Assistant professor in the Department of Population Health and in the Department of Medicine at New York University, Dr. Wu's research synthesizes state-of-the-art methods from statistics, machine learning, optimization, and computational science to address critical and far reaching issues in health services, research and clinical practice. Leveraging large scale data from national disease registries, administrative databases, electronic health records, and randomized control trials. Let’s give a warm welcome to Dr. Wu. Thank you for the nice introduction.

And it’s a great honor to be here with all of you. And so I’m Wenbo, I am from New York. I joined NYU just a bit over a year ago. So I think, ’cause we have so many people here, I think it would be good to run a promotion first.

And so this is our group. So at NYU we have, a tremendously growing group and we have like 24 faculty and we’re about to welcome our newest, like the 25th faculty member into our divisions.
And we have 7 staff. We have a small PhD program, we have 20 PhD students and 10 postdocs. And we have a team of 25 research scientists. And part of the reason I wanna do this is because I wanna encourage you guys to apply to our PhD programs. So if you’re interested, scan this QR code and you apply, okay?

So I have been doing things in provider profiling for the past five years and this is the overview of what it is. So provider profiling is basically the assessment, the evaluation of the performance of healthcare providers. This includes so many different types.
of healthcare providers and stakeholders include, insurance companies, regulation, government, federal agencies. They're all interested in provider profiling, I will tell you why. Providers is basically who are doing profile evaluations and of course patients. So because they are interested in the information, interested in the profiling results so they can make care seeking decisions. Okay? And so I listed here a few outcomes, like emergency department encounters, unplanned re-hospitalizations, which is hospital readmissions. And I will jump into the details later and post-discharge deaths and you can, I mean there are so many different types of outcomes to consider in provider profiling. And one of the goals was to basically identify those providers with very bad performance in terms of patient-centered outcomes. And they can get penalization, like they can have payment reductions from government agencies. Okay?
And as you can see here, this is very important. This is a very important business, and profiling can actually help improve evidence-based accountability for those providers and how facility targeted interventions aimed at improving the care quality.

Alright, so, this is a slide of a few example papers that are about evaluating hospitals across the nations. So they’re mostly from the program called, Hospital Re-admission Reduction Program, which is a very important national level program that I will explain later. But there are just so many papers in this field.

I mean, these are just, like there are publications in top, medical journals, analysts of internal medicine, and New England Journal of Medicine. Okay?

So, this is another type of profiling stuff. So this is, as you can see, it’s a report. it’s called the health report from Massachusetts Medical Society, which is the publisher of The New England Journal of Medicine. Okay?
So they prepared this principles for profiling physician performance, I think many years ago. So this is a list of exemplar profiling programs and they are still existing. So the first one is an interesting state level program which is arguably one of the first programs. It is still administered by the New York State of Department of Health. Basically they’re interested in evaluating hospitals that do coronary artery bypass graft surgeries, and also PCIs and the program have been running for at least 20 years or so. And the second one is another important program, which was launched I think in 2003. And it is, I think it is from the one of the Federal Level Act. And it is currently administered by the US Centers for Medicare and Medicaid Services. And their interest in outcomes for, again, 30-day readmissions and mortality for a AMIs and the heart failure, et cetera. And the next one is another federal level readmission, federal level profiling program, which is also established by Affordable Care Act,
which is Obama care.
You guys probably know that, in 2012.
And so, yeah, they’re also interested in,
evaluating hospitals and they will punish those hospitals
with very bad performance in terms of payment reductions.
Okay?
The last one is an interesting program, which is kind of my focus.
I have been working on evaluating kidney dialysis facilities
for patients with kidney failure.
And there are actually over 7,000 dialysis facilities
across the nation, believe it or not.
But this is the first to pay for performance program
in contrast to other pay for service programs.
Okay.
And the program is called ESRD.
ESRD is short for End Stage Renal Disease.
Basically the patients with kidney failure,
a quality incentive program, okay?
Alright.
So as you can see, there are so many programs,
so many initiatives across the nation about profiling.
And one natural question is about the,
how the landscape of the statistical landscape
of profiling looks like.
And because of the importance of profiling
and here I said,
there are many far reaching implications because providers can get penalizations and it’s high stakes.

