



# Trial Simulation Modeling in the Era of Comparative Effectiveness Research

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# Topics

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- Describe how CER trials differ from traditional registration trials
- Introduce trial simulation modeling and show why it's more complicated to perform for CER trials
- Demonstrate how to perform trial simulation modeling in context of CER
- Provide case study example to illustrate use of trial simulation model for refinement of study protocol

# Trial Simulation Modeling: The Basics

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- What is it?
  - Development of model based on planned trial design to assist in predicting expected trial outcomes, assessing modifications to study design, etc
- Why do it?
  - Because clinical trials can be costly & risky
  - Modeling can leverage existing information to help refine study design to improve efficiency of trial implementation, reduce risk of bad trial outcome
- How to do it?
  - Several modeling techniques can be used, but patient-level simulation best reflects the context of a trial

# Comparative Effectiveness Research: Implications for Trial Design

Characteristic	Registration Trials	CER Trials
Setting	Experimental	Real-world
Patients	Selected to gain insight on pure treatment effect	Selected to gain insight on real-world treatment effects
Comparator(s)	Usually placebo (if active-control then non-inferiority design)	Active, including non-drug interventions
Measure(s)	“Efficacy”, primarily relevant to investigators & pharmacologists	“Effectiveness”, primarily relevant to patients, providers & payers
Blinding	Always (unless infeasible)	Not always
Follow-up	Usually long enough only to assess intermediate endpoints	Usually long enough to capture full episode of care
Analyses	Usually averaged over all patients, with statistical control of heterogeneity of response	Usually conducted overall & for relevant patient subgroups to assess heterogeneity of response

# Trial Simulation Modeling in CER: Key Elements

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- Prediction equations
- Identifying & handling uncertainty
- Assessing predicted trial outcomes
- Use of model to inform modifications/refinements to CER trial design

# Trial Simulation Modeling in CER: Prediction Equations

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- As with any model, an analytic framework to link inputs to outputs is needed
- In trial simulation modeling, equations that predict patient-level trial results from patient characteristics (demographic & clinical) and treatment assignment are key
- Estimation of the prediction equations can be done based on:
  - Patient-level data from prior trials
  - Observational data (eg, registries, database analyses)
  - Rigorous analysis of published data (eg, network meta-analysis)

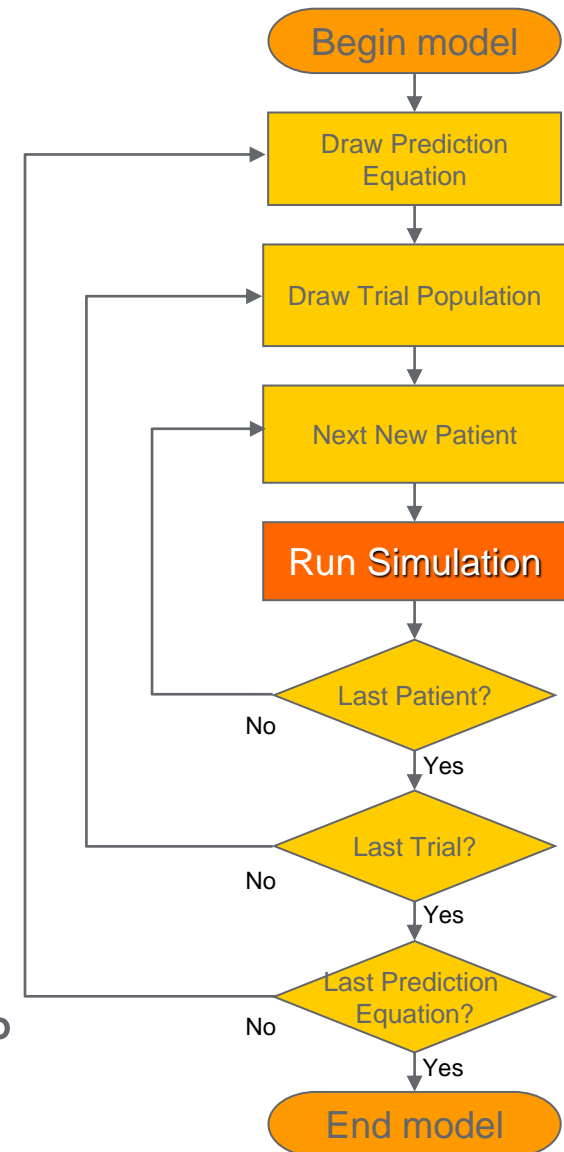
# Trial Simulation Modeling in CER: Handling Uncertainty

