Addressing Administrative Withdrawals in Clinical Trials in Estimation under the Treatment Policy Strategy This is a joint work with Rong Liu (Eli Lilly and Company)
Disclaimer: The views expressed in this presentation should not be construed to represent those of
U.S. Food and Drug Administration.

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Estimand framework [ICH E9 (R1)]

Use a mix of strategies to handle ICEs in a study (Darken et al., 2020; Qu et al., 2020)

- One common drawback in most current clinical studies is that only ONE strategy is used to handle all ICEs
- Strategies for handling ICEs should be based on the underlying reasons
	- ICEs due to AE
	- ICEs due to lack of efficacy (LoE)
- ICEs due to administrative reasons (relocation, family situation changed, COVID-19 control measures, geographical conflict, sanctions, etc.) • ICEs due to lack of efficacy (LoE)

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• ICEs due to administrative reasons (relocation, family situation changed, COVID-19

control measures, geographical conflict, sanctions, etc.)

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	- ICEs due to sufficient efficacy or disease curation

ICEs, intercurrent events

Treating administrative study withdrawals as censoring treatment discontinuations

- In real world, those administrative study withdrawals will not impact patients' adherence status
	- For example, scheduling conflict may prevent a patient participating in the clinical trials due to frequent clinical visits, but it should not prevent patients taking marketed medications in real life
- It automatically handles the unusual circumstances (pandemic, geographical conflicts, natural disasters, etc.) marketed medications in real life

• It automatically handles the unusual circumstances (pandemic,

geographical conflicts, natural disasters, etc.)

• E.g., during the COVID pandemic, many protocols or statistical analysi
	- E.g., during the COVID pandemic, many protocols or statistical analysis plans were amended to handle the COVID related study/treatment discontinuation differently

Different ICEs and study withdrawals are competing events!

Illustration of intercurrent events, study withdrawal, and missing data

Notation

- Y: the outcome
- X: baseline covariates
- U: time to treatment discontinuation
- V: time to study withdrawal (V censors U!)
- D: type of study withdrawal ($D = 0$ for study withdrawal being possible related to study medication or disease severity; $D = 1$ otherwise) • V: time to study withdrawal (V censors U!)

• D: type of study withdrawal (D = 0 for study withdrawal being possible

related to study medication or disease severity; D = 1 otherwise)

• R: missingness indicator (R = 1
- R: missingness indicator ($R = 1$ for being missing; $R = 0$ for being observed)
- $U(i)$: the potential outcome for U if assigned to treatment *i, i* = 0 for control treatment, $i = 1$ for the experimental treatment

Assumptions

- For Scenarios 3 and 4, assume the outcome and the study discontinuation scenario 2
Scenario 3 are independent: $Y(i) \perp V(i) | V(i) > U(i)$
- For Scenario 5.1, assume the treatment scenario 5 discontinuation occurs at the same time as study withdrawal : $Pr{U(i) =$
- For Scenario 5.2, assume the treatment discontinuation censored by study withdrawal: $V(i) \mathbb{I}{U(i), Y(i)} | D(i) = 1$

- Method A: Using the non-missing values for those who are adherent to the assigned treatment to impute the missing values due to study withdrawal.
- Method B: Using the *retrieved dropouts* to impute the missing values due to study withdrawal $\frac{1}{2}$
 $\frac{1}{2}$ is the study withdrawal
 $\frac{1}{2}$
 $\frac{1}{2}$

Imputation Steps:

- Missing data in Scenario 2 is imputed by data $\frac{1}{\text{Scenario 2}}$ from Scenario 1 assuming missing at random (MAR)
- Missing data in Scenarios 4 and 5.1 may be
Scenario 5 imputed by the "retrieved dropouts" in Scenario 3
- For Scenario 5.2
	- Using Kaplan-Meier estimator to estimate the survival function for V and calculate the conditional probability of treatment discontinuation at study end, say p
	- Generate a Bernoulli random variable ζ retrieved dropouts to impute; otherwise, use adherers to impute

Imputation Steps:

- Missing data in Scenario 2 is imputed Scenario 2 by data from Scenario 1 assuming scenario 3 missing at random (MAR)
- Missing data in Scenarios 4 and 5.1 Scenario 5 may be imputed by the "retrieved dropouts" in Scenario 3
- Missing data in Scenario 5 may be imputed by all data (observed and imputed) in Scenarios 1, 2, 3, 4, and 5.1.

