if you're looking top down so that the top
7 two panels here are showing the top view. And on
8 the bottom is sort of the side view of the spike.

9 What you can see is this blue domain
10 here, this light blue domain, that's the receptor
11 binding domain. That's that really important part
12 of the spike protein that has to make contact with
13 the ACE-2 receptor on the host cell.

14 And in the closed conformation, what you
15 can see is that this receptor binding domain is
16 largely covered by glycan. And in fact, if you
17 look from the side, you can see that it's actually
18 sort of tucked down beneath that glycan's field.

19 That's in stark contrast to the open
20 spike, which I'm showing on the right. The open
21 spike presents a very different picture to the
22 host cell. You can see now in light blue that the

1 entire top surface of the receptor binding domain
2 is exposed and ready for binding.

3 And in another sort of striking image
4 you can see from the side how now all of a sudden
5 the receptor binding domain, which previously was
6 buried, is now sort of popped up and ready for
7 binding to the host cell.

8 One of the other interesting things we
9 found was that beyond shielding, so everybody kind
10 of knew that these glycans would play important
11 roles in shielding, because we have known that for
12 some time. But what was unique about this study
13 was that as we were working with the protein, we
14 found that there were two N-link glycans.

15 When we rebuilt their side chains into
16 the, into this one up confirmation, the glycan
17 side chains actually filled up the void space that
18 was created when RBD moved up. And so it occurred
19 to us that these glycans, these two glycans, maybe
20 they were doing more than shielding. Maybe they
21 were actually helping to act like a structural
22 support of the RBD.

1 You can see here how they sort of look
2 like a kickstand on a bicycle helping to prop up
3 that receptor binding domain in the up
4 confirmation. And so this was actually tested
5 with experiment by Jason McLellan and coworkers.
6 And we actually found that when you mutate these
7 residues, actually the ability of the spike
8 protein to interact with ACE-2 is highly reduced
9 because it's sort of pulled off that structural
10 scaffold.

11 So this was actually one of the
12 interesting things, and I think one of the reasons
13 why we made the cover of the Glycobiology
14 Textbook, was because there's a really nice
15 example of using these computational simulations
16 to really learn a whole new element of biology,
17 and to show, I mean, because we showed for the
18 first time that glycans would actually do more
19 than just shield. That they actually played a
20 role in the viral infection mechanism itself.

21 And I know that, you know, the title of
22 this session is biologics evaluation. I just

1 wanted to say one of the really nice outputs of
2 these simulations, as one can imagine, is that you
3 can look at the solvent exposed surface area of
4 these viral glycoproteins to actually determine
5 which epitopes are exposed at particular times.
6 And to help rationalize why some antibodies can
7 bind to some structures and not others.

8 There's many examples of this now in the
9 literature, and I just wanted to show this really
10 interesting one. I mean, I think to me these
11 viral glycoproteins in particular spike is just so
12 fascinating scientifically. What it can do.

13 And also our human, our response of the
14 adaptive immunity. One of the things I found
15 really interesting that was published in late 2020
16 was this finding of an antibody, S2M11, that
17 actually was able to recognize that even the
18 closed version of the spike protein, and it
19 actually did that by using a ordinary epitope that
20 would, or yeah, the epitope actually it was formed
21 across three different subunits. And the antibody
22 actually just binds to this tiny little bit that's

1 exposed at the center top of the spike, which I
2 just find so fascinating. Okay.

3 So beyond just looking at sort of the,
4 sort of the local dynamics around these
5 experimentally characterized space. Right. So
6 the closed state and the open state, we can also
7 use like what I guess I'll call advanced or
8 enhanced sampling simulation.

9 Now, to start with, to actually look at
10 sort of mechanism of opening. Okay. So before we
11 were just looking at the closed state and then the
12 open state, but here what we're doing is we're
13 starting from the closed confirmation of the
14 spike. And you'll see this movie playing here,
15 again, the RBD is shown in light blue.

16 We can use something called weighted
17 ensemble molecular dynamics. To actually sample
18 the whole opening pathway. And this is the
19 biological phenomenon that happens on the order of
20 seconds. But here we can actually retain ties to
21 the structure while we look at that mechanism.

22 And what's interesting about this is

1 that if you just looked at the, there was one
2 additional glycan that we found, actually, when we
3 looked at the opening mechanism, and it's shown
4 here in hot pink, that in our previous study when
5 we just looked at the dynamics of the closed state
6 of this like, this pink glycan is just sort of
7 hanging out by the side down by the side, and it
8 doesn't look like it's doing anything interesting.

9 When we simulated the open state of the
10 spike, it's the same thing. That pink glycan is
11 hanging out at the side, doesn't look like it's
12 doing anything interesting. But when we actually
13 do the work to look at the opening process, what
14 we see is that this hot pink glycan is actually
15 doing all sorts of things to actually promote the
16 opening of the receptor binding domain.

17 It's making all sorts of interactions.
18 And then at the, end actually helps sort of kick it
19 open, almost like a crowbar. And so Jason and his
20 colleagues went in and created more mutations.
21 And what we found was that this glycan at position
22 343 was actually even more important than the two

1 structural glycans that we had previously found.

2 And in fact, if you mutate this, the way
3 this glycan, the virus actually has, can't even
4 infect cells. And that's been something that's
5 been replicated now in many other labs. That was
6 actually also kind of an interesting finding that
7 was derived from simulation.

8 Now in the second part of the talk, I
9 want to talk about cryptic epitopes. So one of
10 the things we're really interested to do is sort
11 of push these molecular dynamic simulations to
12 longer time and length scales that are of interest
13 to biological, you know, questions. Right.

14 So we now can look and use cryo-electron
15 tomography experiments and there was a whole bunch
16 of beautiful data that came out in the late summer
17 of 2020, that used these high resolution
18 techniques. So cryo-electron tomography with the
19 milling to actually catch infections of, viral
20 infection, basically, in situ.

21 And basically the data that we can get
22 out is sort of really what the viruses look like

1 as they're infecting cells. It tells us through a
2 molecular map that we can use to rebuild the
3 virus. Again, sort of computationally.

4 It gives us the distribution and
5 patterning of the spike proteins, as well as can
6 inform on which ones are open, or bent, and so
7 forth. So we use that data together with
8 additional computational simulations that I won't
9 go into detail about, to build the delta variant
10 of the virus.

11 And this had about 30 different spike
12 proteins. We built the membrane. We also, it
13 contains a few copies of the E protein, as well as
14 hundreds of copies of this M dimer, which is sort
15 of like also giving some structural stability to
16 the virus over its life cycle.

17 And then what we're doing is basically,
18 again, we have this structure and now we can
19 simulate the viral, the spike proteins. And if
20 you squint, I don't know how big the screen is
21 there, but you can actually see some dynamics
22 here.

1 This is actually now a system, it's
2 about 305 million atoms representing a full virus
3 of like, you know, standard, you know, size, with
4 a membrane about 90 nanometers in diameter.
5 Probably about 120 end to end diameter.

6 And we can look at its dynamics. And so
7 in addition to studying SARS 2, we've also studied
8 flu. And so here we have large scale simulations
9 of the influenza virus. Influenza, as you can
10 see, is much more crowded.

11 There's two proteins that are of
12 interest here in flu. One is hemagglutinin, and
13 then the other is neuraminidase. Here the
14 hemagglutinin is shown in blue. And the
15 neuraminidase is shown in red. And we can build
16 different strains and then compare their dynamics.

17 And what we find is that when you, when
18 we simulate these glycoproteins in the context of
19 their crowded environment, of their real sort of
20 instant (inaudible) environment, instead of in
21 these dilute solutions, essentially, we see a
22 different landscape of dynamics.

1 And here, I'm trying to draw your
2 attention to hemagglutinin. And this blue
3 molecule, one of the things you'll see is that one
4 of the chains actually sort of begins to open, and
5 to breathe open. And in fact, here's another view
6 of that. And one of the HA's on the surface,
7 there's hundreds of copies of them on the surface
8 of the virus.

9 You'll see that originally it starts
10 like the cryo-EM structure. All of the domains
11 are very tidy and well packed. But over time, you
12 can see this breathing. Look at that breathing
13 here. You can see that happening in this chain on
14 the lower left and here from the side.

15 You can sort of see this breathing
16 motion. And here the glycans are colored yellow.
17 So what we found was that when we actually
18 simulated in the context of the full virus that we
19 sampled this breathing motion, as I mentioned. So
20 here, what we're looking at is sort of what we
21 call a time series analysis. This is showing
22 basically how open the structure is.

1 It's like a distance metric for opening.
2 It's closed at the beginning, close, close, close.
3 And then sometime later, it achieved an open
4 state. And then even achieves what we call a
5 super open state, where you can really see this
6 sort of like this blade open.

7 And this was really curious because it
8 turns out that around the same time, an
9 experimental group, the group of Ian Wilson and
10 James Crowe, found an epitope called flu A-20,
11 which actually was found to bind to an epitope
12 that was on the inside of one of these HA's.

13 And this is really interesting. And
14 I'll comment from their paper that I just want to
15 read here. It says because everybody when we, you
16 know, when (inaudible) give you a structure of a
17 protein. Okay. And if you look across all of the
18 hemagglutinin and spike structures, they mostly
19 look the same. They're like very tidy, they're
20 very packed, and you know they look very pretty.

21 But the truth is that these proteins are
22 so much more than that one snapshot that they're

1 able to characterize experimentally. And we know
2 this as scientists, but it's still so hard to
3 imagine sometimes, you know, what these different
4 intermediate states could look like and so forth.

5 But here from their paper, they say,
6 therefore, the HA molecules on the cellular or
7 viral surface generally have been considered to be
8 stable primers. With the trimer interface
9 regarded as inaccessible and thus not targetable
10 by the immune response of therapeutics.

11 That's generally because people have
12 been shown that cryo-EMAIL structure of everything
13 all pecked up, that's how we imagine it in the
14 actual cells. But here what they go on to say is
15 the ability of flu A-20 to convert in vivo
16 protection strongly suggests that HA molecules are
17 dynamic and more heterogeneous in their
18 confirmations than we have observed previously.
19 And that the trimer interface is partially or
20 transiently accessible.

21 This phenomenon known as breathing. And
22 this is exactly what we sampled with those

1 molecular dynamic simulations, the scale of the
2 virus. We actually saw the opening of this
3 hemagglutinin. And here's this flu A-20 antibody
4 in the closed state. So here you can see a
5 tightly packed trimer. It's total totally
6 clasping. You can't make any sort of like finding
7 mode.

8 In the super open state, it is able to
9 accommodate very nicely this antibody. So we were
10 able to sample this dynamics, which was cool. And
11 then as I was talking to Matharu Kanekiyo at the
12 NIH Vaccine Research Center, I gave a talk there,
13 and we were explaining well something else that we
14 see in the data, because we always talk about HA.

15 But there's also neuraminidase. And one
16 of the interesting things we saw about
17 neuraminidase was that in simulation, it actually
18 had a very big (inaudible). Like so, and again,
19 to me what is still so remarkable is that when
20 people think about the neuraminidase molecule,
21 it's like they generally, structure folks, they
22 think about it, it looks sort of like a bouquet or

1 like a flower bouquet where you have this sort of
2 head domain, where all the kind of interesting
3 neuraminidase enzymes are.

4 And then it's on this long stalk. And
5 we never really thought too much about it actually
6 bending, but we actually sample really large
7 bending motions also for neuraminidase. And it
8 turns out that they had found an antibody from
9 patients that they were calling the dark side
10 antibody because it recognized an epitope that was
11 sort of like underneath the neuraminidase, that
12 was on sort of, that was closer to the inside of
13 the virus.

14 And these, our simulations actually
15 helped them to rationalize how this epitope would
16 actually get exposed. Because when the head bends
17 away from the stalk, there's a different exposure
18 of the epitope. And also you can really, we could
19 clearly model that these antibodies could actually
20 fit inside and bind even in the crowded surface of
21 the environment, just of the virus surface, just
22 based on sort of the structural dynamics that

1 changed, and that we sampled with the simulation.

2 Okay.

3 So I still have, I think, just about 10
4 more minutes because we started 5 minutes late,
5 but I'm going to zip through this last part so
6 that we can get to the questions. You know, a lot
7 of what we do is really focused on basic research.
8 I love discovering stuff just about general
9 biology. For me, that's sort of so much fun.

