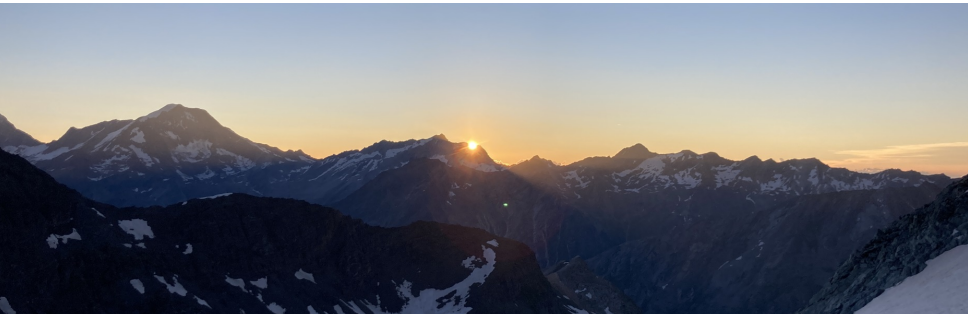

Why clinical statisticians need to know about causal inference

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PSI webinar 19th November 2024



**Claim: clinical statisticians need
to know about causal inference.**

Give me the business case!

Many scientifically valid questions are currently answered making unrealistic assumptions only.

Get out of habits! Ask: **Why** are we doing a certain analysis?

Causal inference appears everywhere in **drug development**.

linkedin post

Why **you need to know
about causal inference.**

Example 1

**Illustration inspired by talk
by Björn Bornkamp.**

2-arm RCT test (T) vs. control (C)

Do responders have longer overall survival?

Test

Control

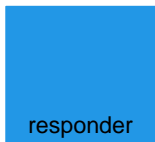


Test





Test



Control



*For every complex problem, there is a solution
that is simple, neat, and wrong.*

H.L. Mencken, American Journalist

**Naive analyses for cohorts built by
postbaseline events are misleading and
do answer causal question only
under unrealistic assumptions.**

**Effect of response, toxicity, dose reduction,
tumor growth inhibition metrics, ADA, ...
on long-term endpoint.**

Principal stratification estimand.

Estimation: Randomization + assumptions.

Assumptions are unverifiable.

Scientific knowledge + sensitivity analyses.

Example 2: table 2 fallacy.

A multivariate sensitivity analysis of PFS will be performed using Cox proportional-hazards regression to assess the treatment effect after adjustment for potential prognostic factors.

Table 2 fallacy: “Adjust for prognostics factors”

Outcome, dependent, effect: y .

Exposure, independent, cause: x .

Regression	Causal inference
“prognostic factor”	Confounder Mediator Proxy confounder Competing exposure

<https://dagitty.net/learn/graphs/roles.html>

Table 2 fallacy: “Adjust for prognostics factors”

...valid estimation of a causal effect requires the delineation of a range of assumptions, both causal and parametric, and there are no reasonable assumptions under which the coefficients of a multivariable regression model simultaneously provide estimates of the causal effects of every variable in the model. If this is understood, it is a short step to ask to what questions, if any, the coefficients of these ubiquitous models provide answers.

Carlin and Moreno-Betancur (2024)

Causal inference tells us which regression model to run.

Example 3: How is causal inference related to the ICH estimands addendum?

ITT?

Causality and ICH E9(R1) addendum

Defines **causal effect** (= estimand) based on potential outcomes – as does causal inference.

Addendum says nothing about **estimation** though.

Five attributes to describe effect of interest:

An Estimand has 5 attributes:



Population



Endpoint



Population-level Summary Measure



Treatment Conditions



Strategies for Intercurrent Events

Past \Rightarrow addendum \Rightarrow causal inference.

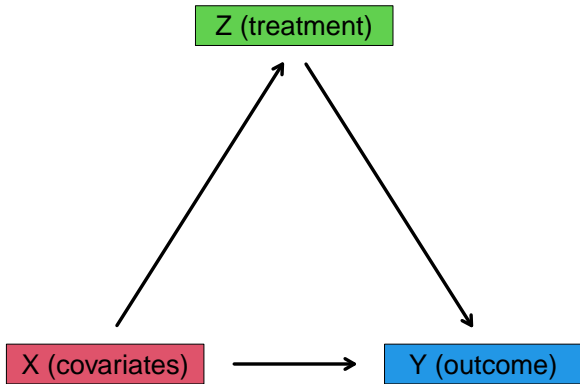
Causality and ITT

- Original ICH E9 introduced **ITT principle** (in 1998):
 - All randomized subjects included in analysis.
 - Effect of a treatment policy can be best assessed by evaluating on the basis of the **intention to treat** a subject rather than the actual treatment given.
 - Not an estimand!
 - “Principle” that refers to analysis sets \Rightarrow entirely pertains to **estimation**.
- Causal inference: ITT = (population) effect of initially assigned intervention.

