Siriraj Informatics and Data Innovation Center

OHDSI
OBSERVATIONAL HEALTH DATA SCIENCES AND INFORMATICS

Mahidol University
Faculty of Medicine
Siriraj Hospital

Hands-on Workshop:
Introduction to International Medical Data Standard OMOP CDM for Observational Research

21 September 2023

Supported by

ศูนย์ความเป็นเลิศด้านชีววิทยาศาสตร์ (องค์การมหาชน)
Thailand Center of Excellence for Life Sciences
(Public Organization)

SiHP
หน่วยวิจัยเพื่อขับเคลื่อนนโยบายสุขภาพ
Siriraj Health Policy Unit

สปสช.
สำนักงานหลักประกันสุขภาพแห่งชาติ

Agenda

https://bit.ly/omop-workshop-slide

เวลา	หัวข้อ	วัตถุประสงค์
09:00 – 09:15	ลงทะเบียน	
09:15 – 09:30	เปิดการอบรม และแนะนำภาพรวม โดย ผศ.ดร.ประพัฒน์ สุริยผล	
09:30 – 10:30	**Introduction to OMOP CDM and OHDSI**	ทำความรู้จักกับ OMOP CDM และ OHDSI
10:30 – 10:45	รับประทานอาหารว่าง (เช้า)	
10:45 – 11:15	**Inspiring Experience from Singapore** **โดย Asst. Prof. Mengling 'Mornin' Feng**	เห็นตัวอย่างการนำ OMOP CDM และ OHDSI Tools ไปใช้ในงานวิจัย และความร่วมมือจากภาคส่วนต่าง ๆ ในประเทศเพื่อนบ้าน
11:15 – 12:00	**OHDSI Tools: Athena & Atlas**	สามารถใช้งานเครื่องมือ Athena และ Atlas
12:00 – 13:00	รับประทานอาหารกลางวัน	
13:00 – 14:30	**OHDSI Tools: Cohort Definition & Characterization**	สามารถกำหนดกลุ่ม Cohort เพื่อการวิจัย และวิเคราะห์เชิงสถิติต่าง ๆ เบื้องต้น
14:30 – 14:45	รับประทานอาหารว่าง (บ่าย)	
14:45 – 15:45	**OHDSI Tools: Patient-level Prediction**	สามารถสร้างโมเดลการทำนายรายผู้ป่วยได้
15:45 – 16:15	**Data Governance for Research**	เข้าใจหลักการทางธรรมาภิบาลข้อมูล เกี่ยวกับการวิจัย
16:15 – 17:00	Networking Event (optional)	สร้างความรู้จักกันระหว่างผู้เข้าร่วมอบรม เพื่อการสร้างเครือข่ายวิจัยร่วมกันในอนาคต

OHDSI, pronounced "Odyssey"

Observational Health Data Sciences and Informatics

[https://www.worldhistory.org/odysseus/]

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Meet Your Today's Guide for OMOP/OHDSI Journey

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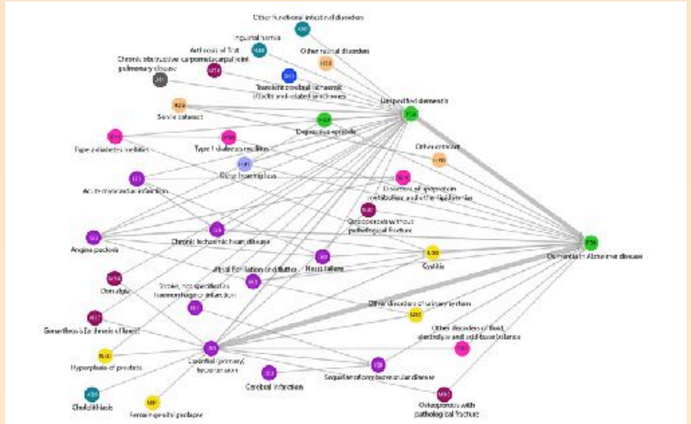
Natthawut 'Max' Adulyanukosol

MSc (*cand.scient.*) in Bioinformatics, BA Hons (*Cantab*) in Natural Sciences, CIPM

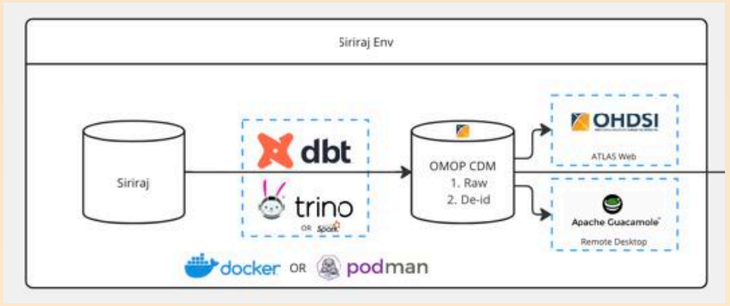
Deputy Director, Siriraj Informatics and Data Innovation Center (SiData+)

PhD Biomedical and Health Informatics Student, University of North Carolina at Chapel Hill, USA

Past Work in Denmark 🇩🇰
Disease Trajectory Model on Danish National Claims Registry



Ongoing Work in Thailand 🇹🇭
OMOP ETL Project Lead at Siriraj & NHSO



There will be a separate workshop focusing on ETL & conversion.

Ongoing Work in USA 🇺🇸
ML & Visual Analytics Platform for Geriatric Hospital System Mgmt

on OMOP CDM

Can we make our model more GENERALIZABLE?

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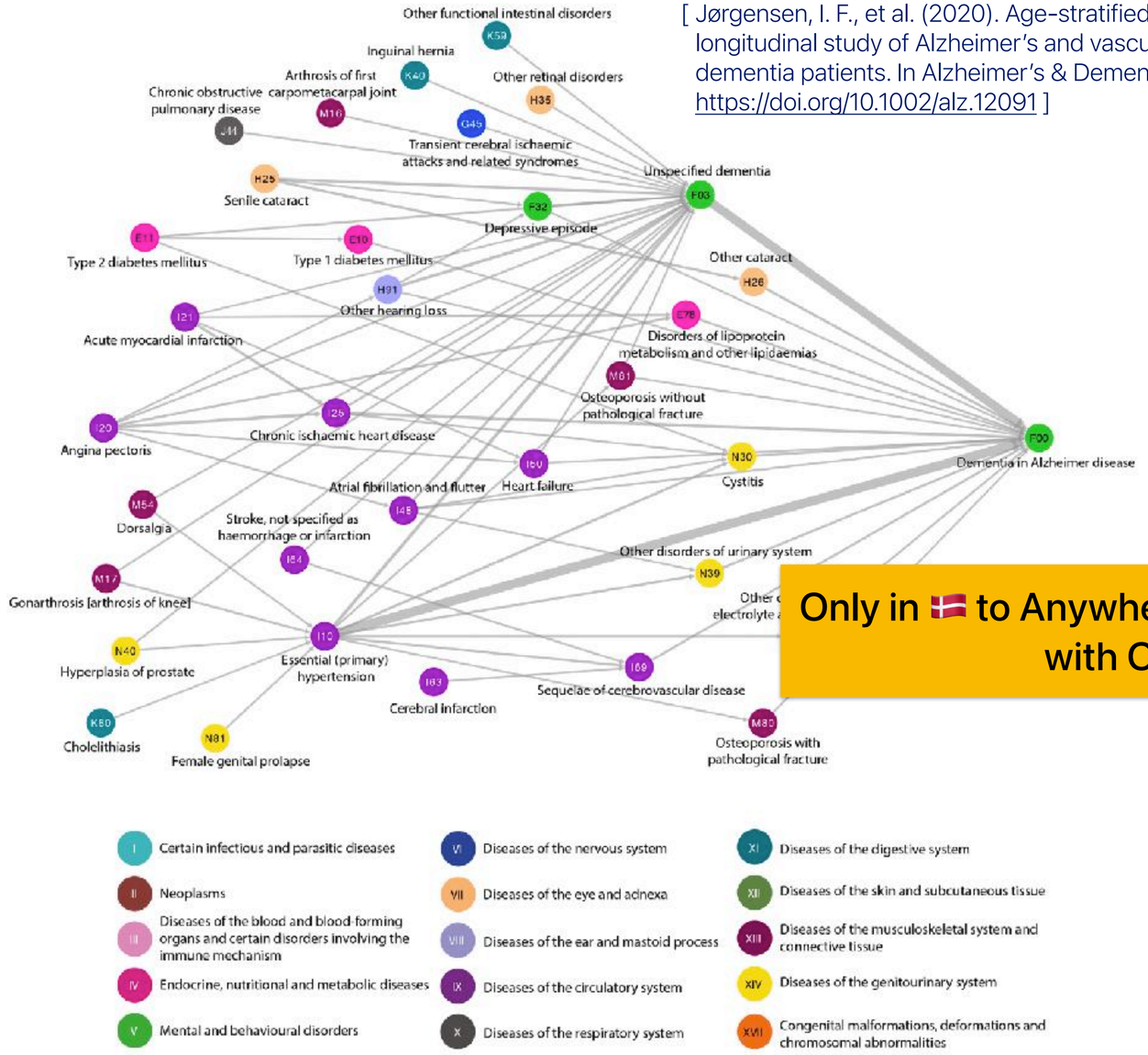


[Jørgensen, I. F., et al. (2020). Age-stratified longitudinal study of Alzheimer's and vascular dementia patients. In Alzheimer's & Dementia. https://doi.org/10.1002/alz.12091]

