

today's speaker is dr diane mold in 9
chemistry and chemical biology at
stevens institute of technology she then
earned a phd in pharmaceutical and
pharmaceutical chemistry at the ohio
state university in 99
for years dr mold was a
pharmacokineticist in the industry where
she specialized in population
pharmacokinetic and pharmacodynamic
modeling

she was also an associate research
professor at georgetown university
currently dr mold is the president of
projection research inc a consulting
company offering pk and pd services

please enjoy today's lecture

hi my name is dr diane mold i'm
president of projections research
and i'm from phoenixville pennsylvania

i'm here to talk to you today about

disease progression models

so there are a lot of motivations for
developing such models primarily to
visualize the time course of disease

both in a treated and an untreated
condition

and we use these models to try to
simulate the future course of the
disease

to understand and simulate various
disease interventions and also to help
develop more informative clinical trials
also disease progression models are
supported by the food and drug
administration and can form a framework
for regulatory submissions

so there are new objectives for clinical
trials in most confirmatory clinical
trials the purpose of the trial is to
test the null hypothesis which basically
is looking at whether or not the drug
and the placebo are effectively the same

and they're focused on testing that
because frankly that's a very easy thing
to test and there's always a hope that
you have an alternative model that can

be accepted in place of that

but testing that is easy is an easy
question to answer

but it actually isn't actually focusing

on the right question which is maybe
there are subsets of patients who would
benefit from different therapies or
different dosing regimens
so as tukey said its far better to
approximate an answer to the right
question which is often vague than to
come up with an exact answer to the
wrong question which can always be made
precise

so basically what were doing with these
disease progression models is trying to
develop an exposure response surface and
thats not an easy question to answer
but maybe its the right question to ask
however in developing these things we
have to make assumptions which can
weaken the robustness of the answers
assumptions can reduce the inferential
certainty because if our assumptions are
wrong

then the conclusions that we make based
on that model may also be wrong
however its the quality of the
assumptions and not their existence that
is really the issue

so typically when we develop these we develop them as part of a team so that we can get input for example from clinicians and from other healthcare providers who actually have a good understanding of the progression of the disease

also a summary of the surface function such as an average over the response surface can still provide robust answers to the simpler questions essentially what we can do then still is address the null hypothesis question which is does this drug work better than placebo or standard of care or does it not

so during drug development patients can have different responses to drugs and theres a lot of different factors that can contribute to the variability in the outcomes of the study

its impossible to study all combinations of treatments in different doses by different patient types so typically when were developing this we may get some data for example from elderly patients from younger patients

from pediatrics and were trying to
develop a dose response surface without
data from every type of patient given
every different dose and duration of
therapy

also the time course of the disease in
the untreated state is also variable so

we want to characterize both the
untreated state and also allow for a
placebo response to better understand
the drug effect

in addition clinical markers are
inherently variable as well so for
example in certain areas where its a
very subjective assessment such as
depression and the hamilton depression
score the error thats associated in
other words the variability from
measurement to measurement that you see
in a hamilton depression score can be
quite notable

so we typically do repeated measures
because were more able to evaluate the
central tendency of that patients
response rather than focusing on a
single

assessment so model based evaluations

can provide a basis for developing an

exposure response by making

scientifically valid assumptions but

again it usually requires input for

multiple people during this development

models actually can help increase the

amount of information recovered from a

clinical trial

people that work in pharmaceutical

industry im sure are familiar with the

fact we have data that didnt quite

reach the p value

and thats because information thats

obtained from any scientific study is

detected based on the ratio of signal to

noise and in any study the information

that we gather is the total variation in

the data and the signal is the variation

due to identifiable causes in other

words did this patient receive therapy

or did they not receive therapy the

noise is the unexplained variation in

the data by building such models and

identifying factors for example patient

sex patient age other concomitant

medications or comorbidities we can
actually begin to reduce the noise and
improve the signal
and by doing that we can actually
improve the amount of information that
you can get from a clinical trial and
oftentimes see a signal of a drug effect
where under traditional assessments you
may not be able to see it
so clinical pharmacology if we think of
it as an equation and im a
pharmacometrician so i think of
everything as an equation
we look at it as the sum of disease
progression plus drug action
it also follows the drug action is
actually a combination of a drug effect
and a placebo effect so understanding
how the drug works involves
understanding the progression of the
disease
and a potential placebo effect as well
as the effect of administering a new
test drug
to do this we look at a variety of
different models including