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- Clinical trials are subject to two major sources of uncertainty:
  - Between-patient heterogeneity of patient characteristics during sample selection process
  - Within-patient randomness in treatment response
- Trial simulation models are subject to another source of uncertainty:
  - In relationships between patient characteristics, treatment assignment, and treatment outcome (ie, in the prediction equations)
- Trial simulation model needs to account for all three sources of uncertainty; How?
  - Multi-level, nested Monte Carlo simulation

# Trial Simulation Modeling in CER: Multi-Level Monte Carlo Simulation

- Simulation involves three distinct processes:
  1. Drawing of alternative prediction equations
    - Do this R times
    - Captures prediction equation uncertainty
  2. Simulation of trials within a given prediction equation:
    - Do this T times
    - Captures uncertainty about composition of trial sample deriving from heterogeneity in population
  3. Simulation of individual patients within a given trial:
    - Do this P times
    - Captures uncertainty deriving from within-patient randomness in treatment response
- Each model simulation therefore involves R·T·P individual patient simulations





# Trial Simulation Modeling in CER: Assessing Predicted Trial Outcomes

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- For each of the R-T trials in any given simulation, the model should:
  - Predict study measures by treatment group
  - Compute p-values for the predicted treatment group differences
- These computations can then be used to estimate likelihood of various trial outcomes; eg, a given treatment group will be favored:
  - Can include a statistical significance threshold (eg,  $p < .05$ ) and/or
  - Can include effect size threshold to predict clinically significant difference
- Facility to assess predicted trial outcomes in user-defined subgroups also key for CER trials

# Trial Simulation Modeling in CER: Illustrative Example

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- Phase IV CER trial planned for inpatient treatment of skin infections in the United States
- Key elements of planned trial design:
  - Head-to-head comparisons of two antibiotics (Drug A vs Drug B)
  - Primary study measure is hospital length of stay (LOS)
  - Patients required to be hospitalized for the infection, but other elements of inclusion/exclusion criteria open for consideration:
    - » Patient demographics (age, sex, race)
    - » Type & severity of infection
    - » Comorbidity status

# Illustrative Example:

## Specification of Prediction Equations

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- Model prediction equations express LOS as a function of
  - Demographics (age, sex, race)
  - Infection type (wound, abscess, diabetic ulcer, non-diabetic ulcer, other)
  - Infection severity (mild/moderate, severe)
  - Comorbidities (BMI, history of vascular disease, history of diabetes)
- Separate regression equations were specified for Drug A and Drug B so as to capture all treatment-by-factor interaction effects

# Illustrative Example:

## Estimation of Prediction Equations

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- Prediction equations estimated using patient-level data from multi-national phase III trial:
  - Head-to-head comparisons of Drug A vs B
  - Cure was primary study measure; LOS was a secondary measure
- Accelerated failure time analysis was used to estimate the prediction equations, assuming a Weibull distribution for the error term
- A total of  $R=1,000$  prediction equations were estimated, using bootstrapping (with replacement) of the overall trial population ( $n=595$ )