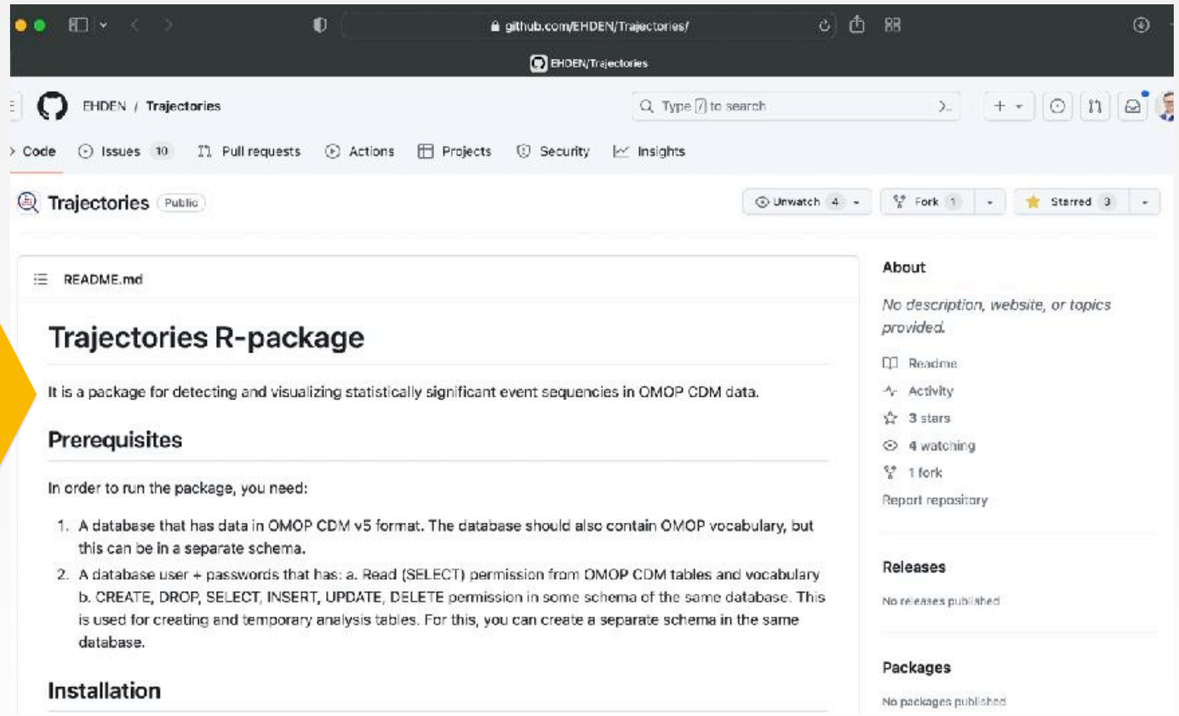
GURE 2 Temporal disease trajectory network of diagnoses given before F00 "*Dementia in Alzheimer disease.*" Fifty significant trajectories with

Only in 🇩🇰 to Anywhere 🌍 with OMOP

Trajectories: a framework for detecting temporal clinical event sequences from health data standardized to the Observational Medical Outcomes Partnership (OMOP) Common Data Model

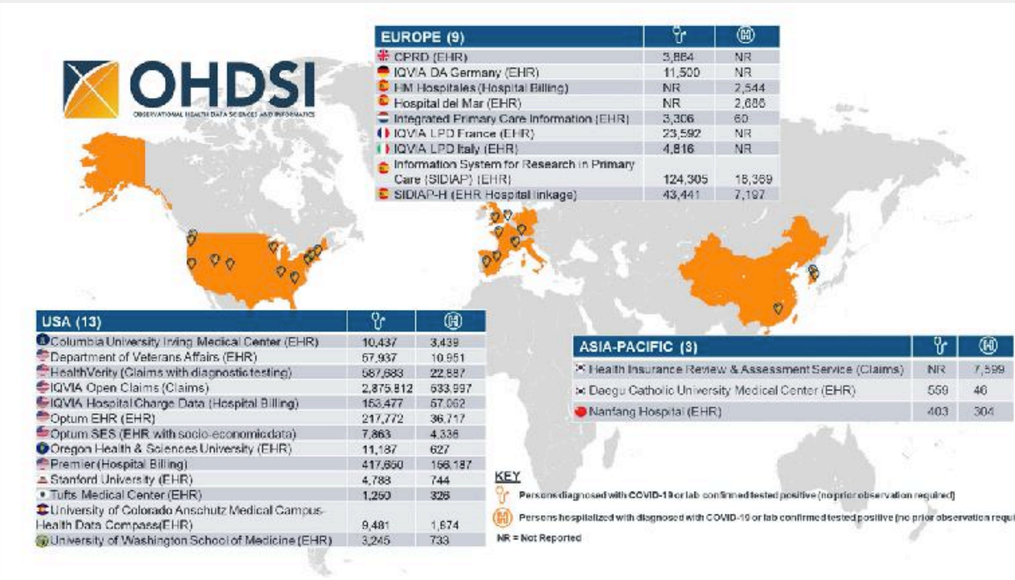
Kadri Künnapuu[1], Solomon Ioannou[2], Kadri Ligi[1,2], Raivo Kolde[3], Sven Laur[1,3], Jaak Vilo[1,3,4], Peter R. Rijnbeek[2], and Sulev Reisberg[1,3,4]

[1]STACC, Tartu, Estonia, [2]Department of Medical Informatics, Erasmus University Medical Center, Rotterdam, the Netherlands, [3]Institute of Computer Science, University of Tartu, Tartu, Estonia, and [4]Quretec, Tartu, Estonia



[Künnapuu, K., et al. (2022). https://doi.org/10.1093/jamiaopen/ooac021]
[https://github.com/EHDEN/Trajectories/]

How can we pool large amount of data for research in a short period of time?



Clinical Epidemiology

Dovepress

open access to scientific and medical research

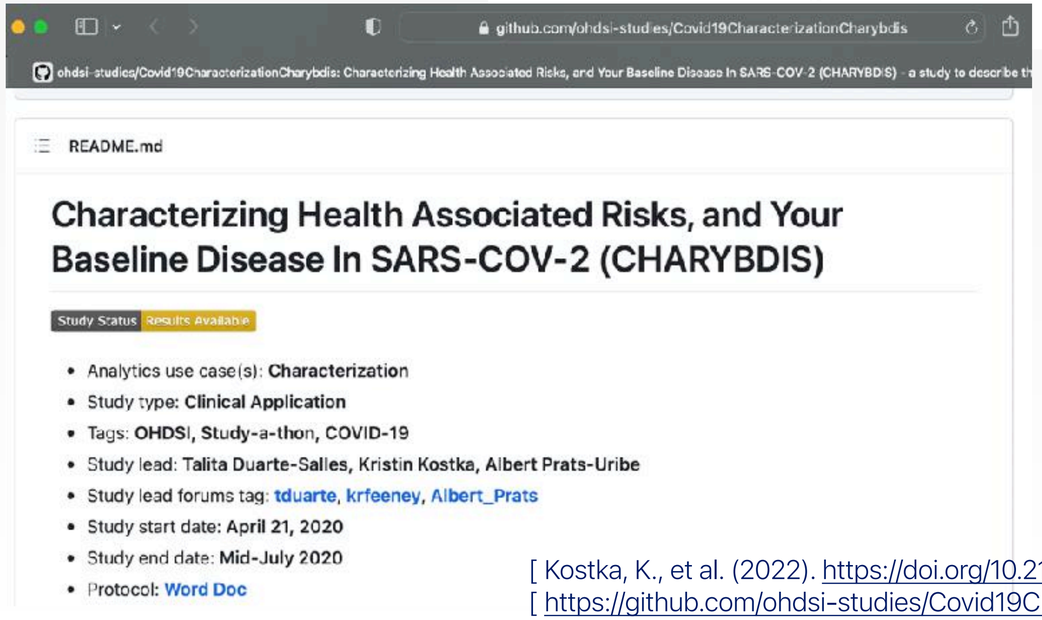
Open Access Full Text Article

ORIGINAL RESEARCH

Unraveling COVID-19: A Large-Scale Characterization of 4.5 Million COVID-19 Cases Using CHARYBDIS

Kristin Kostka[1,2], Talita Duarte-Salles[3], Albert Prats-Uribe[4], Anthony G Sena[5,6], Andrea Pistillo[3], Sara Khalid[4], Lana YH Lai[7], Asieh Golozar[8,9], Thamir M Alshammari[10], Dalia M Dawoud[11], Fredrik Nyberg[12], Adam B Wilcox[13,14], Alan Andryc[5], Andrew Williams[15], Anna Ostropolets[16], Carlos Areia[17], Chi Young Jung[18], Christopher A Harle[19], Christian G Reich[1,2], Clair Blacketer[5,6], Daniel R Morales[20], David A Dorr[21], Edward Burn[3,4], Elena Roel[3,22], Eng Hooi Tan[4], Evan Minty[23], Frank DeFalco[5], Gabriel de Maeztu[24], Gigi Lipori[19], Hiba Alghoul[25], Hong Zhu[26], Jason A Thomas[13], Jiang Bian[19], Jimyung Park[27], Jordi Martínez Roldán[28], Jose D Posada[29], Juan M Banda[30], Juan P Horcajada[31], Julianna Kohler[32], Karishma Shah[33], Karthik Natarajan[16,34], Kristine E Lynch[35,36], Li Liu[37], Lisa M Schilling[38], Martina Recalde[3,22], Matthew Spotnitz[14], Mengchun Gong[39], Michael E Matheny[40,41], Neus Valveny[42], Nicole G Weiskopf[21], Nigam Shah[29], Osaid Alser[43], Paula Casajust[42], Rae Woong Park[27,44], Robert Schuff[21], Sarah Seager[1], Scott L DuVall[35,36], Seng Chan You[45], Seokyoung Song[46], Sergio Fernández-Bertolín[3], Stephen Fortin[5], Tanja Magoc[19], Thomas Falconer[16], Vignesh Subbian[47], Vojtech Huser[48], Waheed-Ul-Rahman Ahmed[33,49], William Carter[38], Yin Guan[50], Yankuic Galvan[19], Xing He[19], Peter R Rijnbeek[6], George Hripcsak[16,34], Patrick B Ryan[5,16], Marc A Suchard[51], Daniel Prieto-Alhambra[4]