10 But you know, we're also interested to
11 do things that are applied and directly useful.
12 And so we started to, we became involved in a
13 project to look at immunogen design. And so of
14 course, all of us, unfortunately, are very
15 familiar with the fact that SARS-CoV-2 is, you
16 know, able to mutate like crazy. Of course, we've
17 given it an enormous number of shots on goal for
18 doing, this because we're not controlling
19 infection.

20 But in any case, and there's been tons
21 and tons of mutations in the S1 domain of the
22 spike protein, which is pretty much everything

1 that I was talking to you about, the RBD's, the
2 NTD's of the spike protein.

3 And these mutations change the
4 available, you know, epitopes and our adaptive
5 immune response and leave us more vulnerable to
6 being infected again. So but we became involved
7 with the project with Jason McLellan and coworkers
8 to try to design an immunogen that would go after
9 some other epitopes on the spike.

10 There's one down in the stem region, and
11 then there's a fusion peptide epitope, which is
12 shown here. But then there's also this what we
13 call an S2 apex epitope, which is on the part of
14 the spike protein. I don't want this to restart.
15 Here, let me pause it.

16 So what we're looking at now is that
17 spike protein that I've talked to you about
18 before, but we've pulled off the S1, because
19 actually S1 does come off. It's basically shed
20 off of the spike protein in the process of
21 infection. And inside here is, the F2 domain of
22 the spike protein is highly conserved across like

1 many of the beta coronaviruses.

2 So we were trying to see if we could
3 help them design an immunogen that would be S2
4 derived. Now the challenge is that this is a
5 highly unstable part of the molecule. And it's
6 unstable for the purposes generally of infecting
7 the host cell, because once you lose that S2 cap,
8 those, you know, the F1 cap, those domains open
9 and then the central helices are like, what did
10 they say, they're like spring loaded.

11 They're like, literally, spring loaded,
12 and it comes, the top comes off. And then these
13 helices basically like polymerize upwards. And if
14 you look mechanically, it's this amazing system.
15 There's all sorts of like structural strain that's
16 evolved into these proteins.

17 Anyway, but what that means is that when
18 you take off S1, S2 is highly unstable. And so
19 many folks are already familiar with the 2P
20 mutations that are part of the spike protein.
21 This was super important for the initial all
22 vaccine development because it stabilized the

1 protein, and the one up confirmation, which was
2 super highly immunogenic. And that's what got
3 into the mRNA vaccines.

4 But then over time, Jason and his group
5 also made this construct of a spike called
6 PeptoPro, which had an additional set of proline
7 mutations, and it had really good experimental
8 performance. Like most labs, many labs, you know,
9 when they're doing various SARS experiments, will
10 use these stable constructs because they express
11 better and so forth.

12 And so the issue, though, is that if
13 you, you can't just directly necessarily use it,
14 it's not a very good immunogen because it's just
15 sort of like, it's just not stable. So it could
16 be expressed, but it doesn't maintain a oligomeric
17 state. And unfortunately, because of that also,
18 they're not able to characterize the high
19 resolution structure using cryo-EM, because it's
20 just too flexible.

21 So we went at this question of can we
22 use simulation, these same types of methods that

1 we use to look at the S1 domain. Could we do that
2 to understand S2 dynamics. To understand how it
3 opens and then to design mutations that would
4 prevent that opening from happening to create a
5 stable construct.

6 So we used, again, the same methods I
7 talked about before. These weighted ensemble
8 simulations to understand how best to actually
9 open and let me play that again. What you can see
10 is that, you can see it sort of falling apart.
11 It's sort of opens. And here it's going slomo.
12 You can sort of it, it begins opening by sort of
13 splaying at the top, and then it sort of rapidly
14 unzips.

15 And so there are, you know, again, this
16 is as many of these fusion proteins, it's a
17 trimer. And so there's three sets of helices at
18 the (inaudible) interfaces that mediate the
19 opening. So you know, we could actually really
20 look at sort of what interactions were happening
21 in opening.

22 And what we saw was that chain A breaks

1 away from chain B initially. Then chain A breaks
2 away from chain C. So like one whole chain kind
3 of comes apart. And then those last two chains
4 separate. And then when we were looking at so,
5 okay, so we understand the mechanism of opening.
6 But now like, let's look at the interactions and
7 try to figure out if we can design mutations that
8 would stabilize, you know, stabilize it in the
9 closed state, to stabilize the apex epitope in
10 that too.

11 And what we immediately saw. So just,
12 and I'm sorry because I don't have too much time.
13 So I'll just say what we're showing here is
14 looking at sort of the interaction profile over
15 the dynamics of each of these, there's like rings
16 of residues that form through the central helix.
17 And they're like residues coming in from these
18 central helixes.

19 And what we saw were there were two
20 positions in particular at the top. This position
21 991, and then two down from that at position 998,
22 where it's really yellow. And yellow means it's

1 not really making good contacts. And these were
2 also some of the first to unzip, because it's
3 unzipping from the top down.

4 So we went in there and we said this is
5 where we want to mutate first to try to strengthen
6 these mutations to slow down opening. And so we
7 actually put in tryptophanes, and it turns out now
8 you've seen all those, the V991 line and the T998
9 line actually go to pink, from yellow to pink,
10 which just means they're really sort of making a
11 lot of contact now.

12 And in fact what we see is that when we
13 put in two of these tryptophan mutations, so
14 tryptophane at this top position, 991, and also
15 998, we see that there's a synergistic dynamic
16 coordination of residues that stabilize the flow
17 state.

18 And there's all sorts of interactions
19 that are happening. I have one last movie to show
20 you. But this is again sort of looking at this.
21 This is the mutations that we made. And you can
22 see how it's, how these sort of rings kind of come

1 together to create this sort of much more stable
2 network of interactions.

3 Not only with each other, but also sort
4 of, you know, in the flanking residues above and
5 beneath and around also. So there's all manner of
6 mutations are happening. And the other thing I'll
7 say that sort of I think fun for me and fun for
8 us, is that it's a way of doing immunogen design
9 where it's very information rich.

10 So there's, you know, there's a way of
11 doing protein design where you just, you know,
12 sort of make a lot of mutations, and then you sort
13 of see what you get. This actually, you know, we
14 go through first learning about the protein,
15 understanding the mechanism, and then designing
16 these.

17 And so with just these two suggested
18 mutations, so very, very few experiments, we
19 didn't make any other suggestions. We were able
20 to develop this construct that was significantly
21 more stable experimentally, in terms of
22 differential scanning. Sort of like temperature

1 studies.

2 As well as it was stable enough that
3 they were able to resolve that high resolution
4 crystal structure or cryo-EM structure. So this
5 is now the most stable S2 construct that we know
6 about. And is sort of being, you know, it's going
7 on, could be used in other types of experiments
8 now.

9 And again, this was the work, the
10 structural work, again of Jason McLellan and
11 colleagues in his group. Okay. And so now I will
12 be really happy to take questions. I know I
13 presented a ton of information, but hopefully was
14 able to give you a view of how you can use these
15 physics based simulations together with a plethora
16 of biological datasets to actually, you know,
17 better understand the system, do biologic
18 discovery, and actually do, you know, design work
19 also.

20 I just want to thank my group. I have a
21 wonderful group here in La Hoya, and just all of
22 the COVID work was just, you know, sort of a very

1 special opportunity for folks to come together and
2 work on some, you know, an amazing, very team
3 oriented science. So it was difficult, but it was
4 also very rewarding.

5 Lorenzo Casalino (phonetic), Christian
6 Seitz (phonetic), Erica Honic (phonetic), are
7 three folks who really worked really hard on the
8 on flu, and also Lorenzo, and Zandra, and Jason,
9 and Ling were really instrumental for the SARS 2
10 work.

11 And of course I want to thank funding,
12 both monetary and also for computing, because
13 these are very compute intensive experiments. And
14 so with that, I'll be happy to take questions and
15 discuss.

16 DR. FRIEDBERG: Thanks very much,
17 Rommie. Do we have any questions in the room? I
18 think we have one. All right, Mustafa. Is it not
19 on? Just come up here.

20 SPEAKER: So I find that the movement of
21 the glycans fascinating. It's almost like there's
22 a current or a wind.

1 DR. AMARO: Mm-hm.

2 SPEAKER: Obviously this structure
3 probably dictates that, but what about the
4 environment, different, for example, the age
5 groups, very old people versus very young, their
6 sera might contain different ions. Do you think
7 they also affect these movements? Therefore,
8 expose the protein epitopes differently.

9 DR. AMARO: That is an excellent
10 question. Thank you for that question. Yes. So
11 you are absolutely right that the dynamics of
12 these, oligosaccharides, essentially these glycans
13 can definitely vary with different conditions.

14 Interesting that you mentioned this in
15 the context of the spike accessibility. That's
16 something I hadn't thought about. We know for
17 very similar molecules like mucin, so I didn't
18 talk about it, but we're really interested also to
19 understand how the virus is actually interacting
20 with like the host cells like (inaudible), and
21 also with things like mucins and heparin sulfate,
22 and all that.

1 And there, it's also, the environment is
2 super important, and we, you know, we know from
3 our studies, and I think now there's a couple of
4 others that depending on the degree of, for
5 example, dilation, so how much, like how many of
6 these might be decorated with sialic acids.

7 These can coordinate to different
8 extents, calcium ions. And when this happens, it
9 actually can occur to, if you have enough calcium
10 there and the right groups, it actually can have a
11 like a local phase change, actually. Where it can
12 almost form like a gel like structure in the
13 vicinity of the virus, which of course will affect
14 all, I mean that also affects all manner of
15 different biological properties, including
16 exposure, but also just infection and so forth.

17 So yeah, there's so much, but there's
18 still really a lot more to be learned there.

19 DR. FRIEDBERG: Thanks. Online
20 questions.

21 MS. ELKINS: Nope. This is actually
22 mine.

1 DR. FRIEDBERG: Oh.

2 MS. ELKINS: And probably a stupider
3 version of the same question. You mentioned
4 solvent effects. But what are your baseline
5 computational models assume in terms of
6 (inaudible), that is salt, pH, buffer molecules,
7 and how much can you vary that within the
8 computational approaches?

9 DR. AMARO: Yeah, that's an excellent
10 question. And sorry. Yeah, I sort of breeze
11 through that, but I am, I'm going to, I'll see if
12 I can find a slide. So in our constructs like of
13 this, where it it's really sort of just the
14 dynamics of the spike, this is really sort of what
15 we do here when it's just a single protein is we
16 try to link to in vitro conditions.

17 So it's usually like 150 millimolar
18 sodium chloride. We're looking at pH 7.4, and
19 then just water. So very simple sort of really
20 like almost like a benchtop experiment. But we
21 can definitely, and one of the things that as I,
22 you know, we can already see hints of and that we

1 know is that as we make the biological environment
2 more complex, that the dynamics change. Right.

3 And so we also in work that I didn't
4 tell you about today, because I was focusing more
5 on sort of biologic evaluation, which I thought
6 meant more like on antibodies. We're also really
7 interested to understand what happens, you know,
8 understanding the dynamics of these viruses in
9 the, you know, sort of like in the institute
10 context, inside the human, and also in aerosol.

11 We're really interested in understanding
12 the structural dynamics of different types of
13 viruses in different aerosol conditions. And so
14 in these experiments, and so I'm showing here an
15 image of the SARS-CoV-2 virus. This is the purple
16 and blue in the aerosol.

17 Here we have mucins, we have albumin, we
18 have ions, we have lipids, we have different
19 types. And what we've done is basically created a
20 computational mimic of like lung surfactant. And
21 so we can actually make, but to answer your
22 question, sorry, that was sort of like a long way

1 around to answer your question.

2 Depending on sort of like what
3 experiment we're trying to mimic, we can tune the
4 ingredients to what we include computationally.
5 And we can actually now include quite a range of
6 substituents that mimic fairly closely the actual,
7 you know, sort of in vivo or in situ conditions.

8 It did take, though, some work. For
9 example the mucins, this was sort of these red
10 molecules here. Those are again very difficult to
11 structurally characterize because they're so
12 highly dynamic. But we've been able to make
13 models, and this is work that is just now in
14 press, sort of developing the sort of the basic
15 constructs that can be used in simulation of these
16 complex scenes. I hope that answered your
17 question.