pharmacokinetic and dynamic models and

these are fairly straightforward and

most people are familiar with them where

we look at kinetic models where we look

at the dose and the concentration we

look at how the drug is handled in

different individuals and patients we

look at the effects of disease state

such as renal and impairment renal and

hepatic impairment

hemodialysis which can also affect drug

concentrations other things like

concomitant medications

and genetic influences

and then we also look at

pharmacodynamics so

now were looking at other measured

effects either through biomarkers or

surrogate endpoints or clinical effects

and endpoints now surrogate endpoints

are a fairly uncommon form of dynamic

assessment these are endpoints that have

been validated as correlating with an

actual clinical endpoint

so disease progression model accounts

for the time course of a disease in a

particular patient and in the literature
you'll see this usually marked as s of t
meaning the status at some time t
and were measuring things like symptoms
or signs and symptoms are usually a
measure of how a patient feels or
functions and the signs could be
physiological or biochemical markers of
disease activity and again we can look
at surrogate endpoints or outcomes where
the endpoints can be validated markers
that are associated with an outcome and
then the outcome itself which may be a
measure of global disease status or it
could be a time to predefine disease
progression or a patient's death
so many of you have seen some of the
other
lectures in this series may be familiar
with the Emax model that's often used
in pharmacodynamic assessments and here
we were looking at the
 e of t
and basically that would be the effect
at some time t but if we think of it as
a status at some time t

and then we can have the e_{naught} which

is a baseline

disease progression

and then a drug effect which comes from

the e_{max}

function on the on the other side of the

equation

this is actually the simplest form of

disease progression model and in fact is

often one that's implemented in clinical

trial designs

basically what we're assuming is that

the patient's disease will not progress

during the course of the study

unfortunately that's not often an

appropriate assumption to make for

example patients with cancer often

progress in their disease during the

course of a trial

other patients who have for example

depression may have a seasonal component

to their disease and it may oscillate up

and down during the course of the study

but this is actually the simplest form

of a disease progression model

we'll start looking at some new ones

but the components of a disease
progression model then would be a
baseline some function describing the
natural history of the disease

a placebo

effect model and then the active
treatment response that you're seeing
so placebo response is something that
people talk about a lot it's the change
in disease

based on patients who have been
randomized to receive placebo and it's
usually seen as a transient improvement
in clinical status followed by a relapse
to the prestudy status so in depression
trials for example patients often feel
better just because they're in a new
situation they have new health care
providers and they're often being
assessed more frequently which actually
does have a beneficial effect

placebo response can be variable both in
magnitude and duration but it's often
more notable when clinical status is
evaluated subjectively

so placebo response is a real issue

there was a publication some years ago
called the powerful placebo which was
subsequently debunked but
actually nonetheless
patients do have a measurable response
to placebo treatment
this is an ad that i found on a online
journal and its an ad for a
an approval of a new drug which is
called sucrosa its actually a placebo
that in this this humorous article was
being allegedly approved
for a variety of indications and there
were a number of side effects associated
with it as well including
potential for developing cavities
but the idea is that the concept of
placebo response is very well
known
even by people who dont work in
healthcare and the pharmaceutical
industry
so as i mentioned earlier when were
building these things we actually dont
work in isolation its always best to
have a group of people that are familiar

with the disease

and

also the treatment of that disease so i

usually recommend speaking with a

disease specialist

what i typically do is draw pictures of

the time course of disease and then try

to translate that into a disease

progression model

ill explain what the model and

parameter is to the specialist and try

to ask them for advice on factors that

may influence patients symptoms or

progression

we then translate the models with

appropriate parameters and covariates

and begin to evaluate the data in order

to get a sense about how that works

lets take a look at the construction of

a disease model

so for example if were looking at

patients undergoing solid organ

transplant in the normal trial setting

were going to look at whether or not

the patient was administered drug or

placebo

and then were going to see whether or
not that patient had any acute rejection
but a disease progression model goes
into the clinical situation a little bit

more thoroughly

so instead we actually go and ask is
this a catavarric donor is it a matched
or unmatched and is that for example
patients first transplant because
they're less likely to have a rejection
on the first transplant than if they've

had multiple transplants

then for example

for many renal transplant patients they
have an up regulation of cd positive t
cells which usually means that their
immune system is actually a little
hyperactive and that can actually be a
factor contributing to rejection

so we can measure those

and then we can look at whether they've
got an immune or inflammatory response

by actually looking at markers of
inflammation il tnf alpha are also
very common assessments

and then we can link that to cell death

that may
precede an acute rejection
and then look at the effect of the
administration of drug and placebo
somewhere on this much longer pathway
and by accounting for all of these
factors we can see the drug effect a
little bit more clearly than simply
asking did the patient have a rejection
or not have a rejection
so this is the next most simple disease
progression model
were looking at the patients status at
some time of t
and we say at the initial time that the
patient enters this study their status
at baseline is s_0
and that we have a slope α
occurring over time
and so based on this very simple linear
disease progression model we can draw a
line and say over time this patients
status will follow this linear
trajectory now you'll notice on the
x-axis that the time does not actually
have units but simply by looking at the