[1]IQVIA, Cambridge, MA, USA; [2]OHDSI Center at The Roux Institute, Northeastern University, Portland, ME, USA; [3]Fundació Institut Universitari per a la recerca a l'Atenció Primària de Salut Jordi Gol i Gurina (IDIAPJGol), Barcelona, Spain; [4]Centre for Statistics in Medicine, NDORMS, University of Oxford, Oxford, UK; [5]Janssen Research & Development, Titusville, NJ, USA; [6]Department of Medical Informatics, Erasmus University Medical Center, Rotterdam, The Netherlands; [7]School of Medical Sciences, University of Manchester, Manchester, UK; [8]Regeneron Pharmaceuticals, Tarrytown, NY, USA; [9]Department of Epidemiology, Johns Hopkins Bloomberg School of Public Health, Baltimore, MD, USA; [10]College of Pharmacy, Riyadh Elm University, Riyadh, Saudi Arabia; [11]National Institute for Health and Care Excellence, London, UK; [12]School of Public Health and Community Medicine, Institute of Medicine, Sahlgrenska Academy, University of Gothenburg, Gothenburg, Sweden; [13]Department of Biomedical Informatics and Medical Education, University of Washington, Seattle, WA, USA; [14]University of Washington Medicine, Seattle, WA, USA; [15]Tufts Institute for Clinical Research and Health Policy Studies, Boston, MA, USA; [16]Department of Biomedical Informatics, Columbia University Irving Medical Center, New York, NY, USA; [17]Nuffield Department of Clinical Neurosciences, University of Oxford, Oxford, UK; [18]Division of Respiratory and Critical Care Medicine, Department of Internal Medicine, Daegu Catholic University Medical Center, Daegu, South Korea; [19]University of Florida Health, Gainesville, FL, USA; [20]Division of Population Health and Genomics, University of Dundee, Dundee, UK; [21]Department of Medical Informatics & Clinical Epidemiology, Oregon Health & Science University, Portland, OR, USA; [22]Universitat Autònoma de Barcelona, Barcelona, Spain; [23]O'Brien Institute for Public Health, Faculty of Medicine, University of Calgary, Calgary, Canada; [24]IOMED, Barcelona, Spain; [25]Faculty of Medicine, Islamic University of Gaza, Gaza, Palestine; [26]Nanfang Hospital, Southern Medical University, Guangzhou, People's Republic of China; [27]Department of Biomedical Sciences, Ajou University Graduate School of Medicine, Suwon, South Korea; [28]Director of Innovation and Digital Transformation, Hospital del Mar, Barcelona, Spain; [29]Department of Medicine, School of Medicine, Stanford University, Redwood City, CA, USA; [30]Georgia State University, Department of Computer Science, Atlanta, GA, USA; [31]Department of Infectious Diseases, Hospital del Mar, Institut Hospital del Mar d'Investigació Mèdica (IMIM), Universitat Autònoma de Barcelona, Universitat Pompeu Fabra, Barcelona, Spain; [32]United States Agency for International Development, Washington, DC, USA; [33]Botnar Research Centre, NDORMS, University of Oxford, Oxford, UK; [34]New York-Presbyterian Hospital, New York, NY, USA; [35]VA Informatics and Computing Infrastructure, VA Salt Lake City Health Care System, Salt Lake City, UT, USA; [36]Department of Internal Medicine, University of Utah School of Medicine, Salt Lake City, UT, USA; [37]Biomedical Big Data Center, Nanfang Hospital, Southern Medical University, Guangzhou, People's Republic of China; [38]Data Science to Patient Value Program, School of Medicine, University of Colorado Anschutz Medical Campus, Aurora, CO, USA; [39]Institute of Health Management, Southern Medical University, Guangzhou, People's Republic of China; [40]Tennessee Valley Healthcare System, Veterans Affairs Medical Center, Nashville, TN, USA; [41]Department of Biomedical Informatics, Vanderbilt University Medical Center, Nashville, TN, USA; [42]Real-World Evidence, TFS, Barcelona, Spain; [43]Massachusetts General Hospital, Harvard Medical School, Boston, MA, USA; [44]Department of Biomedical Informatics, Ajou University School of Medicine, Suwon, South Korea; [45]Department of Preventive Medicine, Yonsei



[Kostka, K., et al. (2022). https://doi.org/10.2147/clep.s323292]
[https://github.com/ohdsi-studies/Covid19CharacterizationCharybdis]

How can we make EHR data readily available for research?

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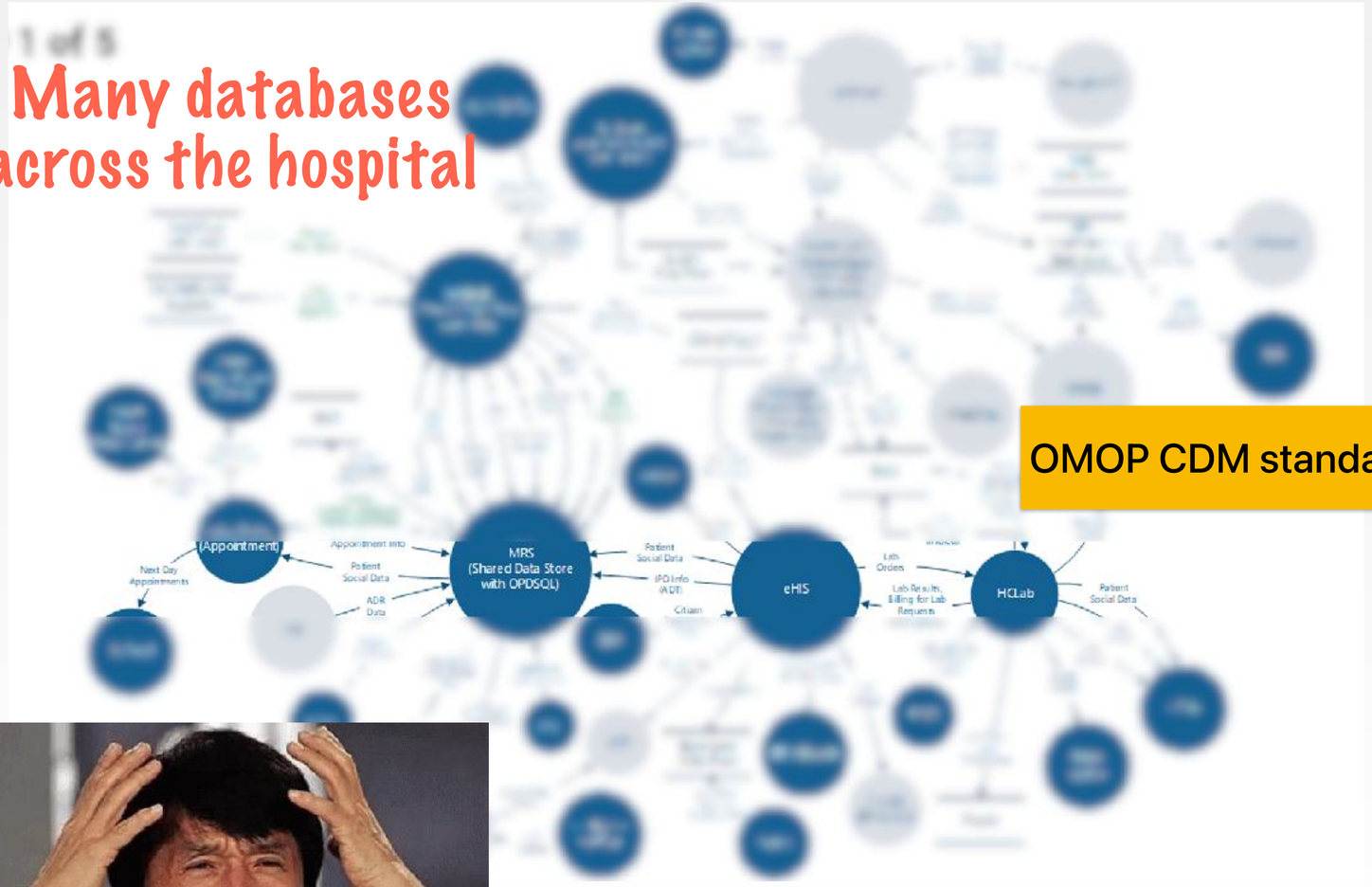
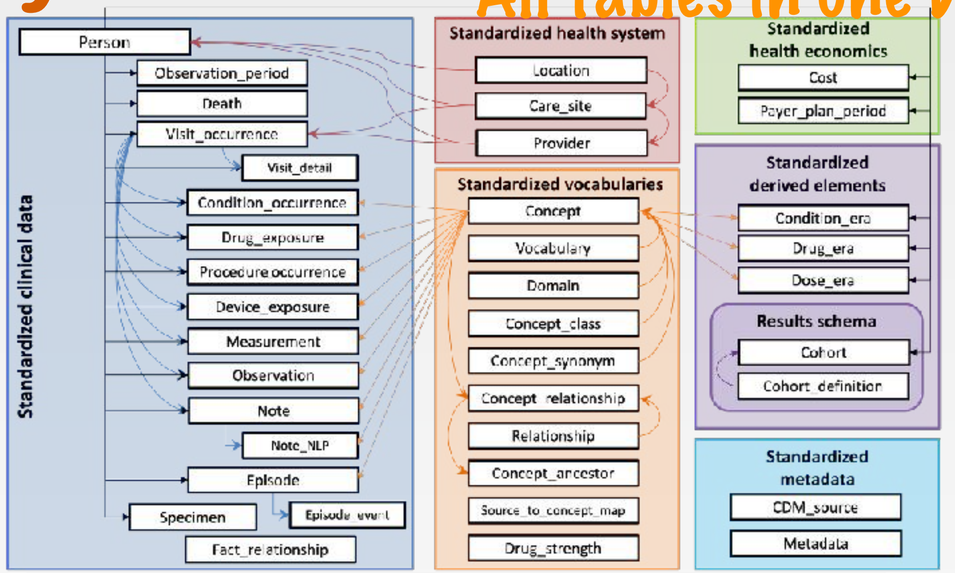
Many databases across the hospital

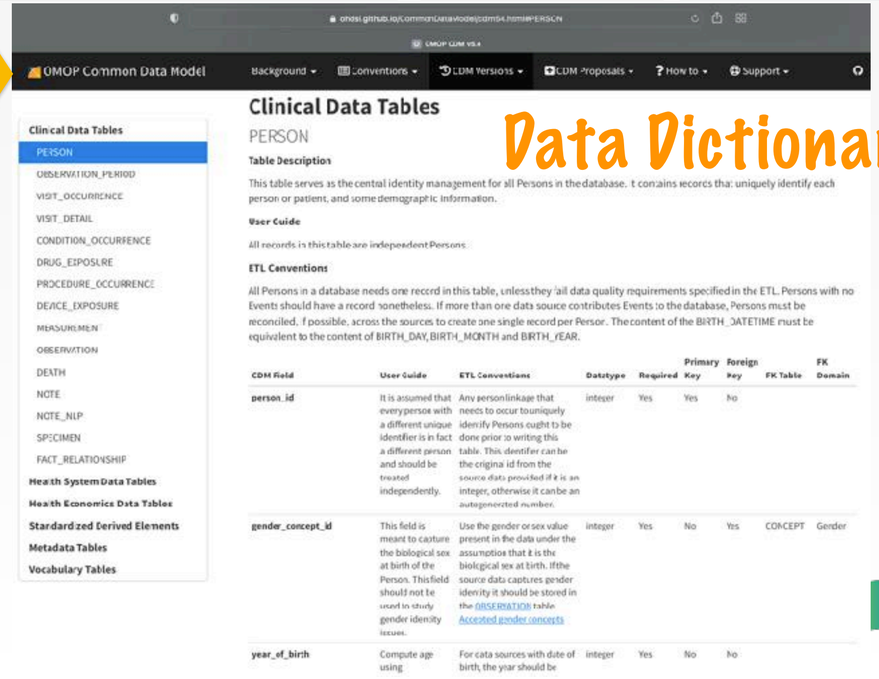


OMOP CDM standard

All tables in one DB



Data Dictionary



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Introduction to OMOP CDM and OHDSI