18 DR. FRIEDBERG: Thank you very much for
19 that. And I'd like to move on to our next talk.
20 Thanks, Rommie.

21 MS. ELKINS: Whoa, whoa, whoa.

22 DR. FRIEDBERG: Oh, sorry.

1 MS. ELKINS: We have a couple online
2 questions.

3 DR. FRIEDBERG: Oh, you have online
4 questions.

5 MS. ELKINS: Do you want to go ahead and
6 take a look at the online ones and let me know if
7 you have trouble seeing those.

8 DR. AMARO: Okay. I can see them if we
9 have time. I'll try to answer these quickly
10 because I know everyone's on a schedule.

11 MS. ELKINS: Sure, go for it.

12 DR. AMARO: One question was about the
13 furin cleavage site. It says the furin cleavage
14 site of SARS-CoV-2 spike is in a disordered loop.
15 And it sure is. Did you find anything interesting
16 in that region in your simulation study?

17 So oh yeah. So we haven't actually
18 published too much about this, but we expect to, I
19 think, over the course of the next year. So yeah,
20 I guess I shouldn't say too much about it at this
21 time. There are a lot of very interesting
22 dynamics, you know, it's a highly charged area,

1 which also means that it attracts particular types
2 of molecules even beyond (inaudible).

3 That there are likely interactions with
4 the host glycocalyx. And then depending on
5 whether or not it's been cleaved or is still
6 intact, there are definitely sort of differences
7 in the dynamics of the spike. And I think, and
8 others also probably suspect that dynamics at the
9 furin cleavage site are probably really important
10 for epistasis and understanding sort of the
11 mutational range of these host proteins, you know,
12 as they're sort of evolving in populations.

13 But so that was a non answer question to
14 your question. So yeah, there's interesting
15 things, but we're still learning about it.

16 And then to the second question from
17 Carol Weiss (phonetic), do the glycans protect the
18 spike from proteases and consequent degradation.
19 That is a good question. And I guess also, or
20 Karen, oh no, she the one I answered.

21 That region like for example, you know,
22 do they protect it from proteases generally.

1 Possibly. Again, also that furin cleavage site,
2 you know, is actually quite exposed from the
3 glycans, which is also interesting.

4 And so it has its own set of dynamics
5 that does leave it exposed even in spite of all of
6 the glycans. So it's, you know, these glycans
7 have evolved certainly with the host protein, and
8 all of the other factors. So you know, in sort of
9 like I'm trying to understand the mechanism of
10 other proteins, and how they interact with it.
11 That's the last question, so thank you.

12 DR. FRIEDBERG: Thank you very much,
13 Rommie, for such an interesting talk. Our next
14 speaker is Frank Delaglio, and while he gets up
15 here, I can say I've known Frank for 30 years now.
16 And it's been a pleasure knowing him. He's always
17 supported us computationally from the, for our NMR
18 studies.

19 And today he's going to tell us about
20 chemometrics and machine learning to enable
21 applications of NMR and biomanufacturing.

22 DR. DELAGLIO: Splendid. Thank you very

1 much for this privilege to present the work of our
2 colleagues at NIST. Very good. Thank you. So
3 the work that we'll present today, it's just this
4 slide. Oh, there. Okay. Okay, very good.

5 So the work that we'll present today was
6 conducted at the Institute of Bioscience and
7 Biotechnology Research, which is a small institute
8 in the neighborhood here, that's run jointly
9 between NIST, the University of Maryland, College
10 Park, and the School of Medicine.

11 And the work that we'll see today is
12 work from a circle of groups at NIST IBBR who
13 develop measurement methods to support
14 biomanufacturing. And the folks on this slide are
15 the folks who are developing NMR based methods to
16 support biomanufacturing.

17 So we'll cover some different areas
18 where we're applying NMR to biomanufacturing
19 topics, works at different stages of completion,
20 and in particular, problems that have associated
21 computational challenges. And we'll try to
22 emphasize a few kinds of analysis methods that

1 might be generally applicable to other folks in
2 their work.

3 At IBBR, we're concentrated on two
4 things, structural biology and biomanufacturing.
5 And both of those topics are quite familiar to
6 everyone here. Monoclonal antibodies have become
7 the largest growing kind of therapeutic. And they
8 account for about \$150 billion a year or more in
9 medical sales.

10 And among the reasons that these are
11 important is because of the fact that on the one
12 hand, we can engineer a monoclonal antibody that
13 will target very specifically just about any
14 target that we can come up with. But also since
15 monoclonal antibodies of a given class are very
16 similar, the methods for expressing them, and
17 purifying them, and testing them, and delivering
18 them are very similar.

19 And so knowledge, biomedical knowledge
20 that we get about one particular antibody
21 therapeutic can give us an advantage with the
22 others. Recognizing the fact that these

1 monoclonal antibodies are so commercially and
2 medically important, NIST, which loves to make
3 reference standards and reference data, made the
4 NISTmAb. The monoclonal antibody reference
5 material.

6 And we'll see applications that take
7 advantage of the NIST map and its existence. Now,
8 in the NMR labs, we developed an NMR method that
9 we call NMR spectral fingerprinting. And it's a
10 straightforward idea. We take an NMR spectrum,
11 and the details of the NMR spectrum reflect the
12 structural details and chemical details of the
13 underlying molecular system.

14 So for example, in this case what you
15 see is an NMR proton carbon spectra, it's what NMR
16 folks like to call hydrogen atoms. Protons and in
17 a spectrum like this one, each one of these peaks
18 represents one CH group somewhere in the
19 monoclonal antibody. Position of that peak in one
20 of the dimensions is the NMR chemical shift of the
21 hydrogen atom. And the position that peak in the
22 other dimension is the NMR chemical shift of the

1 carbon that it's attached to.

2 Now, generally speaking, we don't know
3 specifically which particular atoms and amino
4 acids each of these peaks belong to. But even if
5 we don't have assignments available, we generally
6 know the amino acid type that's associated with
7 these different signals.

8 And just about anything chemically or
9 structurally that happens to the underlying
10 molecule will be affected and observable in the
11 spectrum. Because these positions of the peaks
12 are determined according to chemical bonding
13 partner, hydrogen bonds, dynamics, the solvent,
14 all of these details.

15 So if anything changes about the
16 underlying structure of the antibody, peaks will
17 move, they'll grow, they'll split, they'll
18 disappear. So as an example, we have two cases
19 here. Two kinds of spectra, two related antibody
20 samples in overlay. And one of the spectra is
21 drawn in red, and the other spectrum is drawn in
22 blue on top of it.

1 So we have molecular systems where there
2 are almost no changes. And if a person analyzes
3 this data by eye, it's very difficult to under --
4 well, to find anything quantitative in the data
5 just from a rough visual comparison.

6 So what we would like to do is find
7 numeric methods where we can take spectra like
8 that and convert them into some kind of answer.
9 So for example, over here, we have 2 collections
10 of replicate spectra of 2 kinds of samples that
11 are very difficult to analyze by eye.

12 But I'm going to describe how we can use
13 a technique called principal component analysis to
14 directly take this stack of spectra on two sets of
15 replicate measurements and turn it into an
16 analysis like this, where we can make a
17 determination about whether the two samples are
18 substantially different from each other, or
19 substantially the same.

20 So we're going to use PCA as a method to
21 quantify this kind of spectral similarity. And
22 here's how it works. In order to explain this

1 method, I'm going to refer to a test case where we
2 take the NISTmAb monoclonal antibody and oxidize
3 it with peroxide. And the effect of that is to
4 oxidize methionine side chains on the surface of
5 the antibody.

6 And when these side chains are oxidized,
7 it modulates the therapeutic effect of the
8 monoclonal antibody. It may reduce its
9 effectiveness. It may increase its
10 immunogenicity. So being able to monitor the
11 oxidation state of these methionine's is an
12 important aspect of biomanufacturing.

13 Now, there are many proteins that will
14 bind to a monoclonal antibody. For example, the
15 protein A. So we're going to prepare two kinds of
16 oxidized samples. One, the NISTmAb oxidized all
17 by itself. And then the other, the NISTmAb bound
18 to protein A before it's oxidized, with the
19 assumption that protein A is going to cover up,
20 protect certain side chains from oxidation. So
21 the pattern of oxidation in these two kinds of
22 samples will be different.

1 Here's what the actual spectra looked
2 like. So it turned out that the particular
3 protocol that we use to oxidize these sample,
4 oxidize them both almost completely. So the mAb
5 that's oxidized all by itself is 99 percent
6 oxidized. And the mAb that's oxidized in the
7 presence of protein A is 95 percent oxidized.

8 So the region of the spectrum where the
9 methionine signals show up looks empty on rough
10 inspection. But if we go very low in the contour
11 levels, we can actually see some small residual
12 signals.

13 So in gray here is what the intact
14 native form of the antibody looks like. In blue
15 is the signal leftover in the NISTmAb that's
16 oxidized all by itself. And in red, you see there
17 are a few more signals. That's the sample that
18 was oxidized in the presence of protein A.

19 So some of those side chains were
20 protected by protein A. So we can see a few more
21 signals. But these contour levels are at five
22 times lower than the ones here. So these signals

1 are very small.

2 We would like to find a way to take the
3 entire spectrum and use it for analysis purposes.
4 And the method that we're going to use is
5 principal component analysis directly on the
6 matrix of spectral intensities.

7 And the way this method works is that we
8 consider that each spectrum in a collection is
9 represented as one object in a high dimensional
10 space. And the coordinates of that object are
11 simply all of the intensities in the spectrum.

12 So if the spectrum has 100,000 points,
13 we can represent it exactly as one object in
14 100,000 dimensional space. And if you think about
15 this representation, spectra that are similar
16 means the shape of the spectra, the intensities of
17 the spectra are similar, so they're going to lie
18 in related regions and close together in this high
19 dimensional space.

20 But spectra that are mostly the same,
21 but differ in a few particular features, are going
22 to tend to align along lines and curves in this

1 high dimensional space because they'll have one
2 set of coordinates in common. Those are the parts
3 of the spectra that are similar. And some other
4 collection of coordinates that vary in a
5 continuous way.

6 In principal component analysis, we take
7 this huge high dimensional representation of the
8 spectral series and more or less simply fit it to
9 a series of multidimensional straight lines. And
10 this gives us the direction of maximum variance in
11 this high dimensional data and lets us orient the
12 projection so that we can take data, for example,
13 like our case where we have replicate measurements
14 on two samples and compute the first principal
15 component, which helps us determine a direction of
16 maximum variance.

17 And we make a projection down to a lower
18 number of dimensions to get a result. So we can
19 inspect the results this way in the form of a
20 scatter plot, or as I'll explain, we can also
21 express the results of this kind of analysis as
22 pseudo spectra.

1 But in an analysis like this one, we
2 will project our data down to a small number of
3 dimensions by PCA and look for clusters and use
4 the distance between them as a way to gauge the
5 difference between these different classes in a
6 quantitative way.

7 So here's an example of the case that
8 we've been talking about. Here's a scatter plot
9 of 3 sets of replicate spectra, native NISTmAb,
10 the oxy, and A oxy samples that we've been talking
11 about. And what you see here are the principal
12 component spectra that corresponds to this
13 principal component scatter plot.

14 And as you'll see, the first component
15 is very much like an average spectrum. And the
16 remaining components will highlight the regions of
17 the spectra that are different between the
18 different classes. And so what you see is, in the
19 presence of this oxidation, the signals, which are
20 drawn in red and blue, are in the higher
21 components.

22 So differences associated with oxidation

1 are not limited to just the methionine region of
2 the spectrum. They're actually dispersed
3 throughout the whole spectrum. So there's a very
4 strong and robust collection of information in
5 here, if we could find a way to get it.

6 Now, another way to think about
7 principal component analysis that should make
8 sense to a spectroscopist is as a spectrum
9 decomposition. And I think this is a nice way to
10 understand it, as well. So using a kind of
11 simulated version of our example where we have
12 replicate measurements on two samples, and we have
13 a stack of those, and that's the data that we're
14 going to analyze by PCA.