Simulation

Generating the response under the treatment policy strategy

Simulating treatment discontinuations and missing values

Average Percentage of Subjects in Each Scenario out of 5000 Simulations

RL0

RL0 [@Yongming Qu] I added the % of pts in each scenario. I do not know how you want to present the mean value across the simulations. I just pasted them in another table below. See if you like it. Rong Liu, 2024-05-30T23:37:07.970

Simulation results (10000 simulated samples, 10 multiple imputations for each simulated data)

Notations and abbreviations: BIAS, empirical bias; CP, 95% empirical coverage probability; ASE, mean standard error estimates of the mean; ESE: standard deviation of the estimates;

ASE and CP were based on Rubin's rule to combine the between and within imputation variabilities

Bootstrap inference was not provided due to insufficient numbers of retrieved dropouts in some bootstrap samples

- This simulation setting shows the performance was similar between Methods A, C, and D. More simulation studies are needed to better understand the performance of these estimators
- In Method C, the time to treatment discontinuation was estimated using Kaplan-Meier estimator, which does not adjust for baseline covariates. This method needs further improvement (adjusting for baseline covariates).

Handling missing values considering study withdrawal without imputation

- For Scenarios 3 and 4, assume the outcome and the study discontinuation are independent: $Y \perp V(i) | V(i) > U(i)$
- For Scenario 5.1, assume the treatment discontinuation occurs at the same time as study withdrawal : $Pr{U(i) = V(i) | V(i) > U(i), D(i) = 0} = 1$
-

This analytic method is under further development and will be shared in the future

Application

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- Primary analysis variable: change in HbA1c from baseline to 52 weeks

• We consider "Lost to Follow-Up" and "Withdrawal by Subject" as administrative study withdrawals that are not related to efficacy and safety

study withdrawals and the set of the set o

N = number of randomized subjects

RL1

- RL0 [@Yongming Qu] I have changed your number from 466 to 307 here. Rong Liu, 2024-05-30T19:52:26.338
- RL1 [@Yongming Qu] added this footnote.

Rong Liu, 2024-05-30T20:01:53.890

Treatment discontinuation and missing values

RL0 [@Yongming Qu] I summarized based upon pts who have baseline value. So it does not add up to total N. Rong Liu, 2024-05-30T20:03:00.776

Results

Observed mean change in HbA1c for adherers (Scenario 1): -0.236 for insulin glargine and -0.672 for insulin peglispro Observed mean change in HbA1c for retrieved dropouts (Scenario 3): -0.060 for insulin glargine and -0.031 for insulin peglispro

Better collection of treatment discontinuation and study withdrawal

Current widely used case report form (CRF) for treatment discontinuation

Treatment discontinuation

Study withdrawal

What was the subject's Document the **COMPLETED** \circ **ADVERSE EVENT. LINK TO ADVERSE EVENT:** subject's status for status? \circ the study. If the subject **DEATH** \circ discontinued study **PREGNANCY** \circ **DS.DSDECOD** prematurely, **PROTOCOL DEVIATIONS** \circ record the primary DID NOT MEET STUDY ELIGIBILITY CRITERIA AT \bullet reason for **ENROLLMENT** discontinuation.
 DISOSTERM
 DISOSTERM
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 CHEOULE CONFILETS OR DIFFICULTY

TRAVELING TO SITE.

THE CALC ON THE SITUDY

PERSONALY REASONS NOT RELATED TO

DRUG/DEVICE
 CHEOULE CONFILE AND TRAVE

Summary

- Handling treatment discontinuations due to administrative study withdrawal differently from other intercurrent events has two major benefits
	- Better reflects the real clinical practice
	- Automatically handles unusual situations
- We used multiple imputation to impute the missing values due to study withdrawal differentially by considering the competing risks between study withdrawal and treatment discontinuations
	- There were little difference in the estimates in the simulation without and with considering the competing risk for administrative censoring (Methods A and D)
	- Further simulation studies are needed to understand the difference between Methods A and D
- The current data collection standards for treatment and study discontinuations need to be improved withdrawal differentially by considering the competing risks between study
withdrawal and treatment discontinuations

• There were little difference in the estimates in the simulation without and with

considering the com
	- PHUSE working group "Optimizing the Use of Data Standards" is tackling this problem
- **References**
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