

Large-scale evidence generation across a network of databases (LEGEND) for hypertension

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Current knowledge base for hypertension

Head-to-head antihypertensive drug comparisons



- Trials: 40
- *N* = 102 [1148] 33K

- Driven primarily by ALLHAT
 - just 3 individual drugs
- Focus: efficacy \gg safety
- New RCTs too expensive

Can we provide

- 1. reliable / reproducible concordant extant w/ RCTs
- 2. rich across "all" comparators, outcomes
- 3. relevant inform practice evidence?



Observational research estimates in literature

29,982 drug safety estimates from 11,758 papers



85% have reported *p* < 0.05</p>

• Also note unusual peak along boundary

What is going wrong?

- Observational bias (confounding, selection, measurement error)
- Publication bias
- *p*-hacking (one study at a time)
- Reproducibility across populations



Large-scale evidence generation across a network of databases (LEGEND)

- Aims to generate reliable evidence on the effects of medical interventions using observational healthcare data
- 10 guiding principles; chief among these:
 - Generate at large-scale (completeness, empirical calibration)
 - Systematically driven by best-practices
 - Disseminate everything (open science)





No one person has all the necessary skills



Best-practices: systematic design





Observ. study for comparing two initial therapies



Index: Time zero



Comparison of hypertension treatments



- 39 mono-drugs, 13 mono-classes
- 58 duo-drugs, 32 duo-classes
- 10,278 comparisons

	Theoretical	Observed (n > 2,500)
Single ingredients	58	39
Single ingredient comparisons	58 * 57 = 3,306	1,296
Single drug classes	15	13
Single class comparisons	15 * 14 = 210	156
Dual ingredients	58 * 57 / 2 = 1,653	58
Single vs duo drug comparisons	58 * 1,653 = 95,874	3,810
Dual classes	15 * 14 / 2 = 105	32
Single vs duo class comparisons	15 * 105 = 1,575	832
Duo vs duo drug comparisons	1,653 * 1,652 = 2,730,756	2,784
Duo vs duo class comparisons	105 * 104 = 10,920	992
Total comparisons	2,843,250	10,278



Best-practices: systematic large-scale PS



- >8,000 (regularized) baseline patient characteristics (all dx, rx, tx)
- Address observed (and some unobserved BP control) confounding (Tian et al, 2019, IJE)



Of course, not all comparisons are valid



- Evaluation of propensity score (PS) distributions and covariate balance
- Here: poor empirical clinical equipoise



Best-practices: 58 expert-crafted outcomes

Effectiveness (10): acute MI, heart failure, strokeSafety (48): known side-effects

Phenotype	Logical description	Supporting references
Abdominal pain	Abdominal pain condition record of any type; successive records with > 90 day gap are considered independent episodes	456
Abnormal weight gain	Abnormal weight gain record of any type; successive records with > 90 day gap are considered independent episodes; note, weight measurements not used	7
Abnormal weight loss	Abnormal weight loss record of any type; successive records with > 90 day gap are considered independent episodes; note, weight measurements not used	8
Acute myocardial infarction	Acute myocardial infarction condition record during an inpatient or ER visit; successive records with > 180 day gap are considered independent episodes	9 10 11 12 13 14
Acute pancreatitis	Acute pancreatitis condition record during an inpatient or ER visit; successive records with >30 day gap are considered independent episodes	15 16 17 18
Acute renal failure	A diagnosis of acute renal failure in an inpatient or ER setting; must be at least 30d between inpatient/ER visits to be considered separate episodes	19 20 21 22 23 24 25 26

	Theoretical	Observed (n > 2,500)
Outcomes of interest	58	58
Target-comparator-outcomes	2,843,250 * 58 = 164,908,500	587,020



76 negative outcome controls (not caused by either treatment) help expose and control residual bias. Example: ingrown toenail



p-value empirical calibration models residual bias as exchangeable and adjusts for a (possibly) non-0 mean. (Schuemie et al, 2018, PNAS)



Network of data sources



- US insurance databases
 - IBM MarketScan CCAE
 - IBM MarketScan MDCR
 - IBM MarketScan MDCD
 - Optum Clinformatics
- Japanese insurance database: JMDC
- Korean insurance database: NHIS-NSC
- US EHR databases
 - Optum EHR
 - Columbia University Medical Center
- German EHR database: IQVIA DA Germany

Account for population/practice heterogeneity (Madigan et al, 2013, AJE) Improve generalizibility





- Best-practices systematic design, evaluation and empirical calibration return near nominal performance
- Provide a more complete and reliable evidence basis