numbers you may guess that this could be

something like weeks

and that's because in many cases

diseases progress relatively slowly so

for example people with osteoarthritis

may start with just mild twinges and it

may take years before you really see a

major clinical issue so one of the

components of actually doing disease

progression modeling is often the need

to collect data over an extended period

of time in patients

so

there are a number of different ways of

describing the effect of drugs so if we

again go back to our very simple

linear effect and now we're adding a

drug effect

which is the red line that you see

rising above that where this drug

actually offers some symptomatic

improvement

so that basically what we're doing is

we're simply adding a drug effect and

saying that at any given point in time

that patient's status will be improved

by an average of a certain number of
status point metrics
and typically we use these looking at
any number of things either looking at
the plasma concentration but more
commonly what we use is something called
an effect site model because typically
when people begin taking a therapy it
may take a few days to even a few weeks
before you really can see a measurable
clinical effect and so as I'll show you
in a minute we use these effect site
compartment concentrations as a way of
allowing for a lag between the start of
therapy and actually being able to
detect a clinical response
so basically we can either use measured
concentrations or as I mentioned we can
use this link model
and because of that lag we can actually
account for the fact that the patient
may have been taking drug for several
days to several weeks before we really
see an observed effect
so the effect compartment allows us to
infer from the plasma concentration time

profile

that we have some concentration at an
effect site it could be something for
example like receptor occupancy
or in diseases such as inflammatory
bowel disease we need to suppress immune
response for a certain period of time
before we can actually see mucosal
healing but
the original effect compartment models
attributed the
the transfer from the plasma compartment
to an effect compartment to diffusion
but in this particular case were
actually attributing it to the need for
something to occur before we actually
see a measured effect
so if we take a look at the
effect of eptistigmine on the trajectory
of alzheimers disease now this isnt
even actually a disease progression
model
but we can look at the um
the score for these patients and you can
see that patients that have
historically their

adas cog scores will decay over time but
the administration of eptistigmine does
provide some symptomatic benefit
but you can see that the annual
worsening is actually relatively slow of
about 0 points on the s cog score so
simply capturing information over a very
short period of time like three to six
months you may not really be able to
actually estimate the slope of the
untreated patient
if you remember from your
pharmacokinetics lectures where you
needed data over two to three half-lives
in order to be able to accurately
estimate a half-life for a drug
you similarly
similarly need data over the same period
of time in order to be able to
accurately estimate the slope
and then you can see that you can make
an assessment as to whether or not your
drug is providing some form of benefit
this is some work that was done by Mark
Sales
looking at the effect of AZT on CD

counts for patients with hiv
and you can see that theres a placebo
response where theres a transient
slight improvement followed by a decay
in cd count
where azt actually again increases the
cd count so this again is an example of
a symptomatic benefit thats provided by
the drug to help alleviate the symptoms
of the disease

tachrin which is often used to treat
alzheimers disease
has also been modeled as a disease
progression model
so we have the same basic function with
a baseline disease status of s_{naught}
we have a linear natural history and in
this particular case we accounted for a
placebo response and also an active
treatment response and this is work that
was produced by nick halford and carl
peace

so lets take a look at that function
and as you can see the disease
progression scores the light line thats
the historical score and then you have

the placebo response which is represented by the dotted line and so you have a transient dip in that followed by a return to baseline and then you have a drug effect which is the heavy dash line the net effect is a total difference it looks like a simple shift and a symptomatic benefit but this also provides some useful information because basically the placebo response is still fairly high even two months after initiation of the study which would suggest that if you're trying to make a shortterm proof of concept study with this particular disease a placebo effect may confound your ability to be able to tell if a drug is working in a particular disease so characterizing a placebo effect can actually help you understand data from proof of concept studies which may not be long enough to accurately capture the full benefit of the drug effect but by understanding that a placebo

response may still be active while
you're actually looking at data
can help you separate a placebo response
from an actual drug response and make a
better assessment even from
proof-of-concept studies as to whether
or not the drug has any potential and
should be carried forward for
longer-term clinical trials
this is some work that was done in 99
by Griggs looking at young boys with
muscular dystrophy and he was measuring
muscle strength and you can see a
natural history line and he's testing
the effect of prednisone at two
different doses plus placebo
and you can see as mentioned earlier
even in this data which is not modeled
but simply plotted that you do have a
transient improvement even for patients
who are on placebo
but nonetheless the prednisone at 0
mg per kg shows what appears to be a
symptomatic benefit
at a higher dose 0 we see that the
slope of the line for the 0 mg per