So it’s important that we have principles statistical methods to evaluate them, right?

This is like two examples. The first, it’s a paper published on analysts of internal medicine, but it is written by two statisticians.

They are calling for the improvement of statistical approach in this field. And also the second one, this one is even more important because it is a white paper issued by the Committee of Presidents of Statistical Society.

You probably know about COPS. So one of the most important words in the statistic field, it’s the COPS presence of work, right?

This is a white paper by COPS and also a group of people from the CMS. This is also an important work.

It’s about the statistical issues and assessing hospital performance. So as you can see, there are many people are interested in improving the statistical landscape for profiling.

Alright,
So this is a slight briefly introducing the existing methods.

There are a few.

I grouped them into like roughly four categories.

So the first group, is hierarchical random-effects models, there are many papers in this group, but I just highlighted one paper in, I think in 1997 was published on Jassa by Dr. Sharon Lee Norman at Harvard Medical School.

So it’s about hierarchical random-effects models which is still being used in many settings.

Especially, I mean, not sure whether you guys know that there is a group at Yale called Yale Core, I think Center for Outcomes Research and,

Something. Okay, great, thank you.

So they have been using hierarchical random-effects model for over 30 years, I guess.

And the second stream of approach is fixed-effects models, as you can tell from the names, people are using like a fixed effects in the models.

And this is one example paper, actually was published in 2013 by my advisors. And the next one is,
I mean these groups of papers, they’re not mutually exclusive because, for example, this one, competing risks or semi-competing risks. I mean there are some papers that use higher hierarch random-effects model or they’re also papers using fixed-effects models. But they are just kind of, they’re handling like different types of outcomes.

And also for recurring events, if you take a class in survival analysis, you probably know that, for example, patient can have multiple hospitalizations in a year.

So they are considered as recurring events.

Okay.

And then the last one is, some people are using causal inference and some clustering approaches to handle profiling issues. But these papers are relatively new, and this is one paper here. It was by all statistics, I think. Alright, so I wanna discuss a few limitations of the current landscape, the current statistical in profiling. So the first limitation is, people have been, I think, intensely using models with a linear predictor.
So the limitation is this may not be true when we have very complex outcome and the factor associations. So this is an example. This figure. This is in my one of my papers. So the background, I’ll give you a bit of background information. So this is about, okay, evaluating the effect of covid and the outcome is a 30 day unplanned hospital readmissions. So this, on the left is the surface plot. On the right is the conquer plot. As you can see, we are interested in the variation of the covid effect across, this might be too small, but across post discharge time, post discharge days and also across calendar days because we used data in 2020. So we set time zero at, I think mid-March or, yeah, mid-March. So this is April the 1st. And then May 1st until I think mid-October. So as you can see there’s a lot of variation going on here. So the covid effect is definitely not constant here. So basically it means that we cannot use the linear model to do this.
It's just not valid, right?

So the second methodological limitation is existing methods have been historically driven by cost effective spending.

Like,

I think in the very first program, in those first early programs, people are interested in how to reduce costs by, of course they wanna improve, they wanna improve care quality but cost effectiveness is a very important factor.

So, and these analysis, they basically combine all racial ethnic groups together without accounting for their heterogeneity.

So this is another example. So we basically look at the performance of Organ Procurement Organizations, OPOs.

So we are interested in organization level transplantation rates. And we have data in 2020.

So these are, so on the y-axis we have the normalized OPO IDs, this is just like a three panels of caterpillar plots.