# Illustrative Example:

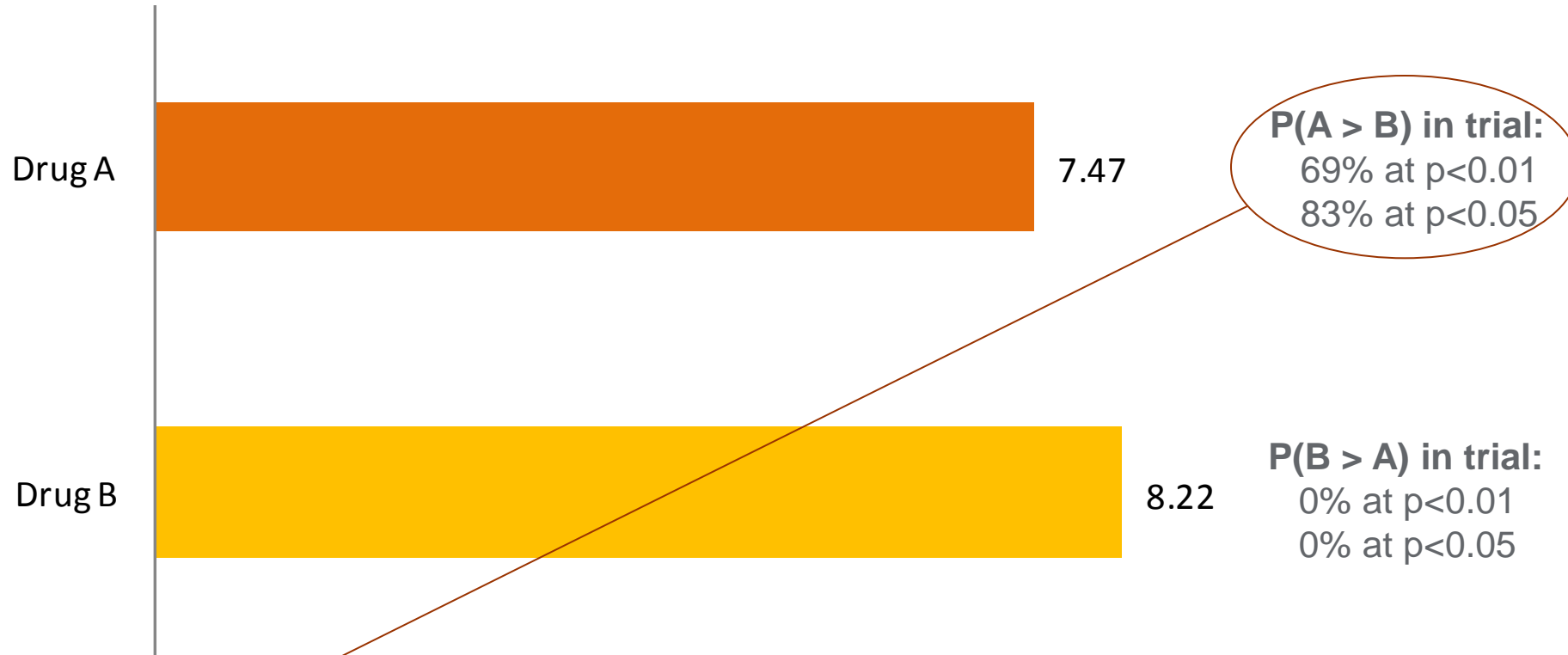
## Model Outputs & Analyses

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- Key model outputs include:
  - Predicted mean LOS for Drugs A & B and predicted mean difference in LOS between treatments
  - Likelihood that predicted mean difference in LOS would favor Drug A or Drug B at p-values of  $<.01$  &  $<.05$
- Key model outputs presented:
  - Over all trial patients
  - User-defined subgroups
- Model also incorporates sensitivity analysis module to identify potential patient inclusion/exclusion criteria that would impact trial results