gig dose
actually is now different from the
natural
course of the disease
suggesting that there may actually be
something additional going on aside from
a simple symptomatic improvement so how
do we deal with that
we start to alter our disease
progression model
so now instead of separating the
effect from the slope we actually put
the drug effect in with the slope and
multiply it by time
and that allows the disease
the effect of the drug on the disease to
alter the slope
and so we can have
patients with differing slopes
as a consequence of therapy and this
suggests that you have a disease
modifying activity of the drug
so for example if we look at the nepazil
on on alzheimers disease we can see
again the natural history is the solid
black line with the dinapazil showing

some difference from the slope of the
the natural history of the disease
suggesting again a potential impact on
the disease progression itself
similarly we can have various
combinations and permutations where we
can combine either a symptomatic or a
disease progression modifying disease or
one that characterizes both
so these different models can be changed
in different ways to try to reflect what
appears to be going on with the data
that you have at hand
so how do we tell these apart
well the easiest way to tell whether or
not you've got a disease modifying drug
or a symptomatic drug is to actually
stop the therapy
so if we look at the panel on the left
we can see that the disease progression
is the black solid line when we add the
drug therapy
we see a decrease in the progression and
then after we stop therapy it returns to
baseline
and on the right panel we can see that

when we stop therapy the red line which is representing the patients that have been treated is not actually returning to baseline and that's a very good indication that the drug is actually modifying the disease progression studies like this are actually very difficult to consider particularly for patients who are clearly benefiting and so are not always considered ethical an appropriate workaround is something called the staggered start model where for example you instead of randomizing patients 0 0 to placebo or therapy we might randomize only a third of the patients to start active therapy right away and then later in the study well randomize another third to cross over to active now why would that make a difference or why would that tell us that one is disease modifying and one is symptomatic if the drug is actually symptomatic regardless of when the patient was

randomized to receive active treatment
they should still reach the same effect
of improvement however if you have a
true disease modifying drug what will
happen is that the patients who received
the active therapy earliest will have
lower scores than patients who were
later randomized and so you'll actually
effectively end up with three different
groups the placebo arm the patients who
were randomized late therapy
and the patients who were randomized
early to therapy and this is a way of
ethically discerning whether or not you
have a symptomatic drug or a true
disease modifying effect
now I'm going to be giving an awful lot
of functions and really the point of
this entire talk isn't so much to
memorize or completely understand all of
the math but to understand that there
are a variety of different functions out
there and that you can utilize functions
like this
with or without colleagues to actually
help develop models and so there are a

host of different functions that can be applied depending on what kind of metric you're using to make a determination about the disease status so this next set of functions are asymptotic progression models and these are typically used when the disease progression has a natural limit where it either falls to zero or goes to some top steady state value so the zero asymptote would be indicative if you have someone had spontaneous recovery so for example a patient who has the flu will eventually recover whether or not they're treated and there's multiple functions that can be used to describe that a nonzero asymptote might be for example with patients with parkinsons where they reach a maximal score on the updrs and they simply cannot actually progress any further so it would be progression to some maximal or in this case what we would refer to as a burned out state

and there again several functions that
can be used to describe that kind of
time course
so the zero asymptote model is shown
here where youve got a symptomatic the
natural history is the black line and
you can have both symptomatic and
protective effects so the symptomatic
would offer a very rapid drop
where the protective effect or a
combination of both has a slower drop
now people have often felt that disease
modifying drugs actually
have a you know better quality of
therapy but thats not always the case
if we were looking at status as
something like a pain score for a
patient whos recently had a wisdom
tooth extracted a zero asymptote model
would certainly apply to that setting
which is sooner or later the healing
will occur and
the incision or the where the tooth was
removed will not be as painful
but for patients like that a symptomatic
improvement that

sets on very quickly
is actually preferred to something
thats got a an alteration in the
progression which as you can see in this
picture would take quite a bit longer so
the
type of drug that you may be looking for
is often dependent very much on what
exact indication youre in and what kind
of benefit the patient would need the
most
so we can look at a variety of different
study designs here as well and so heres
some of ours
zero asymptote functions and here weve
got a simple exponential function and
one of the ways again to tell whether or
not the drug has got symptomatic or
disease modifying effects is by
administering a second dose
as you can see in the top panel when
that second dose is administered theres
another drop
in the score for the patient whereas if
you have a disease modifying effect it
tends to be a smoother transition

so these models can actually be used to
simulate different
study designs that may help you decide
or determine whether or not your drug
has a disease modifying activity or
asymptomatic