And if we focus on a certain OPO, then, for example, in this panel, this is a panel for white patients. And if you look at this is,
I know this is a little bit small, but this is OPO 30 and this,
the conference interval is above the national rate
for white patients.
So it's significantly better than the national average.
But if you look at this panel,
this is also OPO 30 and we have the confidence interval being lower
than the national average for black patients.
And this is a panel for Asian Americans and Pacific Islanders.
We also have the same issue going on here for OPO 30.
So as you can see, there's definitely racial disparity here,
but this was never examined in those early programs.
So this is an limitation of course.
And the last one is,
there is a lack of a unifying framework
to accommodate different provider profiling objectives
and the different performance benchmarks.
I will give you like four different examples.
The first one,
I tried to make the notation very easy.
So say we have a random-effects model here.
We just consider a binary outcome.
Y can be zero or one.
Okay?
And we basically use the logistic regression, here.

So this gamma i, it’s a sum of two things. The first one is mu as the mean effect. And the second one is ID normally distributed, a random variable, okay?

And we can construct a type of, we call it standardized measure. It’s Oi divided by Ei, O is just a sum of all those YiJs. And the Ei is the, basically the sig y function transformation of mu plus beta. Okay?

So here, if you look at the model, we have gamma I here, but when we calculate the expected number of events, we replace this with the mean. Okay?

So this is the first example of course using random effects models. But if we look at the fixed effects model, we have the similar formulation here, but here because this is a fixed-effects model, gamma I is just unknown fixed effect, okay?

And if we define gamma, start to be the median of gamma, this is a vector actually. So it’s a vector of vault fixed-effects. Then this is basically the median of vault provider effects.
or fixed effects.

And so we can also construct this standardized measure,

but this time, this E is defined as this,

and this is gamma star. So we basically use the median of all fixed effects

to construct the standardized measure.

Okay?

So now we have two cases.

We use mu, which is the mean of all provider effects, although it’s a random effects model.

And, here we have median of all fixed provider effects, okay?

So these are two cases,

basically two types of models that have been used before.

And next one is, and some causal papers, they can use a selected set of provider,

it could be a single provider,

let’s say, I’m a a hospital administrator,

I wanna see, okay,

whether my hospital is performing better or worse

than another hospital,

then of course I can use my hospital as the benchmark,

as the reference and compare all other hospital

with my hospital, okay?

So this is the first case.
We can just choose a single hospital or provider as the benchmark. And the second case is we can group a few providers, hospitals in the specific geographic region together.

And to form a benchmark, this is also doable, okay? And it is actually used in the paper. The last one is, we can basically treat all hospitals, you can group all hospitals together into a large super hospital, of course, this is a hypothetical one but we can do that. And that is kind of like a national average thing, right?

These are all reasonable ways to define a benchmark. And there is the last one.

So the last one is kind of more like equity driven thing. So we can form a benchmark such that say, okay, say, from the regulator’s perspective, we really wanna push hospitals to improve their performance for minority patients.

So say, we can set the benchmark to be something like, okay, for within the minority groups, we can intentionally select patients with better outcomes. We can make the proportion to be very large
so that in the benchmark group, we can have a very good performance for minority patients.

And then black non-Hispanic patients. So this is kind of a equity driven thing.

So as you can see, I give you like, at least the four examples. But these are scattered in the literature and there is no unifying framework to accommodate all of these cases.

But we actually can develop a general framework. I will give you the details later.

So the framework that we proposed is what we termed, a versatile deep learning provider profiling.

So we proposed a versatile or probabilistic framework based on the, so-called provider comparators, which is, you can name it as you know, provider comparator, hypothetical provider performance benchmark or population norm.

These are all the same interchangeable terms.

Here versatile means, okay, we can use the framework to do a lot of different things. So they are adaptable to different profiling objectives.
It's why we use the term versatile and here provider comparator, which is defined to be a hypothetical reference provider that is corresponding to your profiling objective. So if you have a certain objective, of course you can define your own hypothetical provider. And if you have a different objective, you can define another one, okay? And the deep learning thing comes into play because it is nice that, generally it relaxed the linearity assumption in most existing portfolio models that relies heavily on linear this assumption.