# Illustrative Example: Predicted Hospital LOS (days)

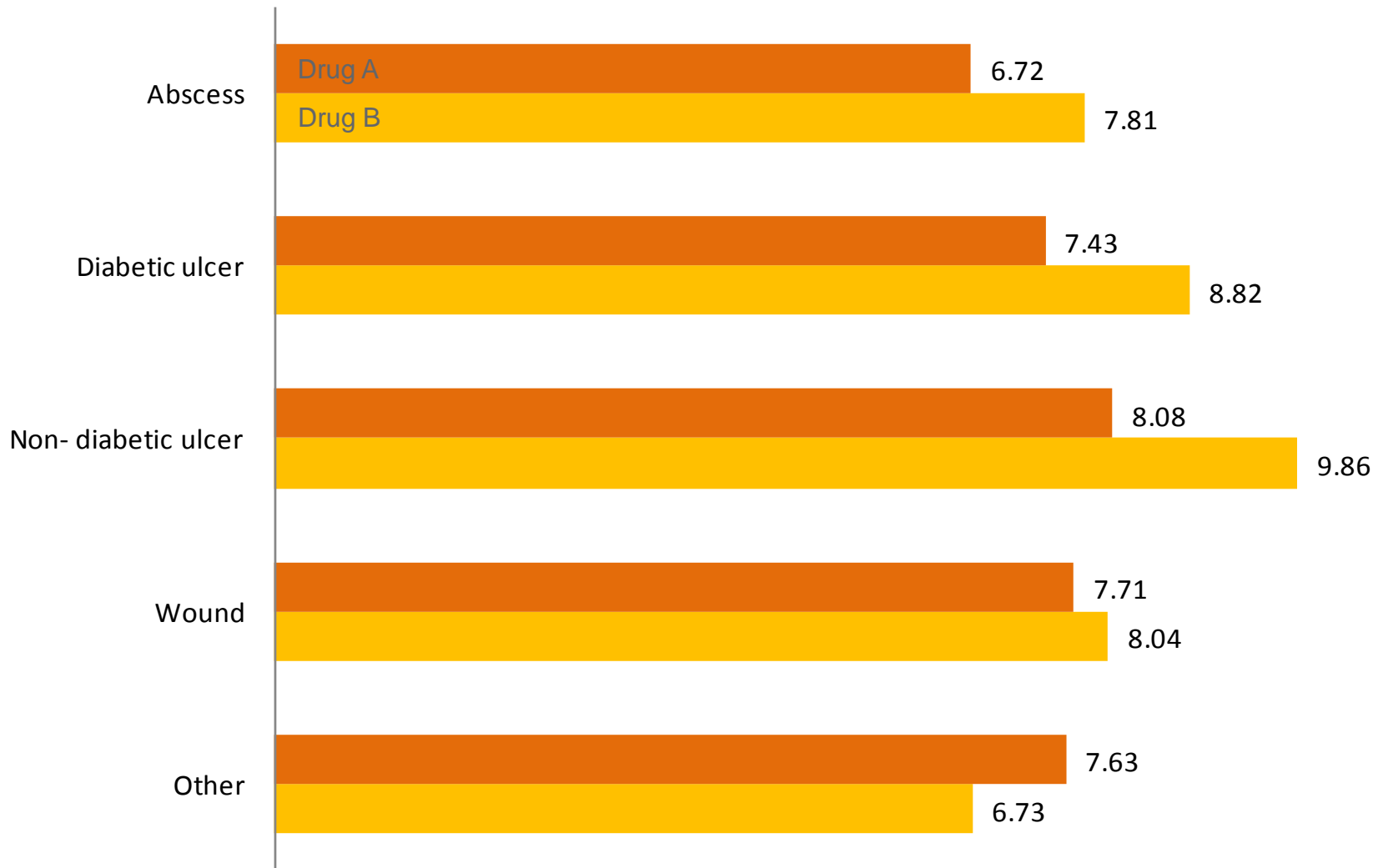
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- Note that  $P(A > B)$  is conceptually similar to statistical power, but model incorporates uncertainty in both effect size & standard deviation, which are usually assumed to be known & fixed in traditional power calculations