the

emax functions can be used the same way
and as you can see this is a simple emax
function but we have a decay where it
actually speeds up over time and again
we can see the discerning between the
symptomatic and disease modifying in
this setting can actually be looked at
by administering a second dose and we
can see that we have an additional drop
in the upper panel indicating that we've
got a symptomatic benefit whereas
administering a second dose as you see
in the lower panel actually just
accelerates the improvement a little bit

so

again simulation

can be a very useful tool in planning a
more informative studies and such models
actually are very very useful for trying

to decide what study design would best
tell you how your drug is working
and what additional things should be
done to help you differentiate and
identify

dosing regimens and understand what the
likely outcome of that study is going to
be

so we have also the possibilities i
mentioned earlier of the so-called
nonzero asymptote model where the
patients status will actually worsen
until it reaches some maximum state
and as we saw before we've got the same
kinds of things that can go on so our

black line here

is natural history and then for the red
line we can have a symptomatic benefit
which is you see

at the time eight point where we've
stopped therapy the patient will
actually return to their untreated
status

but because we have a more complicated
model the drug can actually now even if
it's a disease modifying drug

can actually work in different places
one where we lower the maximum response
thats the
protective steady state so in other
words these patients will not progress
to this
maximum score or we can have some kind
of a product protective model where it
actually slows the progression
so
the more complicated disease progression
models offer a lot of different areas
where a disease effect can actually be
assessed and tested in order to
understand better exactly how this drug
is working in the patient population
so again as was shown before weve got a
fairly elaborate function here where the
patients
disease is progressing over time at some
rate of k progression
and we have a steady state value and
were looking at a drug effect here
where again weve just added a second
dose and we can see that the patients
score is actually drops weve got a step

score going on there

versus whether or not the drug effect

has still got a smooth effect on the

improvement in patient scores so with

all of these models the same kind of

evaluations can be done

these are data that were taken from the

parkinsons study group psg from a study

called data top where they were looking

at patients with parkinsons disease and

they were looking at what the impact of

administering ldopa was to these

patients

so the panel on the upper left is all of

the data and the score you can see how

incredibly variable the data are but

when we look at the patients one at a

time we can see

that the orange triangles those are the

individual updrs scores that were taken

over time

and the sudden change which you see in

particular in patient one where the

score has gone up and then suddenly

drops

thats where ldopa was administered

patient two didn't have quite as much of a response patient three we can see a substantial drop again about year two where eldopa was administered but you can actually see that in this particular patient these scores are actually declining back to a more normal score and you can see that the impact on these different patients is quite variable so in addition to a very strong indication of a symptomatic benefit from ldopa you can see that in many of these patients the progression which would be the slope that's occurring after treatment is initiated is actually often different than it was before treatment was initiated

if we look for example at patient seven up to year two we can see that patient was progressing fairly rapidly after year two where this patient's ldopa therapy was initiated we can see that the slope that goes from two to six years appears to be a lot shallower than it was prior to the administration of ldopa

so you've got in this particular case
indication of both
symptomatic benefit but as well disease
modifying benefit so what does that
really mean in terms of patient care
basically for drugs that are used to
treat chronic diseases that progress
typically
you want to try to
slow the progression down as quickly as
possible and oftentimes that would
suggest if the drug truly does have
disease progression modifying activity
that's often better to start the therapy
earlier rather than later so that the
patient doesn't have a chance to
progress very far before therapy is
initiated so these kinds of models can
actually be used to try to inform not
only how much drug to give and how often
to give it but when to initiate therapy
in order to provide the most benefit for
patients who are taking the
drug now this is something called an
inverse bateman function
and again for those of you who may

remember your pharmacokinetics lecture
in this course series uh if we remember
the one compartment oral model where we
had first order input and first order
output and it forms kind of a little
camels hump thats called abatement
function
this is flipped upside down hence the
term info inverse abatement function
so what we see and what were trying to
describe here is through the hamilton
depression score where patients
typically with depression are often at
their greatest
degree of depression during the winter
months and so theres a seasonal
component that we see
and so typically in the summer their
scores are better in the winter their
scores are worse and this is without
treatment now why is it important to
capture or characterize that variability
in the underlying score
its because during these clinical
trials because enrollment may take over
a year sometimes longer to enroll a

study you'll have patients that are starting therapy at different times in the year so it's important to understand for example a patient who enrolled at their uh worst possible score which would be in the winter and finished at the summer at their best possible score that that is oftentimes just due to the uh cyclical component of their disease and should be captured in order to fully understand whether or not it's your drug or it's just a change of the seasons that's improved that patient's status so what we can see here is a symptomatic drug

the

lines there the dotted lines are the administration of the drug and we can see that this particular drug is improving the hamilton depression score but again when drug is stopped it will return back to its original time course so all of these other models were fairly empiric and in fact most disease progression models are somewhat empiric in nature because in many cases all of