15 So to compute the first component, what
16 we do is find a linear combination of all the
17 spectra in the series. And we choose that linear
18 combination in a way to match the entire series as
19 a whole, as closely as possible, in the least
20 square sense.

21 The coefficients that we use to mix the
22 spectra together to generate that linear

1 combination are the PCA score values. Those are
2 the values that we see in the scatter plot. And
3 the linear combination that we generate is the PCA
4 loading spectrum. So that is the linear
5 combination of all the spectra in the series
6 according to these linear coefficients.

7 And we extract these by different kinds
8 of linear algebra methods. But in a case like
9 this one where we have two samples, the first
10 component spectrum looks very much like an average
11 spectrum across the spectral series. So we have
12 these score values. We have this loading
13 spectrum. We can take this loading spectrum and
14 now subtract it from all of the spectra in our
15 original series and that will generate a residual.

16 We can repeat this procedure as many
17 times as we like. So we can take this residual
18 and find a set of coefficients to make a linear
19 combination of all of these planes. And in this
20 case with 2 samples, 2 kinds of samples, that kind
21 of spectrum tends to look like a different
22 spectrum between the 2.

1 Now, in this case, we have 2 different
2 samples. If the samples don't change during
3 measurement, and if there is no drift during the
4 measurement, then 2 component spectra should be
5 sufficient to describe the entire series, no
6 matter how many spectra there are.

7 And if the series needs more than 2
8 components, it's a diagnostic that tells you that
9 the sample is changing during the course of the
10 measurement.

11 Now NMR spectra are generated in the
12 time domain. We measure them in the time domain,
13 and we convert that data into a spectrum by
14 Fourier transform. In a case of two-dimensional
15 NMR data, we start with a stack of one-dimensional
16 measurements and then we Fourier transform all the
17 rows, and then all the columns, and that gives us
18 a beautiful two-dimensional spectrum.

19 The Fourier transform is a linear
20 operation. So the information content in all of
21 these cases, the original time domain data, the
22 interferogram, and the spectrum, the information

1 content in all those cases is the same. So this
2 linear transformation of the data doesn't change
3 the results that you get from principal component
4 analysis.

5 This is all linear combinations of the
6 data, as well. Now, as a little pointer that will
7 be interesting to folks who do NMR, one of the
8 ways that we can make these measurements more
9 practical is to use a measurement technique called
10 nonuniform sampling, which basically means we
11 randomly skip over some fraction of the data that
12 we would normally measure in a conventional
13 experiment.

14 And we use special compressed sensing
15 reconstruction methods to fill in the blanks and
16 generate a good looking spectrum. Because if we
17 try to Fourier transform data that has gaps in it
18 like this, we get a spectrum, but the spectrum
19 looks kind of crazy.

20 It has these things that seem like
21 random artifacts. They're deterministically, they
22 come in a deterministic way from the pattern of

1 points that we keep and the pattern of points that
2 we skip.

3 But as I said, since the information
4 content in all of these cases is the same, we can
5 apply principal component analysis to a
6 nonuniformly sampled spectrum that's been
7 reconstructed only by ordinary Fourier transform.
8 And a result like this can't be analyzed by eye.
9 But we can extract the same information out of it
10 that we could in a fully reconstructed spectrum.

11 So the take home message here is that
12 not only does principal component analysis give us
13 the advantage to analyze a spectral series
14 directly without having to do any peak detection
15 or complicated preprocessing, but it can also be
16 applied to extract information that's not possible
17 to extract by eye.

18 Now, to show some examples of where this
19 information that we extract by PCA can cross over
20 into issues of biomanufacturing, we'll take a look
21 at some biophysical measurements on these oxidized
22 samples. And so what we see here are melting

1 curves with respect to oxidation time. And we're
2 looking at a change in the temperature of these
3 two melting transition points.

4 And with longer and longer oxidation
5 time, these temperatures get lower and lower as
6 the protein gets destabilized. Then it's easier
7 to melt. So not surprising, but we see this with
8 a time resolved biophysical measurement.

9 We can also gauge the activity, the
10 binding activity of the monoclonal antibody. So
11 we've chosen three kinds of proteins, protein A
12 that we already talked about, which binds the FC
13 domain of a mAb. Protein F, which binds to the
14 fAb. And protein L, which also binds to the fAb.

15 But these two proteins, A and F, cover
16 up some methionine residues on the surface, which
17 protein L doesn't. It binds in a place that's not
18 near to any methionine residues.

19 So protein A activity decreases with
20 oxidation time in the activity measured by SPR
21 binding strength. Same thing with protein F. But
22 protein L, the binding doesn't change.

1 We can also measure details of protein
2 stability and aggregation by the method of
3 relaxometry, also called water NMR. We can
4 measure the water signal and how it behaves. And
5 in particular, the relaxation properties of the
6 water signal, which will reflect the proteins that
7 are dissolved in it.

8 And so, as an example, we can measure
9 relaxation time with respect to oxidation time and
10 see that it changes systematically. One of the
11 beautiful things about these kinds of
12 measurements, they're conducted with low field
13 benchtop NMR instruments, and you can actually
14 take an intact vial or a loaded injectable syringe
15 and put it intact inside the NMR instrument and
16 make a measurement.

17 Not only nondestructively but
18 noninvasively. So it's a very cool technique. So
19 we have these three different ways to characterize
20 the stability and activity of the monoclonal
21 antibody protein. And then look at these
22 beautiful results.

1 The information that we get from
2 relaxometry, from binding activity by SPR, and
3 from thermal unfolding, all of them can be
4 correlated in a quantitative way with the score
5 values that come on a principal component
6 analysis.

7 And we didn't have to do anything
8 complicated. Just take the sample, which is
9 already dissolved in water, put it in an NMR tube.
10 Make these measurements, take the spectra, stack
11 them up, put them in PCA.

12 Now to continue with the topic of low
13 field NMR, talk about another set of projects that
14 is underway in the group, and as a follow on
15 reference material to the NISTmAb monoclonal
16 antibody reference, NIST is now also introducing
17 the NIST show a live cell reference material.

18 It's a show cell that's been engineered
19 to express the NISTmAb. And it's been engineered
20 to express the NISTmAb in quantities that are
21 significant in a biomanufacturing context.

22 So in other words, we optimized this

1 expression system in the same way that a pharma
2 company would optimize an expression system. So
3 now this is another beautiful test bed for
4 different kinds of measurement techniques to
5 support biomanufacturing.

6 Now, as folks know, biomanufacturing of
7 these monoclonal antibodies is done in large scale
8 bioreactors in growth media that have 50 or 100
9 different materials in them. And the properties
10 and therapeutic activity of the end product can
11 vary greatly with small changes in the conditions
12 and protocols.

13 So there are lots of measurement needs.
14 And a lot of them we could imagine could be nicely
15 addressed by NMR. But a superconducting magnet is
16 not very practical to put in a laboratory where
17 either large scale or small scale bioreactions are
18 going on.

19 So we have a project in our lab to build
20 a closed loop system or an at line system, where
21 we use benchtop NMR as a kind of universal
22 detector for monitoring what's going on in a

1 bioreactor.

2 And what we do is monitor the reaction
3 media, not the cells. And the compounds in that
4 reaction media tell us what the state of the
5 bioreaction is.

6 There are many things that we could do
7 with information of this type. For example, very
8 straightforwardly, when we measure a collection of
9 NMR spectra over time, that collection of spectra
10 becomes a signature for the bioreaction.

11 And without any further analysis, you
12 can use it to decide whether one bioreaction is
13 proceeding the same way as a previous bioreaction.
14 So there are all sorts of things that you could do
15 with this, including early detection of failure.

16 And you could also use it to optimize
17 production of the particular materials. But most
18 interestingly and attractively, if we want to
19 develop methods of adaptive manufacturing, methods
20 where the controls and protocols and materials of
21 the biomanufacturing are adjusted in real time in
22 response to measurements, we need a good

1 measurement technique that's time resolved.

2 So as an example, for our early work,
3 here are NMR spectra, an excerpt of NMR spectra,
4 measured on a 100 megahertz benchtop instrument
5 from media collected from CHO cell growth over the
6 span of 23 days. Okay.

7 And we can work with the spectra
8 directly along the lines of what we've seen
9 already with principal component analysis. And we
10 can also do conventional analysis where we
11 identify particular analytes and determine their
12 concentration from the size of signals in the NMR
13 spectra.

14 Now, something that we didn't expect or
15 plan on, but actually turned out to be quite
16 interesting, is that at benchtop resolution, we
17 can also see signals from the monoclonal antibody
18 that's been expressed and secreted into the
19 medium. And we haven't done much with this kind
20 of analysis yet. But the interesting thing is
21 here's what that looks like with 500 seconds of
22 measurement at 100 megahertz.

1 And here's what a similar measurement
2 looks like on a 400 megahertz superconducting
3 spectrometer. And what we've shown previously in
4 other publications is that information that we
5 extract with a 600 megahertz spectrometer and 1D
6 data, is very similar to the kind of information
7 that we can extract from a 400 megahertz spectrum.

8 These are PCA results of those two kinds
9 of cases. Now when I look at this, I'm delighted
10 to see that this antibody signal, even though it's
11 a blob, it has features. It certainly has
12 information in it. So I'm very hopeful that we'll
13 actually be able to do things to analyze the
14 monoclonal antibody signal as well as the media
15 component.

16 Now, in our interest to work with and
17 quantify metabolomics data, we've recently
18 introduced an open source piece of software to
19 automatically identify and quantify the systems in
20 complex 1D spectra. And that software is SAND,
21 it's developed by a graduate student, UAU, in Art
22 Edison's group.

1 So he worked with me to develop this
2 software, and our goal was to get a piece of
3 software that was not encumbered by a graphical
4 interface or anything like that, so that it could
5 be used conveniently in batch mode. And that you
6 didn't have to do anything other than put in a
7 spectrum and the analysis region. And then you
8 would get out a result like this.

9 So what you see here is the measured
10 spectrum in blue. The model created by SAND in
11 yellow, and the individual peaks in the model
12 underneath. The way SAND works is in the time
13 domain, okay, it models signals in the time
14 domain.

15 And I won't talk too much about the
16 details of how this is done, but a critical thing
17 that we do, let's kind of take a page from machine
18 learning, that's not generally done in NMR signal
19 analysis, is use to paradigm that folks in machine
20 learning use by dividing data up into training set
21 and validation set.

22 And so we take our time domain data and

1 subdivide it in these two kinds of classes. And
2 the training data is used to optimize the model,
3 determine where the peaks are and how big they are
4 and so on. And the validation set is used to
5 determine whether or not we need to add more peaks
6 to the model.

7 So that's the decision making part. And
8 we use hybrid optimization of mixture of Monte
9 Carlo and gradient optimization methods to work on
10 this problem. And as an example of the results
11 that we can get, these kinds of complicated
12 mixture spectra like urine spectra that we show
13 here, very difficult to evaluate an automated
14 method. Because even when a person looks at these
15 spectra, it's difficult to make actual rigorous
16 determinations about individual signals.

17 So what we did to make the problem
18 easier, is we took urine and made a four compound
19 mixture that we could spike in in different
20 amounts. And since we put the mixture components
21 in, we know exactly where their signals are. And
22 then we can quantify how those signals grow with

1 addition of more of the spiked material.

2 We get beautiful linear behavior. So
3 that's the result from SAND. And then finally,
4 this is a very early result, but it uses some
5 aspects of machine learning that might be
6 generally interesting to the audience. So let's
7 talk about them too.

8 And as an example of why this is useful
9 in a biomanufacturing context, we'll take a quick
10 look at work from Anu Kaur (phonetic) in our group
11 who's studying the effects of different excipients
12 on mAb structure and dynamics.

13 And so as an example, your three common
14 excipients, salt, polysorbate, and sucrose, salt
15 tends to have a destabilizing effects on most
16 cases. So in these melting curves, adding more
17 salt reduces the melting temperature. Whereas in
18 the case of sucrose, which increases stability,
19 that tends to increase this melting temperature.
20 And polysorbate in this case has no effect.

21 Now when NMR chemical shift assignments
22 are available, that is to say, when we know which

1 peak in the NMR spectrum matches which amino acid
2 in the protein, we can do detailed analysis of the
3 dynamics of the molecule.