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Session Overview

Introduction to OMOP CDM and OHDSI @ 09:30 – 10:30 (60 min)

Why? Background & Questions	How? Methods & Materials	What? Objectives
☐ What are the challenges in healthcare data standardization? ☐ What are OMOP CDM and OHDSI? Why do they exist? ☐ What are real-world data (RWD) and real-world evidence (RWE)? ☐ How can OMOP/OHDSI help my research?	⬟ Selected contents from The Book of OHDSI chapter 1 – 6 https://ohdsi.github.io/TheBookOfOhdsi ⬟ https://www.ohdsi.org	★ Get the big picture of OMOP CDM and OHDSI ecosystem ★ Understand how OMOP CDM handles real-world data (RWD) and generate reproducible real-world evidence (RWE) ★ Take home: Importance of data standardization for reproducibility and collaboration

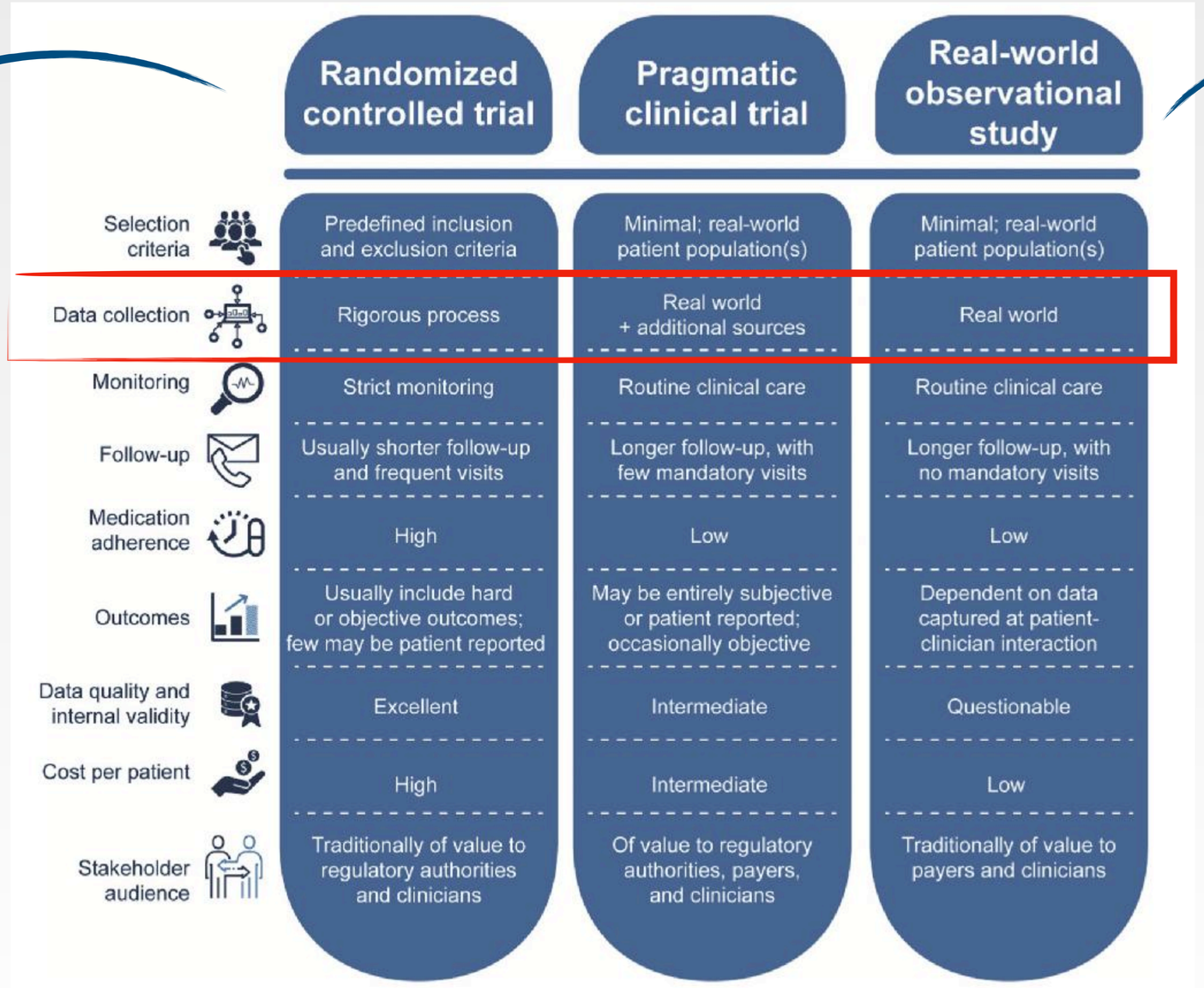

Fig. 1. Comparison of a randomized controlled trial, pragmatic clinical trial, and real-world observational study [14,16–18].

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OBSERVATIONAL MEDICAL OUTCOMES PARTNERSHIP
est. 2009

cdisc

REDCap
Research Electronic Data Capture

i2b2

pcornet
The National Patient-Centered Clinical Research Network

For Healthcare Services
HL7 FHIR

[Anzueto, A., & Kaplan, A. (2020). Dual bronchodilators in chronic obstructive pulmonary disease: Evidence from randomized controlled trials and real-world studies. In Respiratory Medicine: X (Vol. 2, p. 100016). Elsevier BV. https://doi.org/10.1016/j.yrmex.2020.100016]

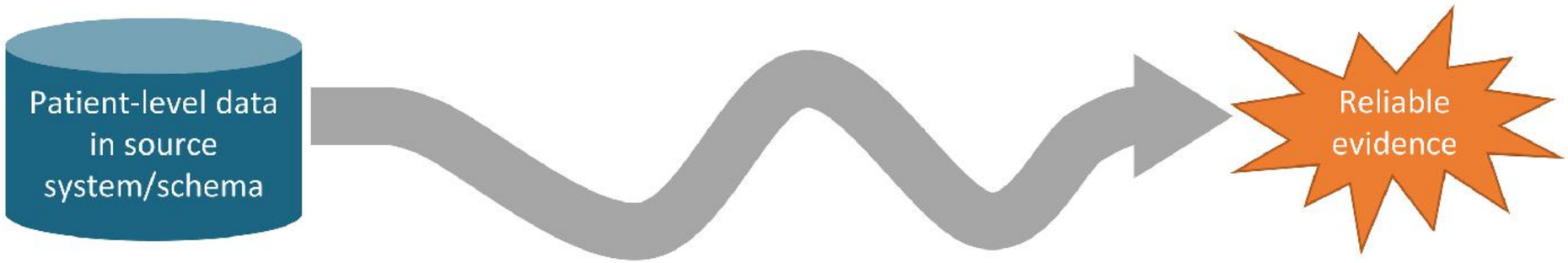
Different types of observational data:

Populations
- Pediatric vs. elderly
- Socioeconomic disparities

Care setting
- Inpatient vs. outpatient
- Primary vs. secondary care

Data capture process
- Administrative claims
- Electronic health records
- Clinical registries

Health system
- Insured vs. uninsured
- Country policies



Types of evidence desired:

Clinical characterization
- Clinical trial feasibility
- Treatment utilization
- Disease natural history
- Quality improvement

Population-level effect estimation
- Safety surveillance
- Comparative effectiveness

Patient-level prediction
- Precision medicine
- Disease interception

[https://ohdsi.github.io/TheBookOfOhdsi/OhdsiCommunity.html]

LEGEND Hypertension Study 2019

Real-world evidence — pharmacoepidemiology

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THE LANCET

Articles

Comprehensive comparative effectiveness and safety of first-line antihypertensive drug classes: a systematic, multinational, large-scale analysis

Marc A Suchard, Martijn J Schuemie, Harlan M Krumholz, Seng Chan You, Ruijun Chen, Nicole Pratt, Christian G Reich, Jon Duke, David Madigan, George Hripcsak, Patrick B Ryan

"The study factors insurance claim data and electronic health records from 4.9 million patients across nine observational databases, making it the most comprehensive one ever on first-line antihypertensives."

"First-Line Thiazide Diuretic Users Experience 15% Fewer Adverse Cardiovascular Outcomes Than ACE Inhibitor Users"

