

Simulating In-Silico Clinical Research Using Diverse Real-World Data



Chetan Paul, M.S. (FDA ORA)
Sarangan Ravichandran, PhD., PMP

Introduction/Hypothesis



- Using Real-World-Data (RWD), develop in-silico models for rapidly identifying repurposed drugs that can lower the risk of death due to Sars-CoV-2 infection
- Risk of death due to COVID-19 is predominantly due to hyperactive host inflammatory responses resulting from infection

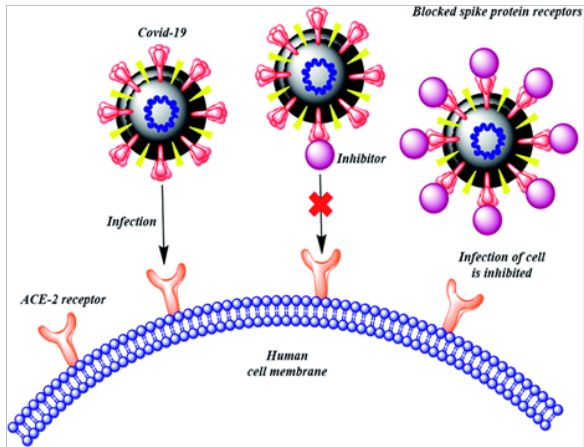


Fig 2 from <https://doi.org/10.1039/D0RA04795C>

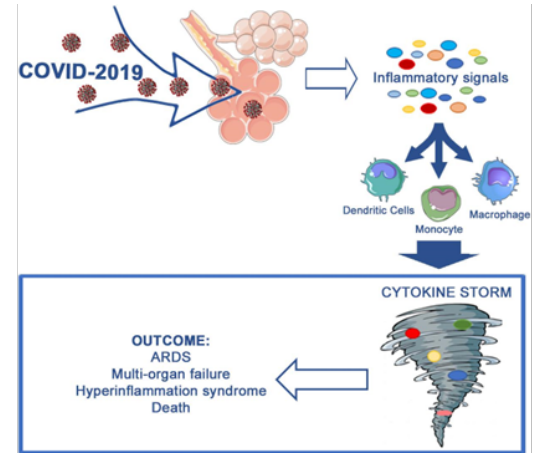
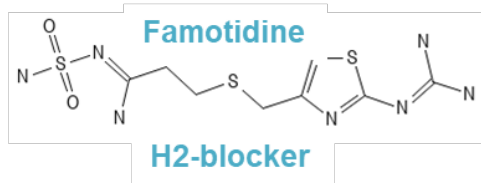
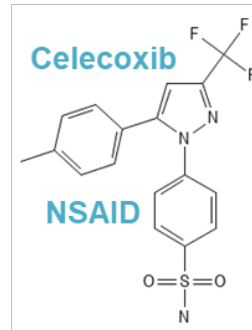


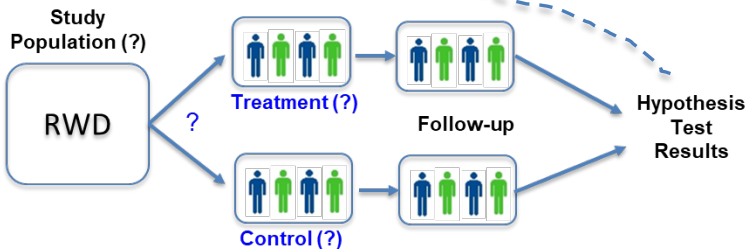
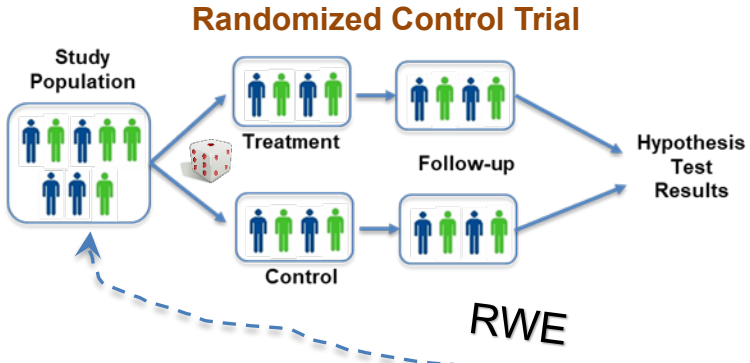
Fig1 from <https://doi.org/10.3389/fimmu.2020.02132>