4 So we can do things about the overall
5 dynamics of the molecule, whether or not it
6 tumbles isotropically, and whether an excipient or
7 other change will change the way in which the
8 protein tumbles, because the structure gets
9 elongated.

10 And we can also measure the internal
11 dynamics of the protein. So in this case what you
12 see is a map of how rigid each particular residue
13 is under a particular circumstance.

14 So I won't talk about the conclusions of
15 this particular work, but this just gives you an
16 idea of what kind of information that we have
17 available when we have NMR chemical shift
18 assignments available. But to get them, to get
19 these chemical shift assignments.

20 So what you see here is a proton
21 nitrogen NMR spectrum. So in this case every
22 amino acid gives one signal in this spectrum, and

1 the position of that signal is the chemical shift
2 of the hydrogen atom and the amide nitrogen that
3 it's bound to. Okay.

4 So from mAb, this spectrum is so
5 complicated that we can't even label all of the
6 assignments together. So in this illustration, we
7 have all of the assignments associated with the
8 light chain. And here's all the assignments
9 associated with the heavy chain.

10 So these kinds of spectra, these kinds
11 of spectra, have hundreds of peaks. And for every
12 peak that you see here, probably 1 or 200 other
13 peaks, related peaks from other two-dimensional
14 and three- dimensional spectra, had to be analyzed
15 and curated by an expert. Okay.

16 So this kind of peak analysis is the
17 labor sink. The time-consuming aspect of trying
18 to apply NMR for structural biology purposes. And
19 so being able to address the peak detection
20 problem in a more automated way is valuable across
21 the board for many kinds of applications, because
22 most every NMR workflow in higher dimensional data

1 requires identifying the peaks.

2 And we have lots of software to help us
3 identify peaks, but generally it doesn't do very
4 well in the case of the presence of small artifact
5 peaks, or cases where peaks are only partially
6 resolved, and they're not well resolved maxima.

7 Now, there are also machine learning
8 approaches to analyzing NMR data in different
9 ways. And universally, they use a representation
10 of the spectrum that's equivalent to a grayscale
11 image. But a human analyst works with this
12 contour graphic.

13 Now, if we want to, what we're going to
14 do is repurpose existing image analysis tools.
15 And as you can expect, the way that you preprocess
16 the data has a big impact on what you can do with
17 it in a machine learning context.

18 So I want to say that identifying a peak
19 in a picture like this, it doesn't depend on how
20 big the peak is. It depends on the shape of these
21 features. Right.

22 So this is not a good representation of

1 the information, because the dynamic range, the
2 brightness is what represents the information in
3 the spectrum, but we don't really care if a peak
4 is 10 times bigger or whatever. We just want to
5 find that it's there.

6 Whereas a picture like this, has
7 predictable brightness, its brightness doesn't
8 change. We have a. Black background and contour
9 peaks. So this is a more suitable data
10 representation for reusing existing image analysis
11 tools.

12 And NMR has a particular advantage in
13 machine learning approaches in that it's possible
14 to generate simulated data that mimics
15 experimental data very well. So as you can see in
16 this case, and we can also use semisynthetic
17 methods.

18 So the results that I'm going to show
19 you work with actual measured spectra, like the
20 one that you see here, where a computer program
21 has identified the existence of particular
22 isolated peaks. And those are confirmed by an

1 expert. And once we identify, say, a dozen of
2 these peaks in a particular spectrum, we extract
3 them from the spectrum and make a hundred
4 different variations in them by adding noise, a
5 little bit of line sharpening, line broadening,
6 phase distortion.

7 So we generate a library of individual
8 peaks that are based on experimentally measured
9 data, and then we can add them together in
10 different ways to generate synthetic spectra.

11 And the method that we're going to use
12 to approach the peak analysis is the commonplace
13 method of image segmentation for which there are
14 many, many existing solutions. And as you know,
15 image segmentation is the task of taking a picture
16 and deciding what each pixel belongs to. Is the
17 pixel in a dog, is it in a cat, is it in a stop
18 sign.

19 And because this is such a general and
20 important problem, there are already fantastic
21 neural networks that have been designed and
22 trained to work on this problem. And the fact

1 that they've been designed is handy, but the fact
2 that they have been trained is critical.

3 And here's why. Here's a diagram of a
4 neural network technique called the U-net. And
5 what we have here is a convolutional neural
6 network. The picture of the spectrum goes in
7 here, and at the end is an output that tells us
8 where the peaks are.

9 And what you see here in these different
10 strata are parts of the network that analyze the
11 image at different scales. So each strata further
12 down analyzes the image at one-half of the
13 resolution of the level above it.

14 So all of these different strata analyze
15 the image for features at small and large scale.
16 And this part of the network learns how to
17 identify lines, and curves, and boxes, and
18 circles, and so on. And that information at all
19 these different scales is combined at the end, and
20 then used to make a classification.

21 So if we want to reuse a network like
22 this one, all we have to do is retrain the end of

1 it that takes the feature information and makes
2 some kind of analysis. So we can take these
3 preexisting networks that are already been trained
4 beautifully on millions of pictures, and dogs, and
5 cats, and retrain them with a relatively limited
6 amount of data to do NMR peak picking.

7 And here's some examples. So in
8 training, we present the neural network with a
9 little image patch like this of several peaks.
10 Since these are generated by adding together
11 individual peaks, we know exactly where all the
12 true signals are. So our ground truth that we
13 want the network to reproduce is just a list of
14 spots where we know the true peaks are.

15 So here's the input. Here's the target,
16 the training target, the ground truth. And here's
17 what the neural network produces in these cases.
18 So it actually does, I would say, about as well as
19 a person can do. And here's a result on a
20 complete spectrum.

21 So that could be of interest to you
22 because it's relatively easy to reuse these

1 existing networks. And even MATLAB has relatively
2 straightforward ways that you can load an existing
3 network and retrain it for an application like
4 this.

5 So I hope I've shown you that, first of
6 all, that there's lots of interesting ways that
7 NMR can be used to support biomanufacturing. And
8 we have lots of exciting analysis methods to
9 support those measurements. So thank you for your
10 patience. I hope it was interesting.

11 DR. FRIEDBERG: Thank you, Frank. Any
12 questions in the room? I have one. In the case
13 of the original PCA that you showed us, you didn't
14 have assignments in the spectrum. Do you need to
15 know assignments?

16 DR. DELAGLIO: No.

17 DR. FRIEDBERG: So --

18 DR. DELAGLIO: Because just the spectra
19 go in as they are in their entirety, every point
20 in the spectrum.

21 DR. FRIEDBERG: Okay. And the blind
22 spot might be a peak that isn't in one dataset for

1 some reason but appears in another, but it's
2 really there, you just didn't detect it in the
3 first slide.

4 DR. DELAGLIO: That's right. Yeah. So
5 what we wind up detecting in these cases are
6 subtle changes in the overall shapes of the
7 spectra. So the peaks are in almost the same
8 positions. So you wouldn't easily be able to see
9 the differences by eye, but across the whole
10 spectra, the systematic differences are all there.

11 DR. FRIEDBERG: Okay. And the last sort
12 of thing on that is as you know, NMR spectra are
13 very sensitive to pH.

14 DR. DELAGLIO: Yes.

15 DR. FRIEDBERG: So how do you, does
16 that, does your algorithm or does PCA have a way
17 to filter that out or to raise a flag and say this
18 might be a pH effect?

19 DR. DELAGLIO: Right. So that's a great
20 question. And when we apply PCA to AMI detected
21 spectra, that's an issue. Most of the work that
22 we do is with proton carbon spectra. And since

1 those hydrogen atoms are not labeled, they don't
2 really change with respect to pH.

3 DR. FRIEDBERG: Okay.

4 DR. DELAGLIO: Thanks again.

5 DR. FRIEDBERG: All right. Thank you.

6 Oh, you do have online questions. You were
7 shaking your head no.

8 MS. ELKINS: Late breaking.

9 DR. FRIEDBERG: Oh, they're late
10 breaking, good.

11 MS. ELKINS: How do you introduce in
12 15C13 in mammalian cell culture?

13 DR. DELAGLIO: With great difficulty.
14 So there are ways to express the mAb in E-coli and
15 in yeast. As we saw in the previous talk, the
16 glycosylation of these proteins is critical to
17 their therapeutic effect. And we only get that
18 glycosylation when the proteins are expressed in
19 mammalian cells. So we worked very hard to make
20 cell lines that can live in minimal media.

21 The difficult part is that for proteins
22 of this size, we have to label them with

1 deuterium-2. And that's the sticking point for
2 mammalian expression. So just we solved that
3 problem with lots of painful trial and error.

4 DR. FRIEDBERG: Anything else? All
5 right. Let's thank Frank again. Thank you,
6 Frank.

7 DR. RODRIGUEZ: So in our next part of
8 our session, we're going to feature three
9 distinguished speakers from the Center for
10 Biologics Evaluation and Research, CEBR. First we
11 will hear from Dr. Nobuko Katagiri, researcher and
12 regulator at the Office of Therapeutic Products.

13 Following Dr. Katagiri, we have Dr. Lisa
14 Parsons, a staff scientist and chemistry
15 manufacturing and controls reviewer in the Office
16 of Vaccines Research and Review. Lastly, Dr.
17 Hussain Ezzeldin, senior digital health expert in
18 the Office of Biostatistics and Pharmacovigilance.

19 After all three presentations, we will
20 open the floor for questions for Drs. Katagiri,
21 Parsons, and Ezzeldin.

22 DR. KATAGIRI: Let me just, right.

1 Okay. Thank you very much for this opportunity.
2 And today I'd like to introduce some of the
3 computational part of the research from
4 Kimchi-Sarfaty's group at CEBA.

5 After giving you some background about
6 how synonymous, why synonymous single nucleotide
7 variations matter, and some concepts related to
8 the codon usages, I'm sorry. I'd like to show
9 some of the highlight of our studies related to
10 the sequence variations.

11 First, what is synonymous single
12 nucleotide variants, or SNB's. Unlike other two
13 types of SNB's, synonymous SNB alter the codon
14 sequence without changing the code encoding amino
15 acid sequence, because the genetic codes are
16 regenerative, regenerate and the same amino acid
17 can be coded by multiple synonymous codons.

18 Now every year, CBER receives a number
19 of biologic therapeutics, and many of them
20 contains a sort of, some sort of sequence
21 variations. And that's why it is so important for
22 us to know which variations are potentially

1 harmful. Among those sequence variations,
2 traditionally, the synonymous variations and codon
3 optimization, which is a combination of numerous
4 synonymous variations, are considered to be least
5 harmful.

6 However, the studies in the last decades
7 identified synonymous variants, which are shown to
8 be associated with the numerous diseases,
9 including cancers, and those are just a few of the
10 longest. But how can synonymous variants can
11 change the function of protein without changing
12 the amino acid.

13 The scientists have been learning over
14 the decade, again, that actually synonymous
15 variation can impact the protein expression and
16 function through multiple mechanisms, not only the
17 splicing, but also in many other steps in both
18 transcription and translational steps.

19 Especially the codon usages being
20 affecting the translation speed due to the
21 different availability of the aminoacyl-tRNA,
22 which leads to the core translational protein

1 folding. And all these steps are analyzed using
2 several nucleotide sequence related parameters
3 such as the (inaudible) or dinucleotides at codon
4 junctions.

5 And as well as codons, but also the
6 codon pairs, which is adjacent codons, are
7 recently also implicated in translational reason.
8 Now please note that those multiple synonymous
9 codons or codon pairs which cause the same amino
10 acid or amino acid pairs, appears in a different
11 frequencies in codon.

12 They are not appears at the same
13 frequencies, and that we call a codon pair usage
14 bias. And this is the important context
15 throughout my talk. In the next several slides,
16 I'd like to show you some snapshot of various
17 codon and codon pair usage table, or CoCoPuts
18 websites that was made in collaboration with Hive,
19 and now widely used by both industries and
20 academia.

21 Basically, this website gives you
22 various types of synonyms, the sequence related

1 parameters in black holes, bar graphs, tables, and
2 heat maps for all species in gene bank. Or in 52
3 human tissues in tissue CoCoPuts. Or in human
4 primary cancer CoCoPuts that provides 32 cancer
5 types and associated normal tissue types.