Alright, so this is slide of the basic setup of this new approach. So let's say we have a ID random sample with Y as the outcome, and the Fi star is the provider identifier, and Zi is simply a vector of variants, and they are one from a population Y, F star, Z.

And we have the following assumptions that these two assumptions, one and two, so F star.

So basically this script F star is the support of this provider identifier, F star. Okay?

So we require that this report for any value
that this F star can pay,
we assume that the probability of F star equal
to F is positive,
which means that in the dataset,
you can at least observe one patient from that provider.
Okay?
Say if this is zero, then basically it means,
we do not observe any patient from that provider,
which is useless, right?
So the second assumption is simply,
so this script F star includes all possible providers,
we wanna evaluate.
So basically this F star has to fall
into this set of values, okay?
So that’s why it’s the probability as equal to one.
Okay?
So we have two important assumptions,
regarding data generating mechanism.
The first one is basically the distribution of this F star.
The provider identifier depends on covariate.
And this is like, okay, so for a patient,
I’m a patient, I wanna choose my provider,
I wanna choose my hospital,
my decision will largely based on,
okay, what conditions I have,
and what insurance I have, right?
And say what is the possible feasible set
of hospitals I can choose from?
Okay?
So these are all covariates
that we can include in the model.
So basically the $F^*$ is the distribution
of a star depends on all those covariates
which is reasonable assumption.
The second one,
The distribution of the outcome $Y$
as a function of $Z$ and $F^*$,
which means that, okay, the outcome,
if I go to the hospital and say I have a certain
disease
and I got a treatment and whether I feel better
or not really depends on, okay,
depends on my conditions,
and also depends on which hospitals I went
to, right?
So the distribution is denoted
as $\pi_i, y$, given $Z$ and $F^*$.
Okay?
So basically these two assumptions gives us the,
basically the basic setting for a patient who
is looking
for care to improve their conditions.
So the main idea in this new framework is reclassification.
we wanna construct a hypothetical provider comparator
as a performance benchmark
that is corresponding to our specific profiling objective.

Okay?

So reclassification here means that we wanna, we reclassify subjects from existing providers into a hypothetical one following a certain probability distribution.

Okay?

To do this, we introduced a random indicator, it’s just a 0, 1. Which we termed reclassifier. This reclassifier is equal to 0. So reclassifier is equal to zero. When the subject is reclassified into the hypothetical provider, if it is equal to one, then the subject is not reclassified. So the patient stays in their original provider, okay?

And with this reclassified redefined, F, so F is different from F star. So F is defined as the product of R, basically R times F star. And we basically add a singleton to this F script F star.

So now we can see, okay, whatever providers we have originally, now we add a single hypothetical provider and we provide the provider indicator, we fix that as zero.

So zero is the hypothetical one.
So now this $F$ can take values, importantly, it can take whatever values from the original script $F$ but now it can also take values to take the value zero, right?

So basically this $R$ is used to manipulate a subject’s provider membership.

So, a subject from a provider $F^*$ equal to $F$.

So here in this case, because it’s $F^*$, it cannot be equal to zero, right?

So we wanna reclassify patients from a certain existing real provider to that hypothetical provider.

You know, this $F$ is equal to zero. So this is a new provider membership for that patient, okay?

But if $R$ is equal to zero, then the patient stays in that original hospital. Okay?

Alright.

We have additional two assumptions regarding this reclassification thing.

So the first one is for any provider, real provider, we have this probability, being less than one.