COVID-19 Real-World-Data Sources

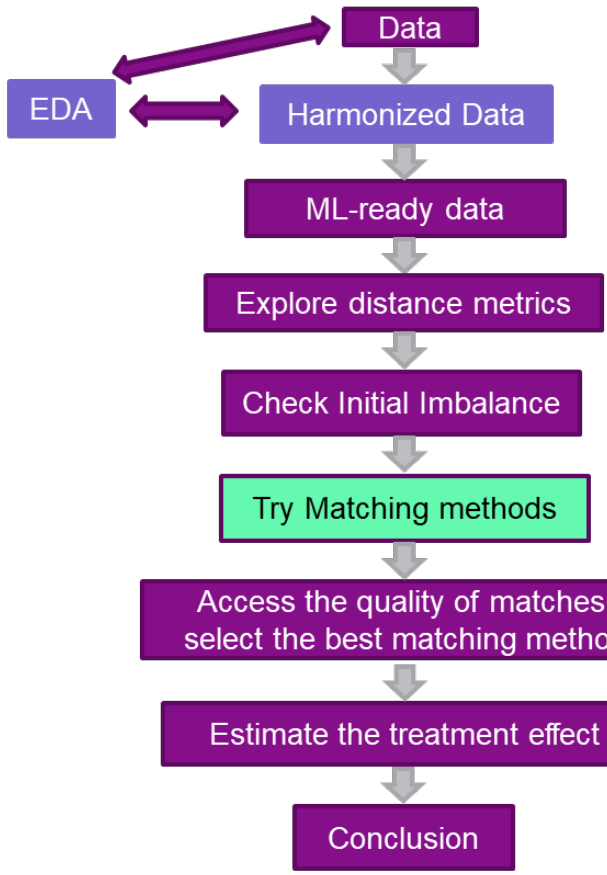
- Two appropriate RWD sources were chosen to model the causal effect of Celecoxib/Famotidine in COVID-19 patients
- Hospital data*
 - Patients (aged 18 years or older)
 - in/out-patients with documented COVID-19 diagnosis from 6/1/2020 – 1/31/2021
- Pharmacy data*
 - 120-day lookback from each patient's earliest hospital visit with a COVID-19 diagnosis

* IQVIA Hospital Charge Data Master; IQVIA Longitudinal Prescription database (LRx)

Causal Treatment Effect Modeling



Areas of focus	Solution
Identify study population, randomization, and removing confounding	Inclusion-exclusion, matching, and DAG



RWD: Real-World-Data
RWE: Real-World-Evidence
EDA: Exploratory Data Analysis
ML: Machine-Learning
DAG: Directed Acyclic Graph

Nearest-neighbor, optimal

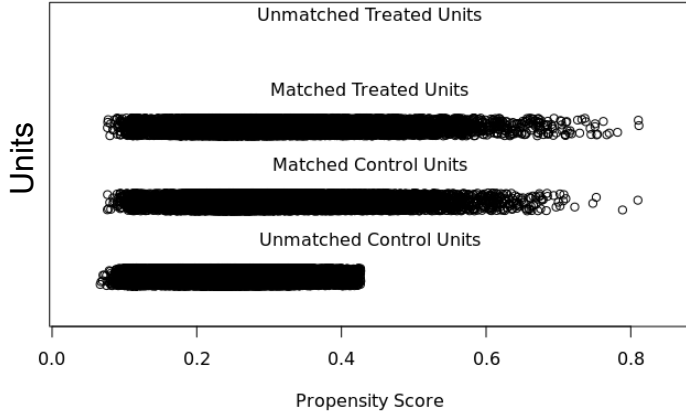
t-test, McNemar's test

Results

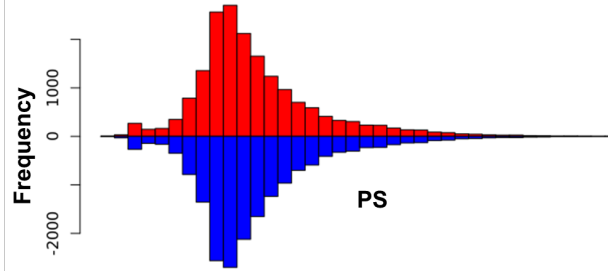
$$\text{Propensity Score(PS)} = \pi_i = P(\text{Trtmnt} = 1 | X_i) \text{ (for a person } i \text{)}$$