6 And this is the example of the heat maps
7 of codon pair usages. Most recently, we added two
8 more new CoCoPuts. One is for mouse embryo which
9 contains various mouse strains, tissues, and
10 embryonic stages, as well as that for the
11 SARS-CoV-2, which has thousands of lineage,
12 lineages starting from the very first report of
13 this genetic sequence to today.

14 And this website has not been released
15 yet but will be soon. And all about the CoCoPuts
16 can be seen in poster number 2. Now using the
17 CoCoPuts information, we calculate the codon and
18 codon usage biases. Usually, those parameters are
19 counted and calculated as the parameters per gene,
20 which we call sequentially.

21 Now, we examined if these parameters or
22 codon position has a statistical significance. In

1 this panel, which is an alignment of this
2 homologous sequence, in sequential method, all the
3 TCA codons highlighted here are counted in the
4 same way. While in the positional method, those 4
5 in codon 2, and 1 in position codon 3, are treated
6 differently by codon position.

7 And codon and codon pair usage biases
8 were compared between permutation tests with these
9 two methods. We observed distinct differences of
10 codon and codon pair usage biases, not only
11 between the sequential and positional method, but
12 also at different positions and in different 4
13 genes.

14 For example, this graph is a potential
15 codon pair usage biases for the codon pair that
16 cause the amino acid LE throughout decoding region
17 of atom TR13 gene. And as you can see in average,
18 on average, those open triangle TCGGHE appeared at
19 much higher preferences compared to the other, all
20 other common pairs.

21 But also it is obvious that the range of
22 the frequencies or preferences has a quite wide

1 range and in some positions those less preferred
2 codon pairs are actually preferred. This
3 positional significance can be effectively
4 incorporated into genetic engineering strategies,
5 including codon optimization.

6 Now let's change the gear a little bit
7 and then take a couple of prediction tools for
8 evaluating the impact of sequence variants. Many
9 of the publicly available tools are capable to
10 predict the effect of nonsynonymous or missense
11 variance in high accuracy. And a few of them are
12 also capable of predicting the effect of
13 synonymous variants.

14 However, their outcome is not that great
15 as shown here. Why is it so difficult? We think
16 there are major, 2 major challenges. The first
17 one is very few entries of disease associated
18 synonymous mutations are found in available
19 databases, because most of the synonymous variants
20 are filtered out at a very early stage of the
21 clinical sequencing pipeline.

22 And therefore, we are manually mining

1 and curating the disease associated synonymous
2 variance. And this is still our current status of
3 our database. Second, most of the amino acid
4 based molecular features cannot be used for the
5 synonymous variants, although they are very
6 critical for the nonsynonymous mutations analysis.

7 And therefore, we explore new venues to
8 evaluate the nucleotide changes, as shown here.
9 Mostly at the nucleotide level, but some of them
10 are protein level. In addition to those which
11 have been already used.

12 And one of the studies on miRNA and
13 sequence variants are seen in the poster number 4.
14 This, the pipeline is already made for this
15 project, and we have created a reliable dataset
16 for disease associated variants and control. And
17 computed nearly hundreds of primary molecular
18 features for each gene, both Y type and variants.

19 And clean the data. And currently we
20 are examining the machine learning tools, such as
21 Random Forest or Support Vector machines. This
22 project is ongoing, and we are trying to get the

1 optimum combination of the molecular features and
2 algorithm to reach this goal.

3 Now most of our product has multiple
4 cooccurring variations. So once we can predict
5 the outcome of the single mutation, how can we
6 make use of them for the multiple variations. To
7 address this question, we took this similar
8 strategies for the first 2 steps. We created a
9 curated, reliable dataset of the double triple
10 mutations, and more mutations. And then scored
11 the selected attributes for each individual
12 variant first. Then we tested 2 pairs of models
13 in how to combine the scores of multiple variants.

14 One is to take additive or maximum
15 scores. The other one is to treat them as coupled
16 or independently. We asked this because,
17 traditionally, when you have multiple mutations
18 and you see one of them are already known for the
19 CDA effect, automatically, that one has been
20 determined as the main sole course for the
21 phenotype.

22 But there is not much proven evidence.

1 And our results showed that additive model is as
2 predictive of the pathogenicity as the maximum
3 model, or slightly more predictive in some cases.
4 And there are no differences between independent
5 and coupled models.

6 That means that the common assumption
7 may not be always the case. Our approach is
8 highly extensible to a wide range of monogenic
9 diseases, does not require machine learning, and
10 can also be instrumental in assessing the safety
11 of biological therapeutics.

12 Lastly, I'd like to briefly mention our
13 interesting finding in codon usage and cancer
14 while we are assessing the relevance of our cancer
15 CoCoPuts in diagnosis, drug development, and
16 regulation. We asked how codon and codon pair
17 usage are related with the various cancer patient
18 metadata and asked the association between snips
19 and each genes expression data from the patient,
20 as well as each patient's cancer type, age of
21 diagnosis, and survival information.

22 Rather unexpectedly, codon usage and

1 gene expression patterns were associated with
2 5-year survival rates in cancer patients. In
3 those panels on the left, the green are low risk
4 group, and red, high risk group, has been
5 distinctly separated using codon usage context.

6 While on the right panel, these two
7 groups were not well separated by using the total
8 nucleotide changes. In summary, we established
9 CoCoPuts, a publicly available resource for codon
10 usage and other nucleotide variations that is
11 periodically updated and used widely by scientific
12 community.

13 Quality and size of SMB datasets for
14 training, and the choice of the attributes of the
15 variations, are critical components towards
16 generating improved prediction models for
17 identifying functional synonymous SNB's.

18 Our approach to successfully predict the
19 effect of cooccurring variants shows that additive
20 model can be useful in some cases. And all these
21 approaches, as well as the use of the positional
22 codon and codon pair usage bias information, can

1 be applied to both therapeutic design and genetic
2 diagnosis.

3 And this research was carried out in the
4 collaboration of multiple institutions, both
5 inside and outside of CBER. Thank you very much.

6 DR. RODRIGUEZ: Next, we will hear from
7 Dr. Lisa Parsons.

8 DR. PARSONS: Hello. Hi. I'm Lisa
9 Parsons, and I work for John Cipollo for the
10 vaccine structure lab in CBER. And today I'm
11 speaking to you on Pythonic applications for the
12 study of glycans. So I'll give you an
13 introduction of glycans, and a little bit about
14 Python, and then I'm going to speak of an example
15 program that I've written.

16 For those of you who aren't familiar
17 with glycans, it's a general term for sugars that
18 are linked together via glycosidic bonds. So
19 glucose is not a glycan, but sucrose is because it
20 has a one to the linkage.

21 And sucrose can be linked together with
22 various carbons, and the numbers refer to the

1 carbons. So you can get lots of different
2 linkages, which is one of the reasons glycans are
3 kind of complicated to study.

4 The picture on the bottom left, that's
5 an N-linked branch glycan. Those are the types
6 of glycans I study. N-linked means it's attached
7 to a nitrogen on a protein, usually via an
8 asparagine. But in publications, you usually see
9 it as a simple nomenclature, as shown on the
10 right.

11 So each shape and color represents a
12 different monosaccharide. So for example, the
13 purple diamonds represent sialic acid. And the
14 reason we study glycans is because they're
15 everywhere. So the picture on the left are some
16 common classes of animal glycans. And in the
17 center there you see microbial cell surface
18 glycans.

19 So you have fungal glycans, and
20 oomycetes, and you also have some gram negative
21 bacteria shown here. And for those of you who've
22 taken biology, of course gram negative bacteria,

1 they make cell walls which contains peptidoglycan.
2 But some bacteria also excrete capsular
3 polysaccharides, as you see on the far right.

4 And capsular polysaccharides are
5 actually important components of some of the
6 vaccines that CEBR regulates. Viruses, as you've
7 seen in some of the previous talks, are also, like
8 can also be glycosylated. So here is the
9 SARS-CoV-2 spike protein in green and yellow,
10 binding to the H2 receptor in blue.

11 And all of those pink blobs are the
12 N-linked glycans. What's interesting about N-link
13 glycans is that they're not all the same. They
14 are structurally and functionally diverse. So
15 there's 9 common monosaccharide in vertebrates,
16 just in vertebrates. Bacteria are a lot more
17 complicated.

18 And they're arranged in different
19 compositions with different linkages and
20 modifications. So in the glycogen database, I
21 found 780 unique N-link, glycans. And when I say,
22 whoops. What I mean by composition is you have

1 some glycans that are high- mannose, and so these
2 green circles are the mannose.

3 And this is what they look like right
4 after they have the sugars put on the protein, and
5 they've come out of the endoplasmic reticulum.
6 And then some of the glycans will get further
7 process as they go through the Golgi. So you'll
8 get complex glycans like you see here.

9 And the complexity that you see in, say,
10 recombinant proteins grown in different cell
11 lines, depends on the cell lines. So MBCK cells,
12 yes, they will form these complex glycans, but
13 insect cells will form much simpler glycans.

14 And CBER's interested in this because
15 some of the sugars that are produced could
16 actually cause hypersensitivity, like some of the
17 insect cell lines. If they put an alpha-1 3
18 linked glucose on the sugar.

19 So glycans, they perform a lot of
20 functions. We've already heard about the folding
21 and transport et cetera. But I thought this
22 example here was interesting because this is a

1 host pathogen example. So here is our flu virus,
2 and the hemagglutinin binds to sialic acid on the
3 host cell. So you see that happening here.

4 But likewise, innate cells will bind to
5 the sugars on the flu and recognize them. In our
6 lab, we study these glycans by mass spec, and we
7 typically want to look at the overall glycan
8 composition of samples. Protein site specific
9 composition, and then the linkages. And we do
10 that by starting with a glycoprotein like you see
11 here. And then we cut it up with different
12 proteases.

13 And we can then look at the
14 glycopeptides by LCMS, or we can separate the
15 glycans from the protein entirely using enzymatic
16 or chemical means and analyze the free glycans.
17 And the program I'm going to talk to you about is
18 involved in analyzing these free glycans.

19 Moving on to Python, the reason I use
20 Python is because I have a lot of complex data,
21 and I find Python to be a very useful tool. It's
22 a high level general purpose programming language

1 that was easy to learn and easy to read.

2 And it has lots of books and online
3 tutorials, a plethora of science based libraries,
4 including for machine learning, which we've heard
5 a lot about. And there's several GUI options. I
6 usually use Tkinter, which is the default.

7 And this language is 30 years old, but
8 continually improving. And this is an
9 application, just an example that I wrote to take
10 a protein sequence, I wanted to optimize my
11 glycopeptides for LCMS. And when I do that I want
12 to make sure I get like a single glycan site per
13 protein.

14 And so I can put in my restriction
15 enzymes and decide which one to use for a protein.
16 So that's how short you can make an application
17 using Python. And here's some other ways I've
18 used Python in the lab. I've used it to do
19 sequence analysis of viral protein databases with
20 special focus on potential glycosylation sites.

21 So this image is an analysis of the H3N2
22 flu virus over time, and you can see the number of

1 glycosylation sites increase as it evolves in
2 humans. I've also pulled information from protein
3 structure files here. I was just looking at the
4 average beta factors in different sections of the
5 protein.

6 I used it to assign glycopeptide
7 fragments and mass spectrometer data, and to
8 coordinate lectin and mass spec data. And also to
9 assign whole labeled glycans in multi experiments.
10 And to prepare a glycan database, which is the
11 example I'm going to talk to you about.

12 But first a little bit more background.
13 So how we do free glycan analysis with mass
14 spectrometry. So we start with our released free
15 glycans, and then we label them. And this helps
16 to improve ionization to protect labile groups and
17 to enable semi quantitative analysis.

18 And these labels can come in three
19 different forms. You can do reducing ends, where
20 this is, the label is added to the end that comes
21 off the protein. You can label specific sugars.
22 In this case, just the sialic acids are labeled.

1 Or you can label every sugar, and this
2 is a classic method where the OH groups on all the
3 monosaccharides are replaced with O CH₃ groups.
4 And then once you have your sample ready, you mix
5 it with a matrix. I typically use 25 dihydroxy
6 benzoic acid. And it's dried on a plate, and that
7 plate is sent into the MALDI instrument.