This means that, okay, so given a set of covariates and given that the patient is in a certain provider, then the patient being reclassified
into the new hypothetical provider, the probability is less than one, which means that we should keep at least a few patients in their original provider so that we can still evaluate the outcome distributions of the original provider, okay? And this actually, if you do some, a simple algebra, we can show that basically this implies that, I mean this, we can basically drop this condition because if you do the sum of the conditional probability thing, you can basically drop this condition and this actually holds. So it’s like, okay, no matter which hospital, no matter which provider the patient is in currently, the probability that the patient will be reclassified is less than one. So not all patients will be reclassified, right? So combining these two, basically, okay, so basically not all patients can be reclassified or also all patients cannot be living in their original providers. Basically we require that, okay, each patient can, so we should have at least a few patients who are remaining
in their original hospitals so that we can evaluate their original outcome distributions.
And also we need a, of course characterize the distribution, that hypothetical reference provider.
Okay?
Alright.
Then the last assumption is, this is kind of an interesting setting. So rather than observing the original data, Y, F star, Z, we can only observe this set. So it’s R, Y, F, Z, this tuple. So the big difference between these two is, for this one, we know exactly for every patient, we know exactly where they’re from, for those patients, we actually don’t know where they come from, right?
But here we assume that we can only observe post-reclassification data. And this actually is nice, I mean this is not always necessary in the practice, but this assumption actually helps, facilitates the implementation of some certain privacy preserving protocols.
and data security protocols.
If say, okay, we don’t want the,
because of certain powerful influential
providers can actually have a strong influence
in policy making.
So, because this is capped like confidential,
so they actually don’t know how we design,
how we choose the re-classification scheme.
So it can help reduce some unwarranted inference
from those very powerful stakeholders.
So this is a nice setting,
but it doesn’t have to be like this in reality.
Alright, so now we have four assumptions,
important assumptions to regarding the data generating mechanism
and to regarding the reclassification scheme.
So, the ultimate goals of profiling is
to first to evaluate all providers,
and then we wanna identify goals,
especially with very bad performance
and we can take additional actions
and so we can, you know,
they can improve their performance in certain way.
Okay?
But yeah,
so this quantitatively or mathematically,
we have the two overarching goals.
The first one is to harness,
to use the post reclassification data,
to contrast the distribution of each existing or real provider.
F star was the newly defined reference group.
So we wanna compare, basically, compare the distribution of these two groups.
I mean each of them because we have so many real providers, and we only have a single hypothetical provider, okay?
We wanna compare them, we wanna do contrasts.
And of course the second goal is to identify those providers with very bad performance.
All right,
so, this actually,
because we introduced this hypothetical provider,
this is really nice actually.
But there is a difficult issue here because we introduced this hypothetical provider,
we actually have to account for or address reclassification dues to bias.
So the details are in this proposition.
So let’s assume that those four assumptions hold and the distribution of the outcome given Z and this F,
F is the newly defined provider indicator.
We can actually write the outcome distribution, like in two cases.
So when $F$ is equal to 0, this is corresponding to the reference, the hypothetical provider. So this is actually the average, you can consider as the distribution of the outcome basically for all patient. If you group all patients together into a single group, this is basically the distribution of that group. Okay? But we have this term here, and this is not necessarily equal to 1, F is equal to 1 then it’s very simple, but it could be unequal to 1. And also in the second case when F is not equal to 0, which means that okay, for those existing providers, their distribution also changes because you basically, you move a few patients to the new provider. So the original distribution changes, right? And because we cannot observe this by assumption. So this is basically the observed outcome distribution for existing providers. But according, as you can see here, it’s a bias distribution. It’s no longer the original one, right? Because this ratio, again, it is not necessarily equal to 1, okay?
Right?

So as I said, you can consider this as the average distribution, basically as the outcome distribution of the whole patient population, okay?

So of course you can write it as a sum of the, you know, weighted probabilities. So the weight being the probability provider membership, and this is basically, okay, within this certain provider.

What does the outcome distribution look like? Okay. All right.

So a few things. This proposition basically outlines a, what we call design based approach to provider profiling, basically, okay.

So, I actually, I mentioned this early, in profiling there are a few different parties. The first one is regulars who initiated the profiling process because they are interested in the performance of these providers.