Currently running LEGEND T2DM study
https://github.com/ohdsi-studies/LegendT2dm

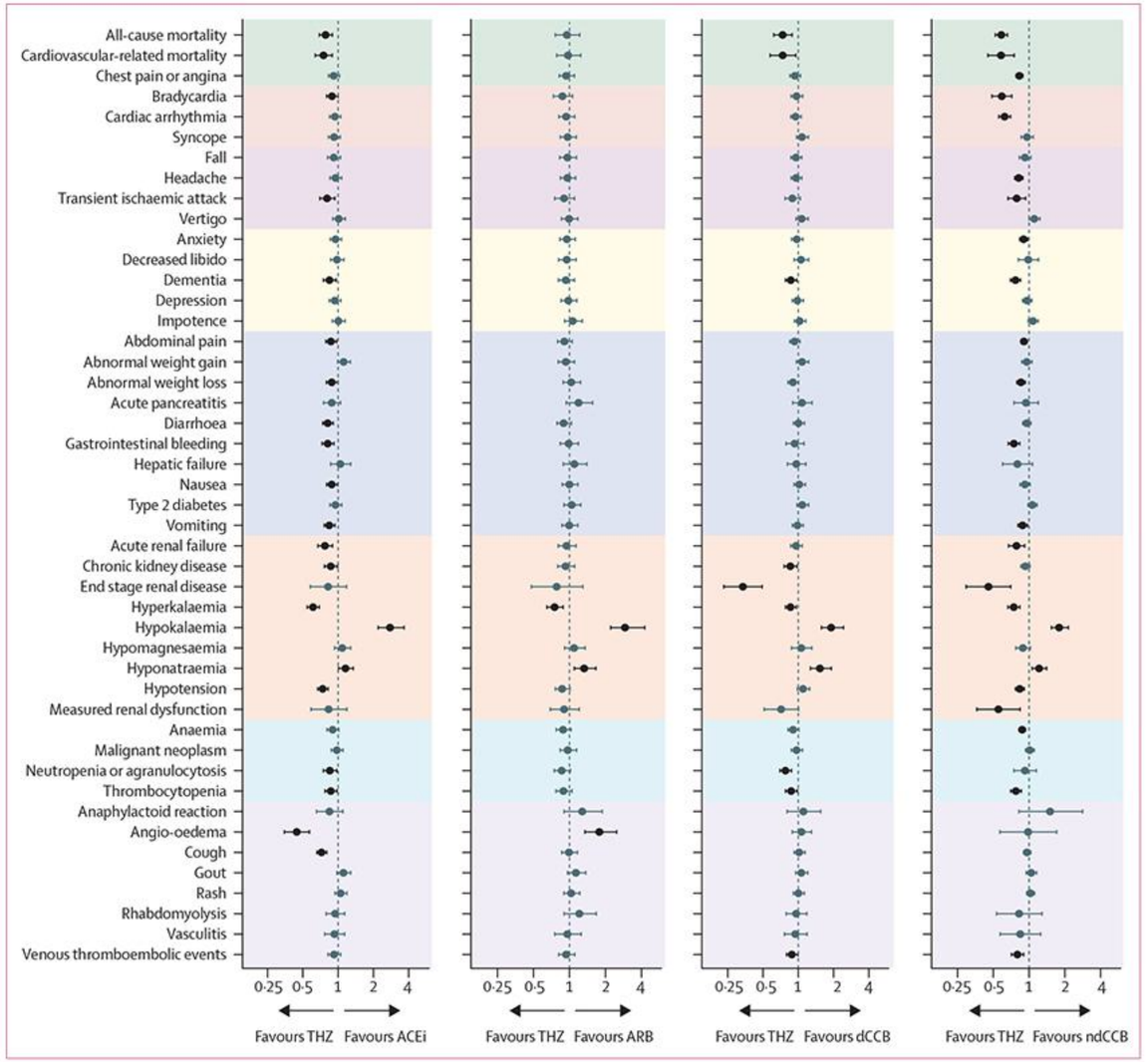
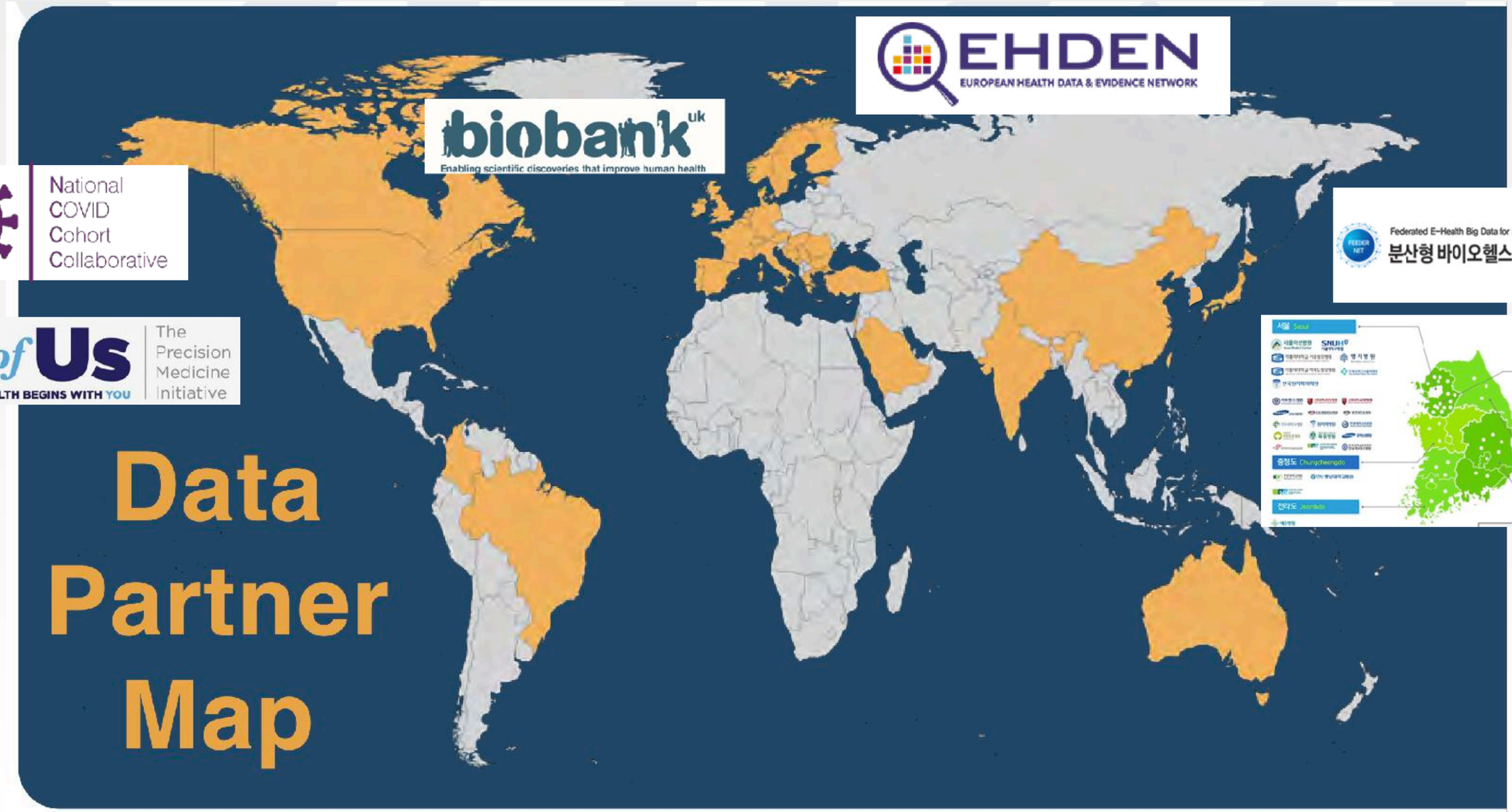


Figure 2: **Meta-analytic safety profiles comparing THZ to ACEi, ARB, dCCB, and ndCCB new users across 46 outcomes listed on product labels**
Points and lines identify HR estimates with their 95% CIs, respectively. Outcomes in grey signify that the CI covers HR of 1 (null hypothesis of no differential risk). THZ=thiazide or thiazide-like diuretics. ACEi=angiotensin converting-enzyme inhibitors. ARB=angiotensin receptor blockers. dCCB=dihydropyridine calcium channel blockers. ndCCB=non-dihydropyridine calcium channel blockers. HR=hazard ratio.

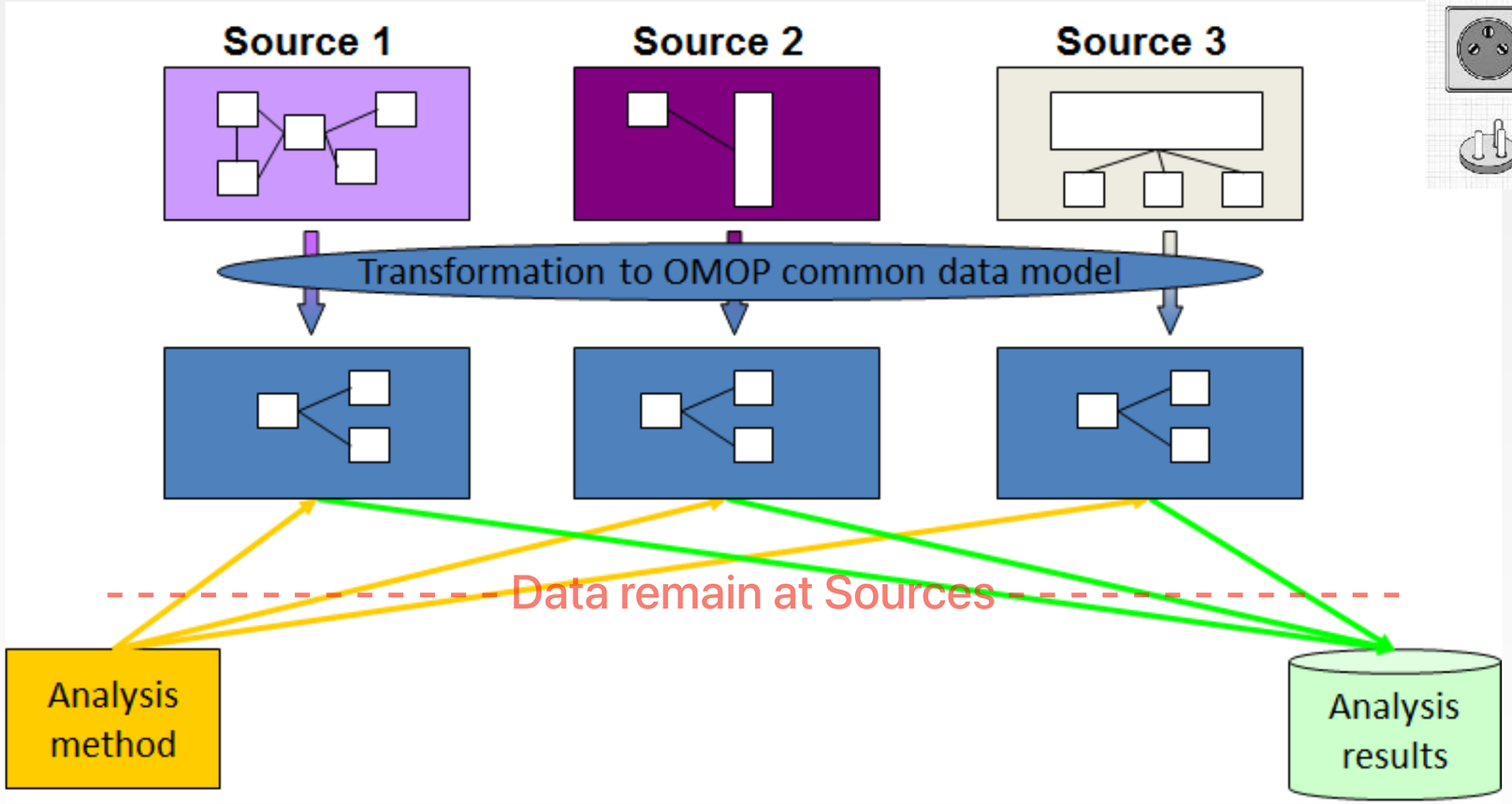
[Suchard, M. A., et al. (2019). https://doi.org/10.1016/s0140-6736(19)32317-7]
[https://www.ohdsi.org/ohdsi-news-updates/legend-hypertension-study/]