the underlying pathophysiology of diseases is not terribly well known but there are diseases for which we can develop physiological models of disease progression and those are usually the preferred models to do so if we for example look at baseline status and we have also a rate of something coming in and a rate of something coming out so for example the level of a particular enzyme or protein in the body in the normal status we have a rate of formation which is our case in and we have a rate of loss which is k_{loss} for a patient for example that has a disease their k_{casein} and k_{deg} may be altered and so basically that can affect the overall for example enzyme level or protein level so if a patient has a compromised synthesis of a particular enzyme then

their status or their concentration of
that enzyme will be low and the disease
will be

manifest as a consequence of a low
enzyme

or if their loss is very high similarly
they'll have a low level

i think of these models as being sort of
analogous to a faucet pouring water into
a sink and then we have a drain coming
out

at steady state the water level in the
sink will be a constant level that's
related to the rate of how much water is
coming into the sink

versus how much water is going out
through the drain

if for example we were to turn down the
tap so that the water flowing into the
sink is reduced the water level in the
sink will drop

alternatively if we were to expand the
drain so that the loss from the sink is
actually increased will lower the water
level

conversely if we turn up the tap the

water level will rise or if we block off
part of the drain the water level will
rise

so the case in is analogous to the
faucet and the k loss is analogous to
the drain

so each of these can change with time
and that's what produces our disease
progression

so this would be an example of some
physiological disease mechanism where
we've got again some marker that were
following

k_{di} where we were looking at a synthesis
and a k loss and a symptom and we can
actually add a drug effect into that and
again we can use the same delay function
such as an effect compartment if for
example adding drug or adding enzyme or
protein

takes some time before you actually see
the symptoms begin to resolve

so for example

if we look at disease progression due to
decreased synthesis so the now the lower
red line which has fallen off to a very

low level might be in the untreated
state
adding drug by inhibiting the loss or
stimulating the expression can actually
reduce the
issue with regard to the disease by
bringing their status back up to a
normal value
now because these are
models that actually move over time we
cannot instantly say ah
our slopes are different therefore this
must be a disease modifying drug the
reason is in this particular case if we
take the drug away the patient will
still return to baseline so again
simulation and different study designs
is often needed to make a determination
in these more complex settings as to
whether or not youve got a disease
modifying drug or youve got a
symptomatic drug
similarly if we have an increased loss
of something for example bone mineral
we can have a fall off where by altering
the rate of loss or

changing the synthesis of something we
can actually bring that patient back up
to a normal value
and thats reflected in some work that
was done on raloxafin which is used to
treat patients with osteoporosis
and you can see here the red line the
bone mineral density is actually falling
over time and these are also three
different doses of relaxant and we can
see
an improvement in the bone mineral
density over time
youll notice that we actually have some
projection out for future years
so again these models can be used to
simulate what we would expect to see
over multiple years of treatment with
these drugs but of course whenever you
do such simulations you have to have the
caveat that you are extrapolating so
those values are much more questionable
than ones where you actually have data
to support that
another physiologic model would be the
use of what we call transit models and

here we use a string of compartments to
implement a delay in response to drug
and these are analogous for modeling
things like anemia neutropenia and other

chronic progressive diseases

so if we look at the top here

if we were looking at for example

hemoglobin and administration of epo

we can see the pulses or the

administration of the drug and we can

see

an improvement in hematocrit over time

and if you remove the drug of course the

hematocrit will go back to its original

value

now one of the interesting things about

these salt transit models is that they

have something called schedule

dependence meaning that if you

administer

very large doses you can actually

saturate the system

and so the plot on the bottom is

actually the same drug the same total

amount of drug just being administered

at a different schedule in the lower

pale line you see there
were administering a very large dose
but were giving it
weekly if you look at the next line
were giving it several times a week and
if you look at the upper red line were
giving the same drug
every day
so why are we getting such a huge
response with daily administration when
were getting a much lower response with
the once weekly and the reason for that
is that when you administer this large
dose youve actually saturated all the
receptors that the drug can work on and
much of the drug thats been
administered
actually has absolutely no ability to
act
so were giving a bigger dose but were
not actually getting everything that we
possibly could out of it
so why isnt epo administered on a daily
basis
heres where we have to look at the
balance between patient compliance and

preference versus clinical activity so

in many cases its better to go to a
less frequent dosing even if we have to
give drug that we know is probably not
going to produce a real clinical benefit
in order to spare the patient from
having to inject themselves on a daily
basis

so cell transit models and in fact many
of these physiologically based models
have this kind of property and you can
actually explore things like dosing
frequency to see which may be optimal in
response but also what may be necessary
in terms of the clinical situation