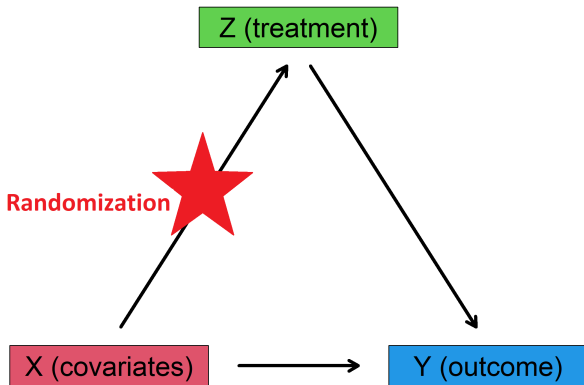
Why **you need to know
about causal inference.**

Example 4

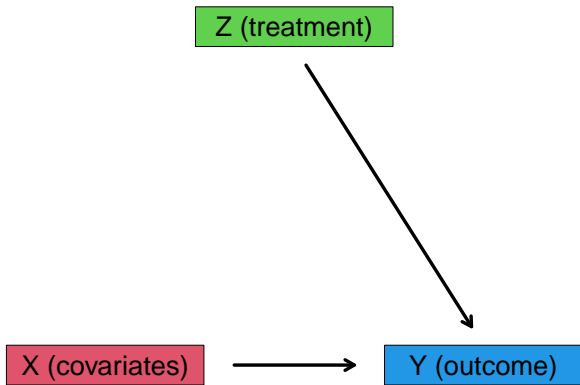
Why do we randomize?



- X: age, comorbidities, disease severity, ... **Confounder**.
- Z: experimental vs. control.
- Y: OS.



- X: age, comorbidities, disease severity, ... **Confounder**.
- Z: experimental vs. control.
- Y: OS.



Causal inference allows mathematical proof, via potential outcomes, that randomization can be used to obtain causal treatment effects.

Why **you need to know
about causal inference.**

Example 5

**Head-to-head comparison in
absence of randomization
using Real-world data.**

Target trial emulation.

**Decisions need to be made even
w/o RCT – maintaining
status quo is also a decision!**

Target trial emulation

- 1 **Ask causal question:** specify protocol of analogous RCT explicitly.
- 2 **Answer causal question:**
 - Identify suitable RWD source(s).
 - Try and emulate RCT using RWD.

Problems with naive analysis of RWD

Asking **wrong or poorly-defined causal question**.

- Explicit representation of causal question as target trial prevents this.

Answering causal question **incorrectly**:

- Not accounting for various biases.
- Not adjusting for relevant confounders.
- Adjusting where we should not.
- Not using appropriate statistical methods.

Result: biased effect estimates, wrong conclusions.

Hernan (2020).

If RCT disagrees with RWD analysis: often, because apples compared to oranges!

Examples and concepts

Example 1: Subgroups built by post-baseline variable. **ICH E9 addendum, POs.**

Example 2: Which regression model to run. **DAGs.**

Example 3: How is causal inference related to the **ICH estimands addendum? ITT?**

Example 4: Why do we randomize? **Potential outcomes.**

Example 5: H2H comparison with RWD. **Target trial framework.**

Structured way to think about:

- **Generalizability:** extending causal effect from RCT to RCT's original target population.
- **Transportability:** extending causal effect from RCT to distinct population.

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Get out of habits! Ask: **Why** are we doing a certain analysis?

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linkedin post

Thank you for your attention.

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Slides can be downloaded on

www.kasparrufibach.ch

References I

- ▶ Carlin, J. B. and Moreno-Betancur, M. (2024). On the uses and abuses of regression models: a call for reform of statistical practice and teaching.
<https://arxiv.org/abs/2309.06668>
- ▶ Hernan, M. (2020). Head-to-head comparisons using real-world data.
Presentation via Cytel.

R version and packages used to generate these slides:

R version: R version 4.3.2 (2023-10-31 ucrt)

Base packages: stats / graphics / grDevices / utils / datasets / methods / base

Other packages: prodlim

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