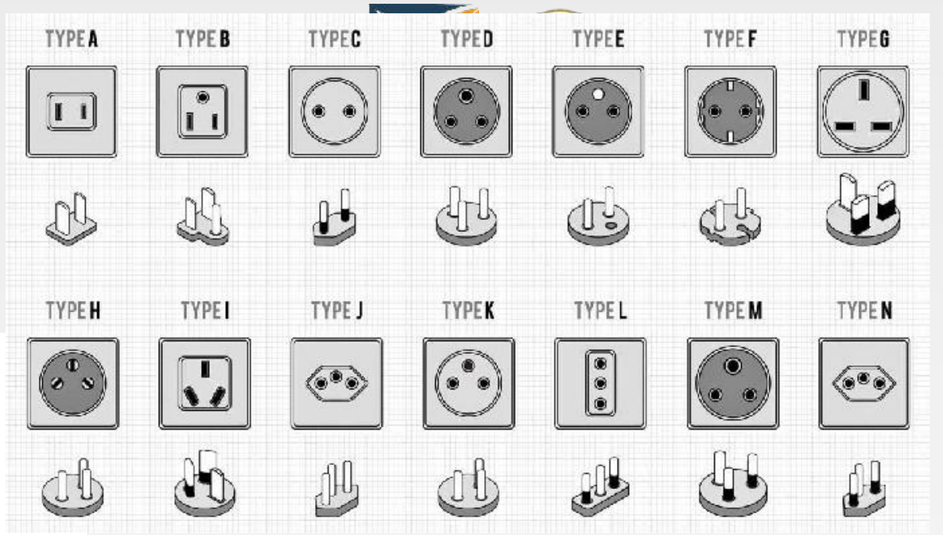
OMOP CDM Data Partners



[https://www.ohdsi.org/wp-content/uploads/2022/10/OHDSI-OurJourney-2022.pdf]

OMOP CDM



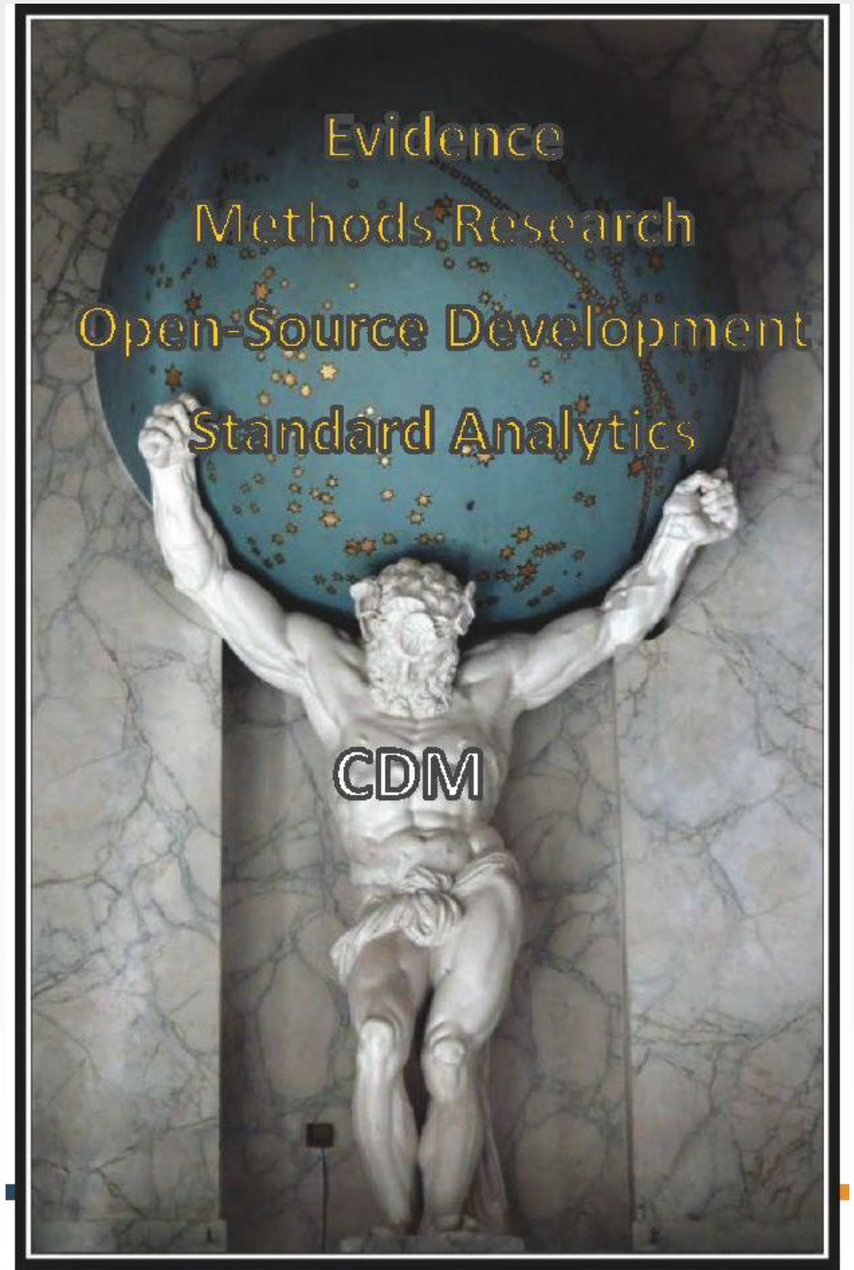


[https://www.ohdsi.org/data-standardization/]

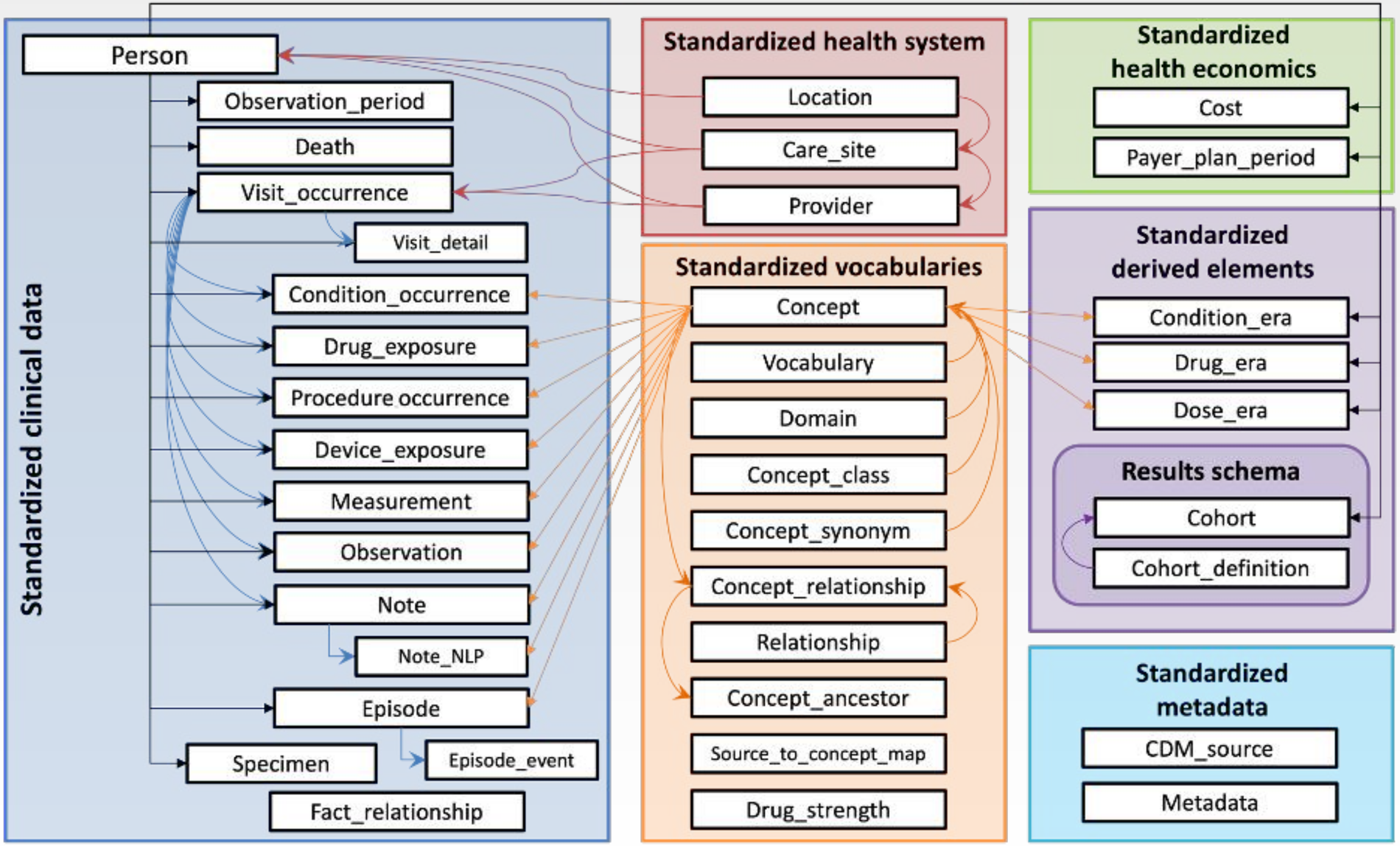
OMOP CDM

The OMOP CDM is **a system of tables, vocabularies, and conventions** that allow observational health data to be standardized.

It is this standard approach that facilitates rapid innovation in the areas of open-source development, methods research, and evidence generation.