And also we have profilers, which basically evaluates the performance, but they don’t have to be the same as regulators.

And also we have of course, providers who are the subject of evaluation.
and we also have patients who need the information to make their decision, okay?

So the design-based approach basically tells us that, okay, so, for regulators, they can basically lead the development of a reclassification scheme because in this framework, we never say what the distribution looks like, where, right? So this is a very general specification and we only made those four assumptions, but we don’t have any distributional assumption here.

So we can make it very general. And so in this framework, regulators will get more involved in this process.

So that’s why they can basically design the reclassification scheme based on their specific objectives, okay?

Alright. So, and given a specific reclassification scheme, of course they can design their own reference group, their hypothetical providers and having defined this hypothetical provider, profilers of course can use post the reclassification data and also the dependence.

Because here, as you can see here, this R actually depends on Y, depends on the outcome covariate.
and the provider identification. So using this information and also the post reclassification data, profilers that can actually do the profiling and we can use the framework to estimate the probabilities reclassification, which is also the propensity scores actually. So the next step would be to use the estimated propensity scores to correct for reclassification induced bias. And then we can basically construct the distribution of the hypothetical provider with the distribution of the existing provider, okay?

Alright. So as sketched in the previous slide, there are a few important things or advantages of the design-based approach. So this approach actually, in this framework, providers can be more involved in this framework. And, so we can use the profiling result, from this new approach can be more relevant to what people are interested in the care decision making process, okay? So, I think I'm a bit over time, but I wanna quickly skim through a few examples. But these examples are basically,
we need a few assumptions like whether the reclassifier is depending on the outcome, so in this example, it’s very simple. Basically the reclassifier is independent of everything. So, actually this reduces to the most simple case. So nothing changes actually after reclassification, but this is an example about the setting. And we also have like a few non-dependent settings. This R can depend on F star and given F star, it can be independent with Y. And we also have some examples, this is called equal rate representation. We also have singular representation, basically the setting where we only choose a single provider and we also have the case where R actually depends on Y, the outcome. So we can basically choose the outcome, sorry, we can choose patients based on the outcome. And I also give an example, this is actually an interesting example, but seems like we don’t have enough time today. So this is the most general case where R is allowed to depend on F and also Y. So we don’t have independence anymore,
but unfortunately this case, we have the unidentifiability issue. So this case won’t work under the post-reclassification data assumption. So we actually developed a framework, we looked at the deep learning methods and the singular representation case. And this is a relatively simple framework. We only consider exponential distribution. I mean the outcome involves the exponential family distribution and we construct a neural network model. So we have the input layer and the fully connected hidden layers and the outcome layer, we use stratify sampling based optimization algorithm. Here, I will skip the detail. And we developed a exact test based outcome distribution, exact test based approach to identify outlined performers. Okay? And this is basically the motivation why we need deep learning here, because simply speaking, the covid effect is not constant over calendar time and we have to easily account for that while doing profiling, but the effect itself is not of interest. Basically a visualization of the profile results.
So here we construct the funnel plot here. We construct what we call the funnel plot here. So the benchmark, the reference, the indicator, we use is again \( O_i \) divided by \( E_i \) and defined where this one is the median. And this is actually the neural network part. And we have the funnel plots. So those dots represent providers, okay? So because this, I mean, the higher, the worse the performance, the lower, the better the performance. So these blue dots here are actually better performers. So as you can see, if you add these two supporters up, this is like over 20%, what does not make practical sense because in practice you cannot identify outliers with over 20%, you know, this is too much. So we have to somehow account for provider level unmeasured confounding. And I didn’t include the technical details here. But after the adjustment, as you can see the proportion of a better and the worse performers are much lower than before. And I think I only have one more slide. So some takeaways. So profiling is very important.
as a major societal undertaking in the United States.

And we have so many applications, important implications and important consequences as well.