8 And MALDI stands for matrix assisted
9 laser desorption ionization, which is exactly what
10 happens. The laser hits the sample, and the
11 matrix assists the laser into desorbing and
12 ionizes the sample at the time of flight tube, so
13 that you get these mass, sorry, you get these
14 spectra of mass overcharge with the smallest
15 molecules on the left of the spectra.

16 And these 3 spectra, because I typically
17 do spots for samples so I can calculate the
18 standard and the average and the standard
19 deviation. So I get an idea of how well my spots
20 were spread.

21 And after I get the spectra, then I
22 calibrate them, I pick the peaks and the isotope,

1 and by the isotope, I mean, if you, these nice
2 sharp peaks down here in the spectra actually look
3 like this here. This is a isotopic window. And
4 this happens because of the natural abundance of
5 C13. And every C13 a glycan gets, it adds
6 (inaudible).

7 But in the glycan library, what you're
8 interested in is just the C12 peak. So I just
9 want to pick the C12 peak and then find the area
10 under the rest of the peak so that I can do
11 semiquantitative analysis. And after we get the
12 peaks picked, then we just compare them to the
13 library, and assign the spectra.

14 A little more on libraries. They are
15 different species of different glycoforms, so the
16 library should contain glycans relevant to this
17 system you are studying. The glycan masses change
18 when the different labels are used, so you need a
19 different library for each label.

20 And libraries could contain hundreds of
21 glycans. It's very repetitive and easy to make
22 errors, if you have to type them in by hand, which

1 makes this an excellent application for Python.

2 And so I had already started this
3 application to make glycan libraries
4 automatically, but a couple of years ago there was
5 a person in the lab who gave me another extra
6 challenge. She was doing linkage specific sialic
7 acid labeling on SARS-CoV-2 spike protein produced
8 in different cell lines, because she wanted to see
9 what kind of sialic acid linkages were present.

10 And there's the alpha 23 links or the
11 alpha linked, and the label she's using, if it's
12 alpha 23 linked, the sugar will have a loss of
13 about a dalton, and if it's alpha 26 linked, it
14 has a gain of 27 daltons.

15 So if you have a molecule like this in
16 your sample, there's actually five different
17 linkage options you could have. So you can
18 imagine how spread your library would be and how
19 painful that would be to turn all those different
20 options into a library.

21 So I decided to modify the program I
22 already had and add the ability to automatically

1 calculate all these labeling options. And when I
2 wrote this program, my object, my objectives were
3 to make the input as simple as possible, so the
4 user doesn't have to type or copy and paste on
5 labels.

6 And so I use a shorthand for each sugar.
7 And if you push that button the calculate, it will
8 give you the label that we want to use in your
9 publications. The calculated math, and that math
10 is based on how you prepared your sample, and the
11 modification you choose, and the ion you choose.

12 And it also calculates the chemical
13 formula. But you don't have to type in every
14 sugar by hand one at a time. You can make a whole
15 list of them and then put it in as a single file.
16 And it writes the whole database file for you.

17 My second objective was to allow the
18 user to define new labels with easy math
19 calculations. So I came up with this. So our
20 label that we were speaking of earlier, it's
21 imidation and demethylation. Sorry. I cannot see
22 that from here.

1 Anyway imidation, you just tell the
2 program where you want it to happen. In this case
3 it's sialic acid, but S is the shorthand for that.
4 And it happens sometimes, and then you just type
5 in the atoms that it gains or loses. And it will
6 automatically calculate the math based on what you
7 put in there. So you don't have to calculate the
8 math.

9 And my third objective was to allow the
10 user to add sugars and other options as needed.
11 So I have another default menu where it's
12 basically the same thing where you put in the name
13 of the sugar you want, the shorthand you want, and
14 then the atoms it has. And then how many methyl
15 groups it would get if you permethylate.

16 So now if we go to our double label
17 problem, here is the challenge that she gave me.
18 And I made it so that you could choose more than
19 one label at once. And if you push calculate, so
20 this is the shorthand form that represents this
21 molecule. And it will automatically print out the
22 labels into your library.

1 And then after you have your library
2 made, you go to the other part of this program,
3 which is to assign MALDI. So assigned MALDI is
4 used to assign those spectra. And the button
5 that's circled, that's how you would get to the
6 library maker.

7 And once you have that made, you put the
8 library here and you point this to the folder
9 where all your spectra are. And you assign it,
10 and you'll come up with this. Like I said, I
11 always collect free spectra.

12 So they're all lined up here. And I
13 know that's overwhelming, but if you then go and
14 click the zoom button, you can see the peaks are
15 picked. The labels are, they're assigned. The
16 isotopic windows are there to show you how well
17 they're fitted.

18 And this is an example of the default
19 GUI, but it allows you to add buttons, which I
20 added buttons up here. There's even an option
21 appeared so that you can pick the peaks you want,
22 and it will make suggestions for you if the

1 assignment is not in your library.

2 And then for publication it will
3 calculate the average and standard deviation, and
4 it will also make a table for publication. And if
5 you're interested in MALDI, this program is
6 available online. We published this last year.
7 And it's available at GitHub.

8 And I'm going to say thanks to the
9 fellow lab members, past and present, for their
10 feedback. And to the organizers for inviting me
11 to talk. And to you for your attention.

12 DR. RODRIGUEZ: So lastly, we're going
13 to be hearing from Dr. Hussain Ezzeldin.

14 DR. EZZELDIN: Thank you so much. And
15 you're here for staying that late. Thank you for
16 that. All right. Let's see. Okay. So today
17 I'll be speaking to you about another side of what
18 CBER does. Most of the work you've seen is
19 looking at the work before the products are
20 developed, maybe scientific, maybe some of the
21 basic science, some of the product development.

22 CBER also does a lot of work on the post

1 market. So once the products hit the market, then
2 we have to follow for safety, and make sure that
3 these products are safe and effective as have been
4 demonstrated in the clinical trials. So I would
5 like to speak to you today about a couple of pilot
6 studies that we've conducted within CBER on ways
7 on improving and expedited biologics adverse event
8 surveillance.

9 So this is the outline. I'll give you a
10 quick background, speak about the journey, and
11 that into our pilot platform that we've built.
12 And then, of course, sum up with the conclusions.

13 This, just to give you an idea about the
14 wide range of products that CBER deal with, from
15 vaccines to gene therapy, genome transplantation.
16 So the number of, or the wide range of
17 participants in our products and the users is
18 vast, from healthy to sick people.

19 And this is challenging. Add to that
20 the healthcare settings where these products are
21 administered. This also complicates our job to do
22 post market surveillance.

1 So what are we looking at here? What
2 are the challenges and what are the opportunities
3 that we have? So in the current method of adverse
4 event reporting, we have manual detection of the
5 adverse events. Meaning that clinicians,
6 practitioners have to go out and be on the lookout
7 for these adverse events, detect them, and then go
8 on to validating these adverse events, making sure
9 that they're actually adverse events.

10 And this requires time, and time
11 intensive processes. They maybe require access to
12 diverse and desperate sources of data. And then
13 of course, added on that the manual reporting
14 step, which is of course labor-some that requires
15 data entry and also requires granularity of the
16 data, which sometimes is not available.

17 So this is the current way of adverse
18 event reporting. What we are hoping to achieve is
19 this is the future that we're looking at. We're
20 looking at an automated or semiautomated detection
21 of adverse events. And this allows us to create
22 batch detection leverage algorithms to do this.

1 And score these adverse events with the
2 ones that are more likely to be adverse events,
3 that can be reviewed. And then this takes us to
4 the validation component, where we are able to
5 extract the evidence that supports maybe an
6 adverse event or not. And present this to the
7 reviewers of these adverse events to make it easy
8 for them to make a determination.

9 And then of course, semiautomated
10 reporting. So once you have this semiautomated
11 detection validation, you can very easily extract
12 all the relevant information, populate it in the
13 individual case safety report, and send this to
14 FDA for review.

15 So this is the future that we are
16 looking at, and we are hoping to move from an
17 existing manual process that creates burden, and
18 sometimes under/over reporting, depending on the
19 media, to a more innovative approach that reduces
20 the burden and increases the quality of the
21 adverse event reports.

22 So I wanted to show you here these

1 couple of reports that we get at the FDA. The one
2 on the left is what we call the vaccine adverse
3 event report, and the one on the right is the med
4 watch, which is for the other type of biologics.

5 So the one on the left is for vaccines
6 only. The one on the left (sic) is for the rest
7 of the biologic regulated products. And the
8 reason I'm showing you this is that this is what
9 ultimately comes out from our platform. Something
10 that the public is familiar with. We as CBER and
11 our viewers are familiar with it as well.

12 And what's highlighted here in yellow,
13 oops, sorry. What's highlighted here in yellow,
14 these are what's called required fields. So any
15 report that gets to the agency has to have at
16 least these fields filled out.

17 But there are additional information
18 that could also be very helpful. Let's look at
19 our journey here. So we started in fiscal year
20 2019, which is October 2018. We started with
21 working with the foundational data partner,
22 started building phenotypes. Phenotypes is a

1 fancy word for algorithm that you can use to
2 detect an exposure and outcome as well.

3 So this is what we call the phenotype.
4 So we worked with our foundational data partner to
5 develop some of these phenotypes and validate
6 them. And working on mapping, how we can use this
7 data into filling an individual case report form.

8 From that, we worked on
9 operationalization of this platform. So we
10 started on enhancing these phenotypes that we
11 built, and we started thinking about how can we
12 scale this this platform so it can be deployed on
13 more than one data partner.

14 And to do that, we built a prototype
15 with an organization that falls within something
16 called exchange networks. So if you're familiar
17 with exchange networks, these are health
18 information exchange networks that allow
19 hospitals, providers, to exchange clinical
20 information amongst them.

21 Primarily for the use case of continuity
22 of care. So if a patient moves from one hospital

1 to another, a hospital can request their clinical
2 information from another hospital so they can know
3 what this person had received in terms of
4 diagnosis in the past, what type of medication
5 they use.

6 And this is happening on everyday basis.
7 It happens to you all the time, probably don't
8 know it. But this happens, and this is done for
9 the continuity of care use case. And this happens
10 probably on the range of billions of records
11 exchanged on a monthly basis between hospitals
12 within the U.S.

13 And we are hoping to leverage these
14 health information exchanges for public health use
15 case. So we are trying to use these networks on,
16 can we go into healthcare providers and ask them
17 to send us information about an adverse event, so
18 we can have a more rich and high quality adverse
19 event report that we can review and maybe form a
20 better decision about whether this is related to a
21 product or not.

22 To do that, we worked with one of these

1 health information exchanges called eHealth
2 Exchange. It's a network that was developed by
3 the Office of National Coordinator. I think now
4 they changed their name.

5 But we worked on a couple of cases,
6 something we called pull use case and a push use
7 case. So from the name, if we are looking at the
8 FDA as the point of view, in the pull use case, we
9 are pulling the data. So we are looking to get
10 additional information about the specific adverse
11 event. And the push use case, the provider is
12 sending us data about the specific adverse event
13 that they have detected.

14 And I will speak about these two. So
15 we're able to conduct this, these two pilots in
16 fiscal year 2022. And I'll share some results
17 with you today about these pilots. And now we are
18 in the phase of pushing this platform to become
19 part of our standard pipeline within CBER.

20 So it's not a very easy step, but we're
21 working towards that. So what is the pipeline
22 that we're speaking about here? What's this best

1 platform that we are going to be using to conduct
2 these pilot studies, the pull and the push.

3 Our pilot platform has three major
4 components. The first one is what we call data
5 quality assessment. So once we pull the data into
6 the platform, we check for the data quality. And
7 I'll speak about this a little bit.

8 And then after that, we have what we
9 call the phenotyping component, or the detection
10 component of the platform. And what we do is that
11 we run these fancy algorithms that we have, to
12 extract the relevant information from the clinical
13 data and present this to the reviewers to validate
14 this.

15 So we have the third component of the
16 platform that's meant for validation and reporting
17 of these adverse event. So this is the platform
18 that we've built to conduct these pilot studies.
19 All right.

20 So what do we mean by data quality
21 assessment. For regulatory grid data, when you
22 are speaking about, is this data fit for purpose,

1 you are looking at 3 components. You're looking
2 at whether this data is conformant, meaning that
3 the data is in the standard that you are
4 expecting.