OMOP CDM: Tables



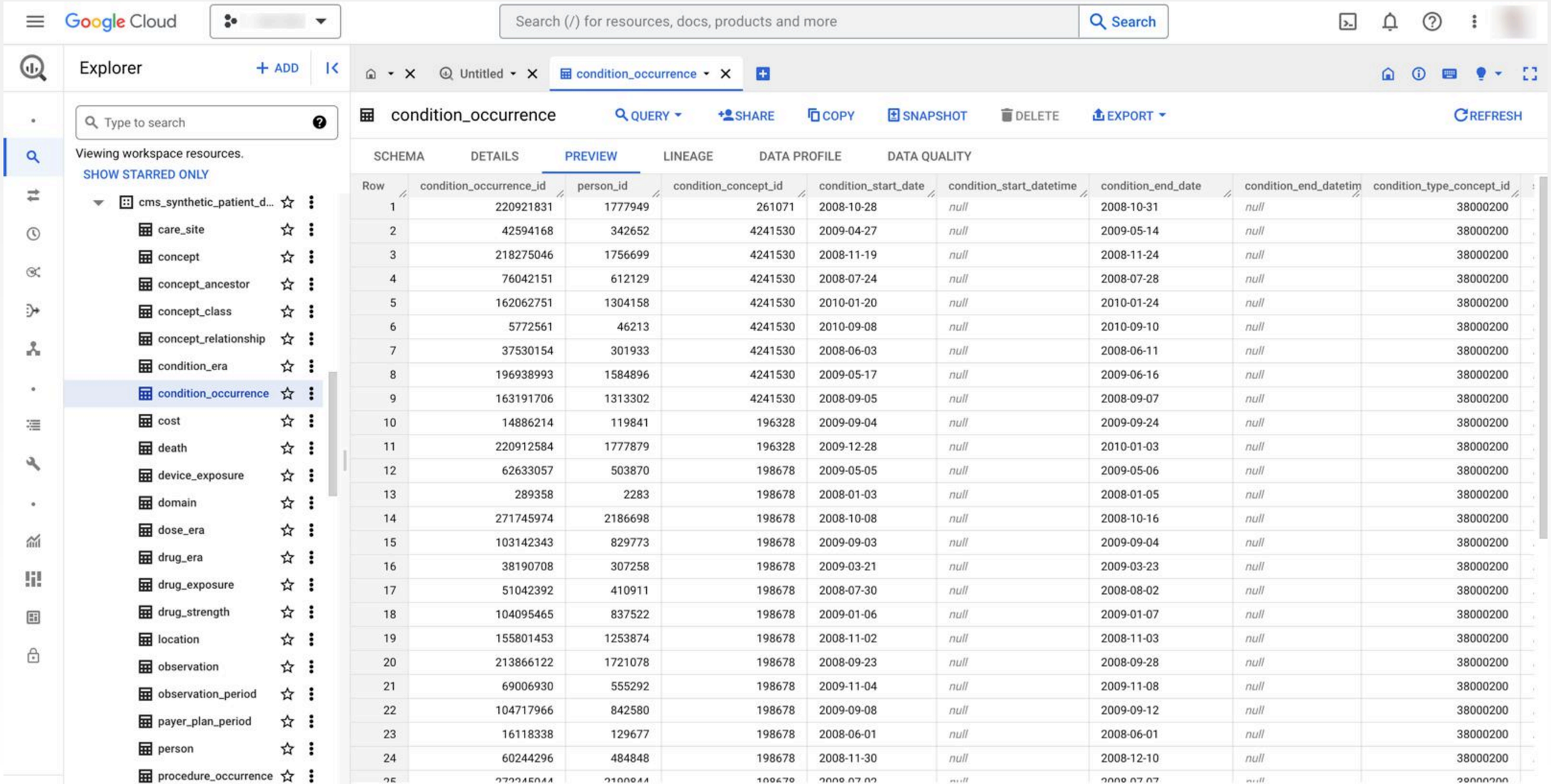
[https://ohdsi.github.io/CommonDataModel]

OMOP CDM: Table Groups

1. **Clinical data** ข้อมูลทางคลินิก มี 17 ตาราง (table) อาทิ Person (ข้อมูลบุคคล) Observation_period (ระยะเวลาที่เข้ารับบริการ) Visit_occurrence (การเข้ารับบริการ) Visit_detail (รายละเอียดการเข้ารับบริการ) Condition_occurrence (ผลการวินิจฉัยและอาการของโรค) Drug_exposure (ยาที่ได้รับ) Procedure_occurrence (หัตถการ) Device_exposure (อุปกรณ์ทางการแพทย์) Measurement (ผลการตรวจทางห้องปฏิบัติการและกายภาพ) Observation (ผลการตรวจอื่น ๆ) Death (การเสียชีวิต) Note (บันทึกข้อมูลผู้ป่วย) Specimen (สิ่งส่งตรวจ)
2. **Vocabularies** คลังคำศัพท์ต้นทาง และ คลังคำศัพท์มาตรฐาน เช่น SNOMED-CT, LOINC, RxNORM เป็นต้น สำหรับการใช้ข้อมูลร่วมกันระดับนานาชาติ
3. **Health system** ข้อมูลเกี่ยวกับสถานพยาบาล
4. **Health economics** ข้อมูลเกี่ยวกับค่าใช้จ่ายในการบริการ
5. **Derived elements** ข้อมูลที่สรุปรวมเพิ่มเติม เช่น ระยะเวลาที่เป็นโรค ระยะเวลาที่ได้รับยา การแบ่งกลุ่มผู้ป่วย (cohort)
6. **Metadata** ข้อมูลประกอบ CDM เพิ่มเติม เช่น ที่มา เวอร์ชัน วันที่ปรับปรุง

OMOP CDM Example data

https://console.cloud.google.com/marketplace/product/hhs/synpuf



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4	76042151	612129	4241530	2008-07-24	null	2008-07-28	null	38000200
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7	37530154	301933	4241530	2008-06-03	null	2008-06-11	null	38000200
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11	220912584	1777879	196328	2009-12-28	null	2010-01-03	null	38000200
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14	271745974	2186698	198678	2008-10-08	null	2008-10-16	null	38000200
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24	60244296	484848	198678	2008-11-30	null	2008-12-10	null	38000200

Who created and maintain OMOP?

2009: **Observational Medical Outcomes Partnership (OMOP)** was a public-private partnership, chaired by the US Food and Drug Administration, administered by the Foundation for the National Institutes of Health, and funded by a consortium of pharmaceutical companies that collaborated with academic researchers and health data partners to establish a research program that sought to advance the science of active medical product safety surveillance using observational healthcare data.

OHDSI
OBSERVATIONAL HEALTH DATA SCIENCES AND INFORMATICS

since 2014: **Observational Health Data Sciences and Informatics (OHDSI)** is an open-science community that aims to improve health by empowering the community to collaboratively generate the evidence that promotes better health decisions and better care.

[https://ohdsi.github.io/TheBookOfOhdsi/OhdsiCommunity.html]

OHDSI's Vision

A world in which observational research produces a comprehensive understanding of health and disease

through these objectives:

Innovation, Reproducibility, Community, Collaboration, Openness, Beneficence

OHDSI Workgroup

as of 2022

APAC (Asia-Pacific)
Current Participants: 289
Lead: Mui Van Zandt

ATLAS/WebAPI
Current Participants: 226
Lead: Anthony Sena

Clinical Trials
Current Participants: 252
Leads: Mike Hamidi, Lin Zhen

Common Data Model
Current Participants: 596
Lead: Clair Blacketer

Data Quality Dashboard Development
Current Participants: 260
Lead: Clair Blacketer

Early-Stage Researchers
Current Participants: 214
Leads: Faaizah Arshad, Ross Williams

Education
Current Participants: 116
Lead: Nigel Hughes

Eye Care & Vision Research
Current Participants: 40
Leads: Sally Baxter, Kerry Goetz

FHIR and OMOP
Current Participants: 214
Leads: Jon Duke, Christian Reich, Dana Stephenson

Geographic Information System (GIS)
Current Participants: 122
Leads: Robert Miller, Andrew Williams

HADES (Health Analytics Data-to-Evidence Suite)
Current Participants: 262
Lead: Martijn Schuemie

Health Equity
Current Participants: 201
Lead: Jake Gillberg

Healthcare Systems
Current Participants: 430
Lead: Melanie Philofsky

Latin America
Current Participants: 48
Lead: Jose Posada

Medical Devices
Current Participants: 130
Leads: Vojtech Huser, Asiyah Lin

Medical Imaging
Current Participants: 114
Leads: Paul Nagy, Seng Chan You

Natural Language Processing
Current Participants: 379
Lead: Hua Xa

Oncology
Current Participants: 241
Lead: Asieh Golozar

Open-Source Community
Current Participants: 118
Leads: Adam Black, Paul Nagy

Patient-Level Prediction
Current Participants: 355
Leads: Jenna Reps, Ross Williams

Phenotype Development & Evaluation
Current Participants: 249
Lead: Gowtham Rao

Population-Level Effect Estimation
Current Participants: 355
Leads: Martijn Schuemie, Marc Suchard

Psychiatry
Current Participants: 115
Leads: Dmitry Dymshyts, Andrew Williams

Registry
Current Participants: 115
Lead: Tina Parciak

Steering Group
Current Participants: 70
Lead: Patrick Ryan

Surgery and Perioperative Medicine
Current Participants: 37
Lead: Evan Minty

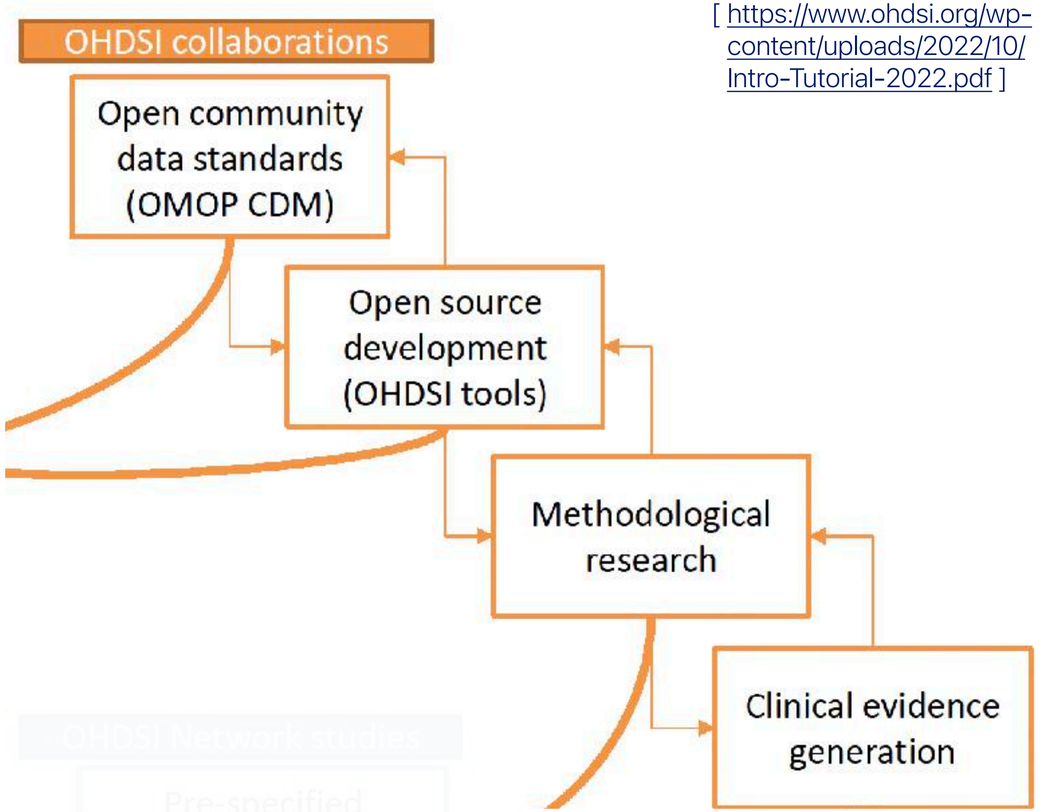
Vaccine Vocabulary
Current Participants: 76
Lead: Adam Black