# Illustrative Example: Subgroup Analysis of Predicted LOS (days)

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# Illustrative Example: Rank-Ordering of Most Impactful Exclusion Criteria

Patient Characteristic	Subgroup excluded	Drug A	Drug B	Diff (B-A)	P(A > B) at p<0.01	P(A > B) at p<0.05	% of patient population remaining
Primary Diagnosis	Wound	7.29	8.42	1.14	0.948	0.981	56.3%
Vascular Disease History	No	8.26	9.30	1.04	0.679	0.756	20.3%
Severity	Severe	7.12	8.04	0.92	0.822	0.901	42.8%
Gender	Male	7.40	8.32	0.91	0.807	0.892	45.8%
Primary Diagnosis	Other	7.49	8.36	0.87	0.817	0.915	93.3%
BMI	Overweight	7.40	8.27	0.87	0.806	0.905	75.4%
Race	White	7.00	7.82	0.82	0.817	0.913	44.6%
Diabetes History	Yes	7.28	8.09	0.81	0.760	0.873	68.6%
Age	65 plus	7.24	8.02	0.78	0.777	0.887	75.8%
BMI	Obese	7.49	8.26	0.76	0.705	0.839	68.9%
Race	Black	7.70	8.46	0.76	0.651	0.786	71.2%
Age	31 to 64	7.71	8.47	0.76	0.593	0.706	38.2%
Race	Asian	7.50	8.25	0.75	0.698	0.845	99.3%
Age	18 to 30	7.61	8.35	0.74	0.652	0.795	95.9%
Primary Diagnosis	Other	7.57	8.25	0.68	0.632	0.765	85.2%
Severity	Yes	7.29	7.98	0.69	0.671	0.730	74.2%
Primary Diagnosis	Diabetic ulcer	7.50	8.17	0.67	0.590	0.747	88.4%
Diabetes History	No	7.95	8.59	0.64	0.526	0.645	31.4%
Severity	Non-severe	7.77	8.40	0.63	0.520	0.671	57.2%
Gender	Female	7.56	8.19	0.63	0.545	0.695	54.2%
Primary Diagnosis	Abscess	7.75	8.37	0.62	0.478	0.630	74.8%
Primary Diagnosis	Non-diabetic ulcer	7.40	7.99	0.59	0.563	0.730	87.2%
BMI	Normal	7.61	8.20	0.59	0.478	0.623	55.7%

Excluding patients with wounds would increase the predicted difference in LOS ...

as well as the likelihood of a positive trial outcome for Drug A

But would severely limit numbers of patients eligible for enrollment in the study



# Illustrative Example:

## How the Model was Used

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- Model sparked heated debate over refinement of study inclusion/exclusion criteria
- As relates to primary diagnosis:
  - Model results suggest trial would have greater likelihood of success if wounds & other infections were excluded
  - However, these constitute about one-half of all patients hospitalized for skin infections, so concerns about slow enrollment and pigeon-holing of treatment were expressed
- As relates to other patient characteristics:
  - It was recognized that several factors (eg, BMI, history of vascular disease, age) could be correlated with diabetes
  - Study sponsor concerned about limiting study to diabetic population

# Trial Simulation Modeling in CER:

## Limitations

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- As with all modeling efforts, model outputs are only as reliable as the model inputs ... and data limitations can be significant in CER
- Although multi-level Monte Carlo simulation permits handling of some key sources of uncertainty, others may remain (eg, omitted variables in prediction equations)
- Single-variable sensitivity analyses assist in refining patient inclusion/exclusion criteria, but ignore intercorrelations between variables

# Trial Simulation Modeling in CER:

## Conclusions

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- Interest in CER has revitalized a range of methodologic approaches for comparative analysis of medical interventions, including phase IV trials
- Trial simulation modeling has long been a valuable tool for trial planning, but is more complicated to perform for CER trials
- Despite its limitations, trial simulation modeling can help improve the design of CER trials for optimum usefulness of study results

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Muito Obrigado!  
Thank You!

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