5 You're looking at completeness of the
6 data. Meaning that do you receive the data that
7 you are looking for or not. And then the
8 plausibility of the data, and I apologize, the
9 format has been a little bit jumbled when they
10 switched the slides around.

11 But anyway, so we are assessing 3
12 components for the data, its completeness, its
13 conformance, and its plausibility. And here are
14 some definitions. If you're looking at
15 performance, are you getting the data, for
16 example, in ISBT 128 format. If you're looking at
17 block products. If you're looking at, for
18 example, at completeness. Are you looking, are
19 you finding your vaccine brand or the lot numbers
20 and your data.

21 And for example, plausibility, if you're
22 looking at, let's say an adverse event rating to a

1 vaccine administration, is this adverse event
2 happening after administration or before. So this
3 is, is this data plausible or not.

4 So these are the three factors that we
5 look at for data assessment. Now let's shift to
6 our detection or phenotyping component of the
7 platform. So for that, we built three types of
8 phenotypes. What we call simple or scalable
9 phenotypes.

10 And the reason for this is that if you
11 look here on the right, when you go down this
12 spectrum, the complexity of these phenotypes is
13 going to increase, but at the same time, their
14 positive predictive value is going to increase as
15 well.

16 On the other hand, the interoperability
17 of these phenotypes is going to increase. What do
18 I mean by interoperability? If we are thinking
19 about scaling this approach, meaning that we want
20 to use our phenotypes and have a lot if not all
21 the healthcare providers use them, if you are
22 going from a simple scalable, which only relies

1 on, for example, diagnostic codes, to a more
2 complex one, then on the interoperability of these
3 phenotypes is going to be very hard.

4 Meaning that less and less people are
5 going to be able to use your phenotypes and
6 implement them on your on their platform. So it's
7 a trade off. You can use simple phenotypes with
8 maybe low predictive value, or you can use more
9 complex phenotype with a high predictive value,
10 but maybe less people are going to be able to
11 implement them.

12 All right, so these are the phenotypes
13 that we have. We have three of them. So you can
14 see here this is the claims comparable, which are
15 the simple phenotypes. They only use diagnostic
16 codes, and we have like a GitHub library with
17 these phenotypes.

18 So this, the top one is looking at acute
19 myocardial infarction, anaphylaxis, appendicitis,
20 Bell's palsy, and all the outcomes that we are
21 interested in. More specifically for vaccines.

22 And then if you are looking at the

1 second tier, you are adding to these diagnosis
2 codes. You're adding some procedure codes, maybe
3 some observations, sometimes some medications.

4 And then of course, if you look at the
5 more complex phenotypes that we have, we also
6 include on top of that, terms. And what do I mean
7 by terms? I mean that for the complex phenotypes
8 you're actually relying on notes, with the
9 different types of notes, whether it's like
10 nursing notes, clinical notes, discharge notes.

11 But at that point you have to implement
12 some sort of natural processing, natural language
13 processing pipeline to extract this information.
14 And if you are able to do this, then you are able
15 to leverage different terms to improve the
16 performance of your phenotypes for detection of
17 these outcomes that you're interested in.

18 And I know I'm going very fast. I'm
19 trying to get you home, so apologies for that.
20 All right. So well, what I'm showing you here,
21 this is what we call the chart review tool. This
22 is part of our pilot platform that I showed you.

1 And this is a platform that allows our
2 reviewers to look at different components. It
3 allows them to look at exposure. So they can look
4 at the data that we received from this product.
5 And all this are clinical data that we received
6 from this eHealth exchange, this health
7 information exchange network.

8 It's clinical data, so they can look at
9 the data, ascertain exposure. They can ascertain
10 outcome. And then they can also based on the data
11 available if they feel comfortable, also speaking
12 about imputability.

13 Meaning that if they can ascertain
14 causality, if they have enough evidence to say
15 yes, we can say that this outcome happened due to
16 this product. They can also speak about that.
17 And they can also speak about the severity of the
18 outcome itself.

19 So they can do all this within our BEST
20 platform. And in our pilot, what we've added here
21 in addition to our pilot platform that has the
22 data quality assessment, the detection, the

1 validation components, now we can communicate with
2 eHealth Exchange, which has members in its network
3 which are different hospitals.

4 Hospitals that can pull clinical
5 information from, pass it on to our platform so we
6 can conduct these validation and reporting steps.
7 So I spoke about a couple of use cases, the pull
8 use case. And it starts with FDA knowing a
9 certain adverse event.

10 So if we know a certain adverse event,
11 let's say from an adverse report, we can go into
12 our BEST platform, send the request to eHealth
13 Exchange, which is in orange here. Telling them
14 we have knowledge of this adverse event. We want
15 to get additional information.

16 EHealth Exchange takes this request.
17 Sends it out to its members in the network, which
18 are the different healthcare providers, and does
19 what's called patient discovery. If it finds this
20 patient that we're looking for, it pulls this
21 additional clinical information, pulls it back,
22 sends it to our BEST platform, and then we can

1 start our validation step and make a report about
2 this adverse event.

3 So this is what's called the pull use
4 case. We conducted this pilot study with 11
5 healthcare providers across the country. And then
6 of course, when we did the study, we were able to
7 look at if you are looking at an adverse event
8 related to vaccine, can you assess the quality of
9 this data that you received from the study, and
10 look at the different types of information.

11 Do you have the required data fields, do
12 you have optional data fields or not. So if you
13 recall, we are looking at completeness,
14 conformance, and plausibility. So we conducted
15 different number of tests and here on the right we
16 have like 39 tests. Sorry, 21 tests looking at
17 required fields, 44 tests looking at optional, and
18 then helpful fields.

19 And these are about 330 tests in total
20 looking at the different aspects of data quality,
21 completeness, conformance, and plausibility. And
22 what I'm showing you here is that your green is

1 completeness. You're kind of pinkish is the
2 plausibility. And the orange-ish is your
3 conformance.

4 So you can look here at the green. More
5 to the right means that this is complete data. In
6 the middle means that partial completeness. And
7 of course on the left means that this data is
8 really not up to what we expected.

9 So the more to the right is better. So
10 you can see here the green is probably more to the
11 right. So the data is more complete. We have
12 maybe less luck with conformance, which is
13 expected. So standards is a major issue. And
14 data, and real world data of course.

15 And then so as we mentioned here, we
16 received about 270 post vaccination adverse events
17 from different, 11 different providers' electronic
18 health records. And then we assessed this as you
19 can see here on the right.

20 One of the very interesting things that
21 we found out is that if you are receiving an
22 adverse event and you are requesting clinical

1 charts to review this adverse event, this probably
2 takes between 4 to 6, sometimes 8 weeks.

3 In our pilot study, we were able to
4 receive this information from the moment we
5 request the data to the moment that we receive it
6 within our pilot platform.

7 The range here is probably about for the
8 limited case window, meaning that we are limiting
9 the information that we're getting with defining
10 some dates around the adverse event itself, took
11 about on average 52 minutes to receive from the
12 moment that we request the data to the moment that
13 we receive it.

14 For the entire case period, so if you're
15 looking maybe years in the past, this maybe goes
16 all the way to an hour and a half. And here on
17 the right are the medians. And then you, of
18 course, you have the minimum, the maximum.

19 So looking at something like this, for
20 example, for public health emergency use case, if
21 you can get the data for a known adverse event
22 within an hour, this is a huge, of course,

1 improvement on the current methods that are being
2 deployed and implemented.

3 So we did the root cause analysis to
4 this variation that I showed you for these
5 differences in the completeness, conformance, and
6 plausibility. And we were able to put our hands
7 on some of these challenges. And of course it
8 comes down to the United States core data for
9 interoperability.

10 We found that there are some challenges
11 with immunization data. We found some missing
12 information with medication compliance. Now, of
13 course, there were some technical issues with the
14 implementation of this infrastructure itself.

15 Second thing that we did is the push use
16 case. And this is probably the more exciting one
17 is that healthcare providers taking the phenotypes
18 that we developed, running them on their back end
19 electronic health records, flagging cases, which
20 is this automated detection.

21 So here it starts, the healthcare
22 provider itself, there's an exposure to one

1 biologic, there's an automated outcome detection.
2 They send the data to eHealth Exchange, which is
3 this health information exchange network.

4 EHealth Exchange pushes this information
5 to the BEST platform. We received it, and then we
6 can start our review case from at that point. So
7 we did this with Cedar Sinai, which the one that
8 has this pull and push use case, as well as the
9 VHA was another participant in our push use case.

10 One of the interesting things that we,
11 this is just a view of how we build our phenotype.
12 We look at exposure, we look at the diagnosis, and
13 then we try to add some additional information,
14 observation, procedure, or medication to increase
15 the performance of our phenotype.

16 But one of the very interesting things
17 that we found is that if you have sufficient
18 information in your data that you received, you
19 actually have much better performance for these
20 phenotypes, which is not really very surprising.

21 But this actually speaks about the
22 importance of looking at the data that you are

1 receiving, and really speaks about the importance
2 of us working with the Office of the National
3 Coordinator, that regulates electronic health
4 records, and their vendors, to improve the data
5 quality so we can have high performance operating
6 phenotypes that would allow us to automatically
7 detect cases, send them to our phenotype.

8 So in summary, we conducted these two
9 pilot studies. We were able to find that overall
10 the data quality meets the general requirement for
11 CBER. So this is very exciting for us to move
12 forward with this approach leveraging health
13 information exchanges.

14 Of course, there are some variabilities
15 even among the same electronic health record
16 vendors. But there are gaps, of course, dependent
17 on the data standards. But we are continuing to
18 work on enhancing our platform, as well as working
19 with our federal sister agencies to improve the
20 data quality, and of course improve our querying
21 capabilities, and enhance the efficiencies of
22 these adverse event detection logic.

1 And of course, conduct more evaluation
2 and validation studies. Of course, this work has
3 been supported by many people within CBER. With
4 our BEST contractors. IBM doing these pilot
5 studies.

6 And then of course, this work has not
7 been possible without the help from eHealth
8 Exchange, and our pilot participants.

9 There are some references here and
10 that's everything. If anyone is still awake, you
11 have questions, please let me know.

12 DR. RODRIGUEZ: Thank you very much. So
13 now we're going to open the floor for questions
14 for our last three speakers.

15 DR. FRIEDBERG: So if anybody has any
16 questions, step up to the mic. And if not, I had
17 a question for you, Lisa.

18 DR. PARSONS: No.

19 DR. FRIEDBERG: No? Actually I have two
20 questions for you. How do you handle or know if
21 you're dealing with an impurity in your system?
22 Do you have some code or something to pick up

1 impurities, or do you do intensities?

2 DR. PARSONS: Yes. I do have a, it's
3 sort of an average, okay. You have to take the
4 noise into account. I have a noise cutoff
5 basically.

6 DR. FRIEDBERG: Okay. Just curious.

7 DR. PARSONS: Yeah.

8 DR. FRIEDBERG: The second question was
9 how do you, it's kind of related, how do you know
10 if you miss a peak? So you've got the noise
11 threshold, how much above the noise threshold is
12 considered a peak in your case? So I guess below
13 it doesn't count, right?

14 DR. PARSONS: The user sets it.

15 DR. FRIEDBERG: Oh. Okay.

16 DR. PARSONS: I tried to make it, the
17 user can change everything.

18 DR. FRIEDBERG: The user can do
19 everything.

20 DR. PARSONS: Yes.

21 DR. FRIEDBERG: Got it. All right. It
22 looks like we have nothing online. We're kind of

1 over on time. So I'm very sorry. But thank you
2 very much for your talks this afternoon. It was
3 great. Thanks everybody for coming.

4 (Whereupon, at 4:35 p.m., the
5 PROCEEDINGS were adjourned.)

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I, Michelle Begley, notary public in and for the District of Columbia, do hereby certify that the forgoing PROCEEDING was duly recorded and thereafter reduced to print under my direction; that the witnesses were sworn to tell the truth under penalty of perjury; that said transcript is a true record of the testimony given by witnesses; that I am neither counsel for, related to, nor employed by any of the parties to the action in which this proceeding was called; and, furthermore, that I am not a relative or employee of any attorney or counsel employed by the parties hereto, nor financially or otherwise interested in the outcome of this action.

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