Defining estimand for win ratio

How to separate true effect from censoring

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Outline

- Background
- Censoring's impact on estimand
 - Time frame of comparison
- Two approaches to clarity
 - **Nonparametric**: fix the time frame
 - Semiparametric: posit a time-constant feature
- Summary and discussion

Introduction

Composite Endpoint

Traditional composite endpoint (TCE)

- Time to first event
 - Major adverse cardiac event (MACE): death, heart failure, myocardio-infarction, stroke, etc.
- Limitations:
 - Lack of clinical priority
 - Statistical inefficiency (waste of data)
- Hierarchical composite endpoint (HCE)
 - Example: Death > nonfatal MACE > six-minute walk test (6MWT)/ NYHA class

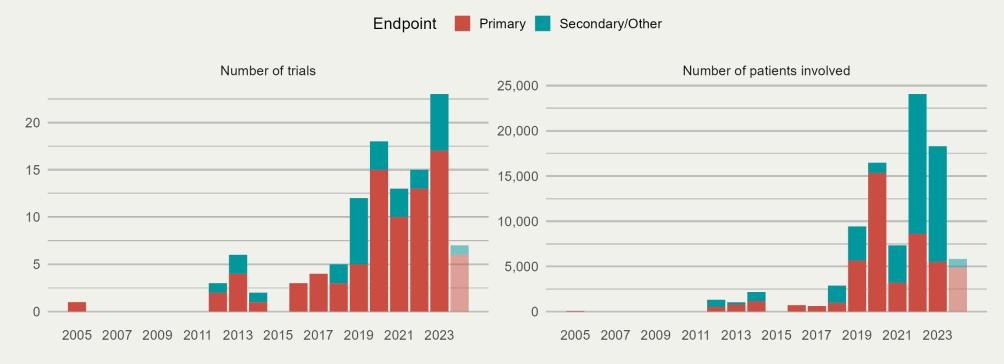
Win Ratio: Basics

- A common approach to HCE
 - Proposed and popularized by Pocock et al. (2012)
 - Treatment vs control: generalized pairwise comparisons
 - Win-loss: sequential comparison on components
 - Longer survival > fewer/later nonfatal MACE > better 6MWT/NYHA score
 - **Effect size**: WR = wins / losses
- Alternative metrics
 - **Proportion in favor** (net benefit): PIF = wins losses
 - Win odds: WO = (wins + 2^{-1} ties) / (losses + 2^{-1} ties)

Win Ratio: Gaining Popularity

• More trials are using it...

Registered trials by start year
With win ratio-like approach to hierarchical composite endpoints



Source: ClinicalTrials.gov as of December 2023

Estimand vs Censoring

An Important Caveat

- WR's estimand depends on censoring ...
 - Luo et al. (2015), Bebu & Lachin (2016), Oakes (2016), Mao (2019),
 Dong et al. (2020a), Li et al. (2024), etc.
- What is an estimand?
 - Population-level quantity to be estimated
 - o Population-mean difference, (true) risk ratio, etc.
 - Specifies how treatment effect is measured
 - **ICH E9 (R1) addendum**: estimand construction one of the "central questions for drug development and licensing" (ICH, 2020)

Time Frame of Comparison

- Cause of dependency on censoring
 - Censoring → time frame of comparison → magnitude of win/loss probabilities

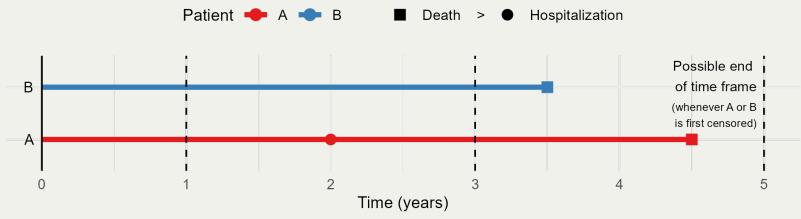
• Example

- Pair 1: one patient censored at year 1, the other > 1 year
 - Compared over [0,1] year
- Pair 2: neither patient censored until year 5
 - \circ Compared over > [0, 5] years
 - \circ More events \rightarrow fewer ties \rightarrow higher win/loss proportions
 - Prioritized components more likely conclusive, harder to pass