Distribution of Propensity Scores



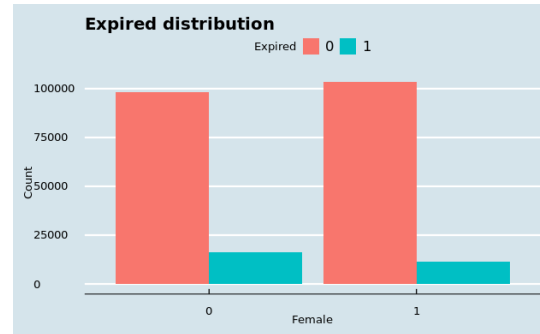
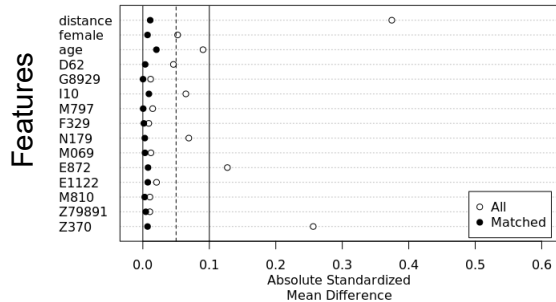
Propensity Score (PS), Red: Treatment vs Blue: No-Treatment



Results shown for Famotidine;
Celecoxib results are similar

$$SMD = \left(\frac{\bar{x}_{treatment} - \bar{x}_{control}}{\sqrt{\frac{s_{treatment}^2 + s_{control}^2}{2}}} \right)$$

Estimating Balancing
(few features are displayed)



This Photo licensed under [CC BY-NC-ND](#) or [CC BY-SA](#) or [CC BY-SA-NC](#)

Findings

In both treatment options, among the discordant pairs, we see that there is a bigger number where the treated is the person who died, so this suggests that the treated group is at higher risk.

Paired-Outcome Observations

		Treatment	
		$Y^0=0$	$Y^0=1$
Control	$Y^1=0$	a	c
	$Y^1=1$	b	d

$H_0: p_b = p_c$; $H_A: p_b \neq p_c$
 $p = \text{proportion}$; $\alpha: 0.05$; 2-sided



Exact McNemar Test

Run	Celecoxib				Famotidine			
	N	OR	CI (95%)	P-value	N	OR	CI (95%)	P-value
1	1013	2.3870	1.5498, 3.7573	3.276e-05	17916	2.400	2.2254, 2.5898	< 2.2e-16
2	999	4.5882	2.6903, 8.2730	1.642e-10	17892	2.5143	2.3304, 2.7145	< 2.2e-16
3	1019	2.0000	1.3148, 3.0927	8.200e-04	17622	2.5978	2.4045, 2.8085	< 2.2e-16
4	1026	2.3636	1.5545, 3.6669	2.326e-05	17897	2.4851	2.3029, 2.6833	< 2.2e-16
5	1046	2.4838	1.6175, 3.9002	1.115e-05	17916	2.5967	2.4056, 2.8050	< 2.2e-16

R libraries

tableone
 matching
 ipw
 survey
 tidyverse
 Matchit
 sandwich

Conclusions



- We have created a procedure to emulate an in-silico randomized control trial for estimating the causal treatment effects
- Our matched case-control study results for both Celecoxib and Famotidine show $OR > 1$ indicating that the exposure is associated with higher odds of death for COVID-19 patients
- This procedure can help shorten drug development, review and approval timelines, eliminate bias in data and adequate representation of trial population
- The RWE Methods pipeline can be expanded to add additional methods for new use cases like drug safety, and sequencing

OR: Odds Ratio; **MSM:** Marginal Structural Model; **IPTW:** Inverse Probability Treatment Weighting

Thank you!



U.S. FOOD & DRUG
ADMINISTRATION