And the new framework actually increased the regulators engagement in this process.

And it’s called versatile because we can handle different profiling objectives.

And it is compatible with many different model specifications, machine learning models, data science models.

And here we use deep learning because it relaxes the linearity assumption when we do this profiling stuff.

And it is often a good idea to account for provider level measure confounding when we do this profiling stuff.

And that’s all for today.

Thank you very much Dr. Wu for your presentation.

I know we only have like two minutes.

Yeah, We have two minutes.

Thank you very much Dr. Wu for your presentation.

Any questions in the audience?

Anyone online?

Just giving everyone a chance.

No, I’ll ask a question.

So I think it’s really cool to be able to identify providers who are doing really well.

or doing bad.
What do you do with that? Now that you have that result? Like do you tell the profiler or the patient get to give it to say, "Oh, I don’t wanna go to them, they’re bad." Yeah, that’s a good question.

So actually CMS, they have many programs say, one is for dialysis patients, they have dialysis facility compare, which is an online program. So patient can have access to different types of information like whether diet facility is good or bad and many other different fields. So they can choose their favorite providers. Yeah, that’s possible.

And it’s something that is going on, yeah. Oh, I think we have questions. Oh, I think we have questions. Just very briefly, because I know we’re out of time but.

To what extent do you feel that, if this is true, I guess, and doesn’t matter, the patients don’t necessarily have meetings. So for example, like I grew up in a rural county, we had one hospital, you were going to a hospital, you were going there. Even in New Haven,
911 00:49:59.640 --> 00:50:02.160 there are two campuses of Yale New Haven Hospital,
912 00:50:02.160 --> 00:50:06.030 but there's only one hospital in metro area.
913 00:50:06.030 --> 00:50:11.030 So, I mean, choice is kind of not a real thing.
914 00:50:11.160 --> 00:50:12.570 How does that affect?
915 00:50:12.570 --> 00:50:16.950 <v Dr. Wu>Right, that's a very good point, so-</v>
916 00:50:16.950 --> 00:50:17.790 <v Questioner>We are actually in city,</v>
917 00:50:17.790 --> 00:50:19.140 I understand there’s more than one.
918 00:50:19.140 --> 00:50:21.130 (Host laughs) Right, there are so many.
919 00:50:21.130 --> 00:50:23.130 <v Dr. Wu>Yeah, but that's a very good point</v>
920 00:50:23.130 --> 00:50:27.030 because we are actually considering another framework
921 00:50:27.030 --> 00:50:29.670 which is also clustering framework,
922 00:50:29.670 --> 00:50:32.010 which basically gives you
923 00:50:32.010 --> 00:50:34.080 under certain conditions you can choose,
924 00:50:34.080 --> 00:50:36.000 there’s a feasible set of providers
925 00:50:36.000 --> 00:50:37.290 that you can choose from,
926 00:50:37.290 --> 00:50:39.420 of course, under certain strengths,
927 00:50:39.420 --> 00:50:44.420 say your insurance, your location, many other conditions.
928 00:50:45.240 --> 00:50:47.793 But I mean, in this framework,
929 00:50:49.320 --> 00:50:51.130 maybe we can address that issue
930 00:50:52.590 --> 00:50:56.760 in the set of areas that we included here.
931 00:50:56.760 --> 00:51:01.760 But yeah, I mean, you know, very important issue.
932 00:51:05.602 --> 00:51:06.435 <v Host>Unfortunately, that’s time.</v>
933 00:51:06.435 --> 00:51:08.768 So let’s thank Dr. Wu again.
934 00:51:11.897 --> 00:51:15.027 If you haven’t signed in, please sign in before you speak.
935 00:51:15.027 --> 00:51:16.773 You are registered.
936 00:51:16.773 --> 00:51:18.834 Oh no, it’s good, I don’t know.
937 00:51:18.834 --&gt; 00:51:22.167 (indistinct chattering)