Win-Loss Changes with Time

• Illustration

Win-loss status, and deciding component, changes with time



Year 1: Tie; Year 3: B wins on hospitalization; Year 5: A wins on death

- Longer follow-up ...
 - Parameters: win/loss proportions ↑ (WR uncertain); tie proportion ↓
 - ∘ **Relative contribution**: prioritized ↑; deprioritized ↓

Trial-Dependent Estimand

Actual estimand

- Average WR mixing shorter-term with longer-term comparisons
- Weight set (haphazardly) by censoring distribution
 - \circ Staggered entry, random withdrawal \rightarrow non-scientific

• Testing vs estimation

- **Testing (qualitative)**: okay
 - \circ Valid under H_0 , powerful if treatment *consistently* outperforms control over time
- Estimation (quantitative): not okay
 - Needs a generalizable target quantity (scientific estimand)
 - Unaffected by length of trial, rates of patient accrual/loss to follow-up, etc.

Two Approaches to Meaningful Estimand

General Strategies

- Goal: a meaningful, generalizable WR estimand
 - Unaffected by censoring distribution
- Key strategy
 - Be *proactive* on time frame of comparison
- Approaches
 - Choose a fixed time (nonparametric)
 - Model time trajectory with a constant parameter (semiparametric)

Time Restriction - Univariate

Outcome data

• $D^{(a)}$: survival time for a patient in group a (1: treatment; 0: control)

$$\circ \ S^{(a)}(t) = P(D^{(a)} > t)$$

• Time restriction: a familiar concept

- *Five-year* survival rate of breast cancer patients
 - \circ Estimand: $S^{(1)}(\tau) S^{(0)}(\tau)$
- *Five-year* average survival time
 - \circ Estimand: $E\{\min(D^{(1)}, \tau)\} E\{\min(D^{(0)}, \tau)\}$
 - Restricted mean survival time (RMST)
- Restriction time $\tau = 5$ years (pre-specify)

Time Restriction - WR

- Two-tiered composite
 - $D^{(a)}$: survival time; $T^{(a)}$: time to (first) nonfatal MACE
- Restricted win/loss probability
 - Image all patients followed up to τ

$$w_{a,1-a}(au) = \underbrace{P\{D^{(1-a)} < \min(D^{(a)}, au)\}}_{ ext{win on survival}} + \underbrace{P\{\min(D^{(1)},D^{(0)}) > au,T^{(1-a)} < \min(T^{(a)}, au)\}}_{ ext{tie on survival, win on nonfatal event}}$$

■ Restricted WR: WR(au) = $w_{1,0}(au)/w_{0,1}(au)$

Time Restriction - Estimation

General case

- Formulate win/loss probability as function of time based on uncensored outcomes
- Pick restriction time τ
- Estimation: must handle censoring properly
 - Inverse probability censoring weighting (IPCW, Dong et al., 2020b, 2021)
 - **R-package**: WINS (Cui & Huang, 2023)
 - **Multiple imputations** for data censored before τ (T. Wang et al., 2023, 2024)

Time Restriction - A Variation

• Take time difference into account

- $w_{a,1-a}(\tau)$: win probability by $\tau \to \text{average win time by } \tau$
- Restricted mean time in favor: $w_{1,0}(\tau) w_{0,1}(\tau)$ (Mao, 2023)
 - R-package: rmt (rmt?)
 - \circ **Colon cancer trial**: levamisole + fluorouracil (n = 304) vs control (n = 314)

Table 1: Restricted mean times in favor of treatment in a colon cancer trial by $\tau = 7.5$ years.