Unbiased LEGEND dissemination

LEGEND Basic Viewer

About Specific research questions										
Indication	Show 15 📴 e	ntries								
Hypertension 👻	Analysis		🌵 Data sou	rce 0 HR	0 LB	0 UB	0 P 0 G	al.HR 🕴 Cal.LI	B 🕴 Cal.UB	🍦 Cal.P 🛛 🕴
	PS stratification,	on-treatment	CCAE	1.78	1.35	2.31	0.00 1.	72 1.32	2.28	0.00
Exposure group	PS stratification,	on-treatment	Meta-ana	ysis 1.39	1.04	1.84	0.02 1.	34 1.03	1.74	0.03
Drug or procedure *	PS stratification,	on-treatment	Optum	1.32	0.95	1.79	0.08 1.	36 1.01	1.84	0.04
Include combination exposures	PS stratification,	on-treatment	Panther	1.10	0.80	1.48	0.54 1.	00 0.75	1.36	0.79
Target	Showing 1 to 4 o	f 4 entries							Previou	us 1 Next
Chlorthalidone *	Power Pr	opensity scores	Covariate balance	Systematic error	Forest (lot				
Comparator	Table 1a. Numbe comparator (Hvd	r of subjects, follo rochlorothiazide) a	w-up time (in years), nu roup after stratification,	mber of outcome ev as well as the minim	ents, and ev ium detecta	ent incider ble relative	nce rate (IR) p risk (MDRR).	er 1,000 patient year Note that the IR doe	s (PY) in the target (s not account for ar	Chlorthalidone) and w stratification.
Hydrochlorothiazide •	т	arget Cor	nparator Target	Comparator	Target	Cor	mparator	Target IR (per	Comparator IR	(per
Outcome	Source si	ubjects sub	jects years	years	events	eve	ents	1,000 PY)	1,000 PY)	MDRR
	Optum 7,	600 187	,991 4,952	130,195	43	811	1	8.68	6.23	1.64
Hyperkalemia	CCAE 1-	4,034 286	,039 8,455	199,397	62	687	7	7.33	3.45	1.62
	Panther 1	5,030 214	,815 5,578	79,201	45	551	1	8.07	6.96	1.59
	Summary 3	5.664 688	.845 18.986	408.794	150	2.0	49	7.90	5.01	1.31

• Open source protocol and end-to-end executable code

- http://data.ohdsi.org/LegendBasicViewer (all result artifacts for each study)
- http://data.ohdsi.org/LegendMedCentral (gimmick)



Head-to-head HTN drug comparisons



- Trials: 40
- *N* = 102 [1148] 33K

- Comparisons: 10,278
- *N* = 3502 [212K] 1.9M



Efficacy outcome: myocardial infarction, heart failure, stroke



Data source: meta-analysis, $\sim 1 - 2M$ total patients per study

- Beta blockers underperform alternatives
- Unexpected: THZs > ACEs. Reliable?



Large-scale propensity score model controls for observed confounding



Fig. 2. Preference score distribution for T2Ds and ACBs new users errore score is a transformation or the propensity score that adjusts for prevelence di erences between populations. A higher overlap indicates that subjects in the two populations are more similar in terms of their predicted probability of receiving one treatment over the other. Cohort stratification / balance:

- Achieved across all 10,868 baseline characteristics (CCAE)
- Blood pressure (pop. means in mmHg) (Panther)

	THZs	ACEIs	$ \Delta $
before	145/89	145/87	0.13
after	145/88	145/87	0.02

No BP measurements used in PS model, but still balanced after stratification



Calibration returns near nominal HR estimate coverage



- Good diagnostics → comparable cohorts (observed and unobserved); calibration → controls for residual systematic bias
- THZs are more effective than ACEIs in preventing MI



Ideal positioning for COVID-19

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Renin-angiotensin system blockers and susceptibility to COVID-19: a multinational open science cohort study

Daniel R Morales, Mitchell M Conover, Seng Chan You, Nicole Pratt, Kristin Kostka, Talita Duarte Salles, Sergio Fernandez Bertolin, Maria Aragon, Soct L. DuVall, Kristine Lynch, Thomas Falconer, Kees van Bochove, Cynthia Sung, Michael E. Matheny, Christophe G. Lambert, Fredrik Nyberg, Thamir M AlShammari, Andrew E. Williams, Rae Woong Park, James Weaver, Anthony G. Sena, Martin J. Schuemie, Peter R. Rijnbeek, Ross D. Williams, Ionifer C. E. Lane, Albert Pras Urbe, Lin Zhang, Carlos Areia, Harlan Krumholz, Daniel Prieto Alhambra, Patrick B Ryan, George Hripcsak, Marc A Suchard

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This article is a preprint and has not been peer-reviewed [what does this mean]. It reports new medical research that has yet to be evaluated and so should not be used to guide clinical practice.

Abstract	In

History Metrics

🗅 Preview PDF

Abstract

Introduction: Angiotensin converting enzyme inhibitors (ACEs) and angiotensin receptor blockers (ARBs) could influence infection risk of coronavirus disease (COVID-19). Observational studies to date lack pre-specification, transparency, rigorous ascertainment adjustment and international generalizability, with contradictory results. Methods: Using electronic health records from Spain (SIDIAP) and the United States (Columbia University Inving Medical Center and Department of Veterans Affairs), we conducted a systematic cohort

- Over 1.1 million antihypertensive users
- Active comparator, prevalent-users
- Executed within new EHR data partners
 - SIDIAP (universal primary care in Catalonia)
 - US VA
- End-to-end (almost) transparency



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