so models describing growth are actually
very common these are semiphysiologic
models and they can look at things like
antimicrobial growth viral growth and
also tumor growth and here were looking
at the change in response over time
where we have a k growth which is the
rate of growth and then a rate of death
and then theres a drug effect on that
so basically

what weve got is a circular rate so

that in other words if we were looking at
a tumor cell as you know a small tumor
initially won't appear to have grown in
diameter very much but as it gets bigger
and bigger it'll appear to grow more and
more quickly

you'll see more and more metastases so
basically what's happening is it sort of
feeds on itself

and then we have
a loss or death of the tumor cells for
example

and our drug can actually work on
increasing the rate of tumor cell death
so it would be a stimulatory function to
try to reduce cell counts

models like this as I also mentioned can
be used for looking at antimicrobials or
viral agents as well

remember the effective drug is to
stimulate the loss of response here
which would be the tumor cell size or
the cell count for

microbes or viral count
so these growth functions basically show
that you have a growth going on over

time and then as you administer
treatment you would expect that whatever
it is you're measuring would decrease
but when you stop therapy you'll see
that there is in fact
a beginning of the return to baseline
but again this is not a
symptomatic benefit this is not a disease
modifying benefit because you haven't
completely removed the thing that was
growing in the first place so despite
the fact that the slopes in these cases
are different this is not a disease
modifying it's simply a symptomatic
improvement Gompertz functions are
somewhat more elaborate growth models
and here we actually can do a somewhat
better job as I'm sure uh people that
have done research in cancer are aware
that there's often a group of tumor
cells that are senescent or are
resistant and here we have two different
populations the sensitive which is S
and the resistant which is R
and cells can actually transit back and
forth between a sensitive state and a

resistance state and we can imply the

drug effect the E_{max}

function to the growth rate of the

sensitive cells

so basically drug effect is delayed via

a link model or limited to an E_{max}

model but cells that are in the

senescent or resistance state will not

be affected by the drug effect and so

what that allows you to do

is understand

relapse that can occur so if we look

here for an untreated low and high dose

the untreated is the blue line and we

can see that the tumor will grow to a

certain maximum value

in the red line we can see a low dose

where we've reduced tumor size but again

on cessation of therapy you would have

regrowth of the tumor

but at a very high dose we can barely

see anything

but because we have that resistant

population we can later see regrowth and

this would explain in cancer

chemotherapy for example why a patient

can appear to be disease free sometimes
for two or five or more years before
evidencing
a relapse of their original
cancer another form of analyses that we
do is looking at something called a
survival function and we use those to
describe disease progression as well so
these are empiric means of evaluating
the relationship between drug effect and
the time course of disease progression
so we can link these very fancy
pharmacodynamic models
to a measurement of outcome
so our survival functions basically we
look at the survival at some time of t
as being the probability that something
will occur at
that is before the end of the study
and these are monotone decreasing
functions so survival is one at time
zero but zero as time approaches
infinity
and the rate of decline varies according
to the risk of experiencing an event
so basically this the survival at time t

is an exponential of a hazard function

over time

um to think about it in more simple

terms i like to think about this as like

a game of musical chairs where you have

a number of chairs and one plus the

number of chairs children circling the

chairs when the music stops everybody

scrambles to get on a chair and one one

student or child actually is eliminated

from the game they remove a chair and

they do the same thing so everybodys at

the same risk

while theyre circulating the chairs but

when the music stops its time to see

whos still in the game and whos not

and thats actually a very effective way

of looking at a survival function

so the hazard function defines the rate

of occurrence whether its an

instantaneous progression in many cases

here well use the pkpd model to act on

the hazard function so in other words

can it reduce the hazard of something

occurring

cumulative hazard is the integral of the

hazard over a predefined period of time
and usually that's the duration that the
study is ongoing and that describes the
risk of an event occurring so this
translates these very fancy mathematical
pharmacodynamic models into a useful
measure of outcome
so for example if I were to administer
G-CSF to a patient who's receiving
chemotherapy I would expect to reduce
the risk of that patient actually
developing febrile neutropenia
so we can look at the benefit or adverse
events and compare them with existing
therapy fairly easy
so we define t as a time to some
specified event and if we're again
talking about G-CSF we could be things
like fever infection or sepsis following
chemotherapy
 t is continuous that's our time and it's
characterized by the hazard or the rate
of occurrence of the event the
cumulative hazard or risk and the
probability of the event not occurring
before time equals little t which as I