	Estimate (yrs)	95% CI (yrs)	P-value
Death	0.62	(0.20, 1.04)	0.004
Recurrence	0.35	(0.21, 0.49)	< 0.001
Overall	0.97	(0.47, 1.46)	< 0.001

Temporal Modeling

- Cox proportional hazards (PH) model
 - Time-varying hazard $\stackrel{\text{PH}}{\longrightarrow}$ time-constant hazard ratio (global effect)
 - Checking proportionality: score residuals
- A proportional win-fractions (PW) model
 - Time-varying win-loss probability \xrightarrow{PW} time-constant win ratio (global effect) (Mao & Wang, 2021; T. Wang & Mao, 2022)

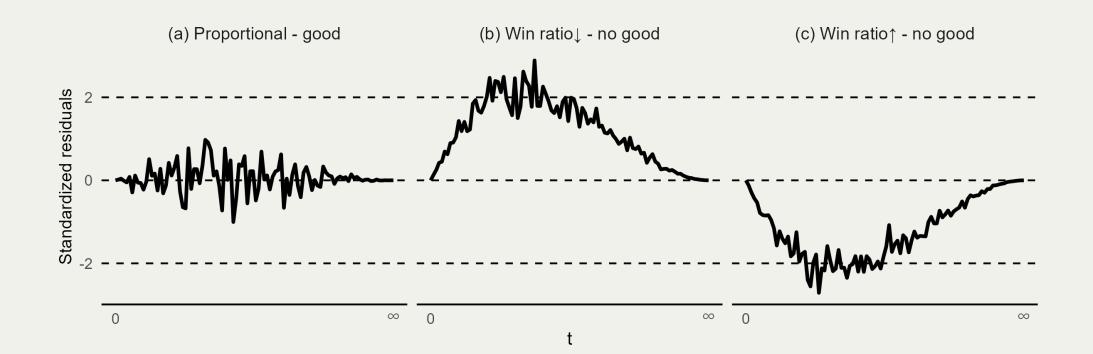
$$rac{w_{1,0}(t)}{w_{0,1}(t)} = \exp(heta) ext{ for some } heta ext{ and all } t$$

- $\circ \exp(\hat{\theta})$: standard or time-weighted WR statistic
- R-package: WR (WR?)

Checking Proportionality

Cumulative residuals

 $\hat{resid}(t) = (Observed wins by t) - (Model-based wins by t)$



Covariate Adjustment

• HF-ACTION trial

Exercise training (n = 1051) vs usual care (n = 1054)

$$rac{w_{z,z'}(t)}{w_{z',z}(t)} = \exp\{ heta(a-a') + eta^{\mathrm{T}}(x-x')\} ext{ for all } t$$

■ **Covariates** *x*: sex, etiology, CPX, medical history, etc.

Table 2: Multiple PW regression for death > hospitalization in HF-ACTION.

	Win ratio	95% CI	P-value
Training v usual	1.06	(0.95, 1.19)	0.275
Male vs female	0.72	(0.63, 0.82)	< 0.001
Ischemic vs non-ischemic	0.87	(0.76, 0.98)	0.027
CP exercise test (minute)	1.11	(1.09, 1.13)	< 0.001
Atrial fibrillation	0.80	(0.70, 0.92)	0.002

Conclusion

Summary

- How to separate true effect from censoring
 - Make a conscious choice on time frame of comparison
 - Fix it (nonparametric) or model it (semiparametric)
- Time restriction vs temporal modeling
 - **Restricted win-loss**: model-free estimand, less efficient (WINS, rmt)
 - **PW regression**: may be more efficient *if proportionality (constant WR) holds* (WR)
- Combine the two
 - IPCW + working model for locally efficient estimation?
 - Nonparametric estimand but semiparametric inference

Future Work

Sample size estimation

- Standard tests: Gasparyan et al. (2021), Mao et al. (2022), Yu & Ganju (2022), B. Wang et al. (2023), etc.
- Restricted WR: ??

• Intercurrent event

- Treatment non-response/toxicity/discontinuation (ICH, 2020)
- Hypothetical: win/lose had treatment continued → imputation?
- **Composite**: death > *treatment failure* > lesser events?
- Principal strata: win/lose among those who would not experience treatment failure if assigned to either group (identifiability)

For More

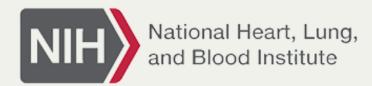
Main paper

Mao, L. (2024). Defining estimand for the win ratio: separate the true effect from censoring. *Clinical Trials*, 21, 584-594. https://doi.org/10.1177/17407745241259356

• Slides URL: https://lmaowisc.github.io/ce/win_ratio_estimand.html

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