said is usually the end of the study

we assume the hazard is a continuous

function and it can be a function of

biomarkers and there are a number of

transit models for example which you

just saw earlier that can describe

neutrophil count over time after

patients have received

chemotherapy the hazard functions can be

adapted from any clinical endpoint

and the hazard function then is

integrated over time to yield a

cumulative probability of experiencing

an event by some specified time

so what does that all mean

if we define a hazard is constant rate

and the cumulative hazard then is h of t

is equal to k

then we can see that the survival if we

go through all the math over there is an

exponential of negative k times t

and this may look somewhat familiar to

you

and if it does i say that would be

absolutely excellent because it looks a

lot like a one compartment iv bolus

falloff so basically if we think of this
in terms of for example molecules of
drug after you're administered an iv
bolus of
drug you have a constant hazard of being
cleared over time and that's the lower
line along the bottom
and the actual survival of the drugs is
measured by that exponential fall off
and then the cumulative hazard is the
amount of drug that's been eliminated
over time
so these all link back to functions that
you should be familiar with or may have
heard about before
and essentially should help make it a
little bit more familiar to you
so if we think about our neutropenia
situation again here we're looking at
white cell count over time
and what was applied here was the simple
hazard function where we assume that
once the cell count falls below a
certain level
that patient is at an increased rate our
risk of developing neutropenia uh

febrile neutropenia infections sepsis
that sort of thing
so the the period of time that were at
great risk is that those that
represented by that red line
and the um survival uh which is the
patients that are not developing these
adverse events
is represented by the green line and
then the overall cumulative hazard which
is the yellow line actually as you can
see increases over time
so the longer that patients neutrophil
counts are at this low level the greater
their cumulative hazard and the less
likely it is that they're going to not
have one of these problems occurring
this sort of thing can actually be used
to compare to new forms of therapy that
may help ameliorate the
neutropenia
and were showing here
our functions
so if we add another molecule you can
see what it's doing is not only reducing
the number that is occurring in this

experimental molecule its also reducing

the duration of time

that this patient is at risk of

developing febrile neutropenia or

infections

and thats represented by the so you

would have a better survival which is

represented by that very light green

line and that the cumulative hazard is

also quite a bit lower

so what does that really mean for us

it means that we have a better survival

so in order to be able to understand

valuations of the importance or the

improvement that were seeing in terms

of clinical benefit we can apply this

kind of analysis to

studies of patients that are receiving

either gcsf or for example this new

hypothetical gcsf

and

on with a much shorter study duration

make a determination as to what patient

risks are being

improved simply by shortening the

duration of time that the patients at

risk for developing severe complications
of neutropenia

so disease progression models have been

developed for a variety of different
diseases

including alzheimers disease diabetic
neuropathy parkinsons disease and
osteoporosis

in fact theres a lot of them that have
been developed by the fda as well and i
certainly recommend that you actually
evaluate their

publications on that

for alzheimers disease its typically a
linear function and the drugs effects
have generally been identified as being
symptomatic

for diabetic neuropathy again generally
a linear function but there are some
indications with some of these newer
molecules that there may actually be
both a

symptomatic and also potentially
modifying impact

for parkinsons disease because that
does have a maximum score asymptotic

models are typically used
and for osteoporosis for example as you
saw earlier inhibition of bone loss has
been
a common marker in most cases as i
mentioned earlier the functions that we
use to describe these disease markers
are empirical but whenever possible its
best to use mechanistic models that
should be used for most
of these agents usually because the
complete disease mechanism isnt always
fully understood
so in summary accounting for the disease
progression is a very important
uh component of understanding how the
drug is actually working
by having that youre better able to
discern the true effect of the drug
and it improves your reliability when
youre doing simulation work
particularly in designing new trials
that can be more informative and better
powered and can also
increase the signal to noise so that you
can better see whether your drug is

working or not and more importantly on
which patients is working best in which
patients receiving much less benefit

so its very useful during the
development of new drug candidates it
helps you visualize ways of using the
drug better

and it helps convert data into
understanding

there are issues that are associated
with building disease progression models
particularly a lack of available data

for untreated patients

however there are different ways of
actually getting such data

the nih actually does have
some databases that they can make
available on older data older studies

also as you

saw earlier in some cases you have to
collect data over very long periods of
time so

at least when youre building these
initially you may require a lot of
time to collect this data

for people working in the pharmaceutical

industry its often helpful to go back
to older studies and take the placebo
arms of studies in related diseases in
order to begin developing these disease
progression model

and also because some of these markers
are quite variable as you saw earlier
the hamilton depression score can have a
lot of variability in it

you often need data from a large number
of subjects to determine parameters
accurately so again going back to larger
available databases that are available
to scientists or in the pharmaceutical
industry historical studies is often a
good place to start in order to be able
to get data thats of sufficient quality
enough patience and over sufficient
period of time that you can begin to
build a very robust model

thank you very much i hope you found
that this information was useful
and if you have any questions please
contact the program coordinator