[https://www.ohdsi.org/wp-content/uploads/2022/10/OHDSI-OurJourney-2022.pdf]

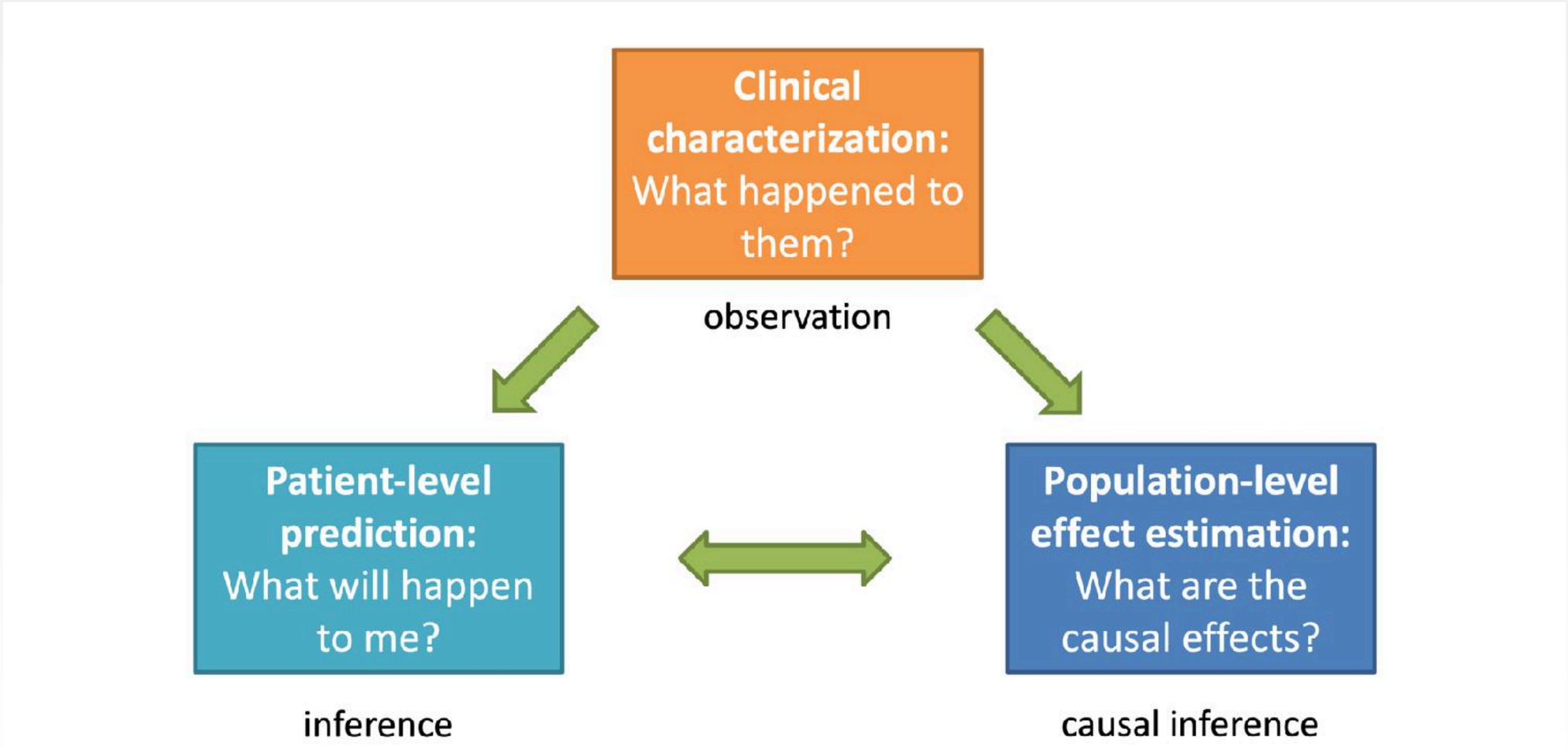
OHDSI

To improve health by empowering a community to collaboratively generate the evidence that promotes better health decisions and better care

[https://www.ohdsi.org/wp-content/uploads/2022/10/Intro-Tutorial-2022.pdf]



Main Analytics/Research Use Cases



Characterization

Mahidol University
Faculty of Medicine
Siriraj Hospital

Typical Questions	Desired output
• How many patients…? • How often does…? • What proportion of patients…? • What is the distribution of values for lab…? • What are the HbA1c levels for patients with…? • What are the lab values for patients…? • What is the median length of exposure for patients on….? • What are the trends over time in…? • What are other drugs that these patients are using? • What are concomitant therapies? • Do we have enough cases of…? • Would it be feasible to study X…? • What are the demographics of…? • What are the risk factors of…? (if identifying a specific risk factor, maybe estimation, not prediction) • What are the predictors of…?	• Count or percentage • Averages • Descriptive statistics • Incidence rate • Prevalence • Cohort • Rule-based phenotype • Drug utilization • Disease natural history • Adherence • Co-morbidity profile • Treatment pathways • Line of therapy

Population-Level Estimation

Population-level effect estimation: What are the causal effects?

causal inference

Mahidol University
Faculty of Medicine
Siriraj Hospital

Typical Questions	Desired output
• What is the effect of…? • What if I do intervention…? • Which treatment works better? • What is the risk of X on Y? • What is the time-to-event of…?	• Relative risk • Hazards ratio • Odds ratio • Average treatment effect • Causal effect • Association • Correlation • Safety surveillance • Comparative effectiveness

The data can provide answers to questions like:

- For patients newly diagnosed with atrial fibrillation, in the first year after therapy initiation, does warfarin cause more major bleeds than dabigatran?
- Does the causal effect of metformin on diarrhea vary by age?

Characterization

Mahidol University
Faculty of Medicine
Siriraj Hospital

Typical Questions	Desired output
• What is the chance that this patient will…? • Who are candidates for…?	• Probability for an individual • Prediction model • High/low risk groups • Probabilistic phenotype

The data can provide answers to questions like:

- For a specific patient newly diagnosed with major depressive disorder, what is the probability the patient will attempt suicide in the first year following diagnosis?
- For a specific patient newly diagnosed with atrial fibrillation, in the first year after therapy initiation with warfarin, what is the probability the patient suffers an ischemic stroke?

Catalog: Published Studies

https://dash.ohdsi.org/pubmed

Catalog: Past & Ongoing Studies

https://data.ohdsi.org/OhdsiStudies/

OHDSI Studies

OHDSI is a global, open-science community that is committed to generating real-world evidence to both support clinical decision-making and advance the methodology within this field. We have collaborated on many network studies across our community, many of which (both past and ongoing) are listed in this table. Please click on any listing that interests you to learn more about the study, and how you can potentially collaborate to generate reliable, reproducible evidence.

Show 15 entries

Search:

Title	Use cases	Study type	Tags	Status	Lead(s)	Start date	Last change
All	All	All	All	All	All	All	All
Deep Learning Comparison	Patient-Level Prediction	Methods Research	Deep Learning	Repo Created			2023-09-12
Large-scale Evidence Generation and Evaluation acr...	Population-Level Estimation	Clinical Application		Results Available	Marc A. Suchard		2023-09-11
Small-Sample Comparative-Effect Estimation Evaluat...	Population-Level Estimation	Methods Research		Started	Martijn Schuemie	2020-12-03	2023-09-11
Phenotype Library Diagnostics	Characterization	Clinical Application		Results Available	Gowtham Rao	2020-10-08	2023-08-31
Covid-19 vaccine adverse events of special interes...	Characterization	Methods Research	Phenotype error correction, In...	Repo Created	James Weaver		2023-08-21
Incorporating Measurement Values into Patient-Leve...	Patient-Level Prediction	Methods Research	Bayesian Inference, Missing Im...	Repo Created			2023-08-11
Development and evaluation of an algorithm to link...	Characterization	Methods Research	Maternal and infant health	Results Available	James Weaver		2023-07-25
Is fluoroquinolone use asscciated with the develop...				Repo Created	Jack Janetzki, Nicole Pratt, S...		2023-07-12
Health Equity Research Assessment (HERA) Character...	Characterization	Clinical Application	OHDSI, Health Equity	Started	Noemie Elhadad		2023-07-06
Risk of kidney failure associated with intravitrea...		Population-level estimation		Repo Created	Cindy X. Cai		2023-06-08
Relative Risk of Cervical Neoplasms Associated wit...	Characterization and Populatio...	Clinical Application	iud	Design Finalized	Matthew Spotnitz and Karthik N...	2019-09-23	2023-05-24
Quantitative bias analysis for outcome phenotype e...	Population-Level Estimation	Methods Research	QBA	Results Available	James Weaver		2023-05-18
olgImmCovid	Patient-Level Prediction	Clinical Application	COVID-19	Started	Jiayi Tong, Yong Chen, Jenna R...		2023-05-17
dGEM (Decentralized Algorithm for Generalized Line...	Patient-Level Prediction	Clinical Application	COVID-19	Design Finalized	Jiayi Tong, Yong Chen, Jenna R...		2023-05-02
Adverse Events of Special Interest within COVID-19...	Characterization	Clinical Application	COVID-19	Complete	Erica A Voss	2021-11-02	2023-04-18

Showing 1 to 15 of 97 entries

Previous 1 2 3 4 5 6 7 Next

Select a study to see details

Last updated: 2023-09-15 05:34:06 (Updated every 24 hours)

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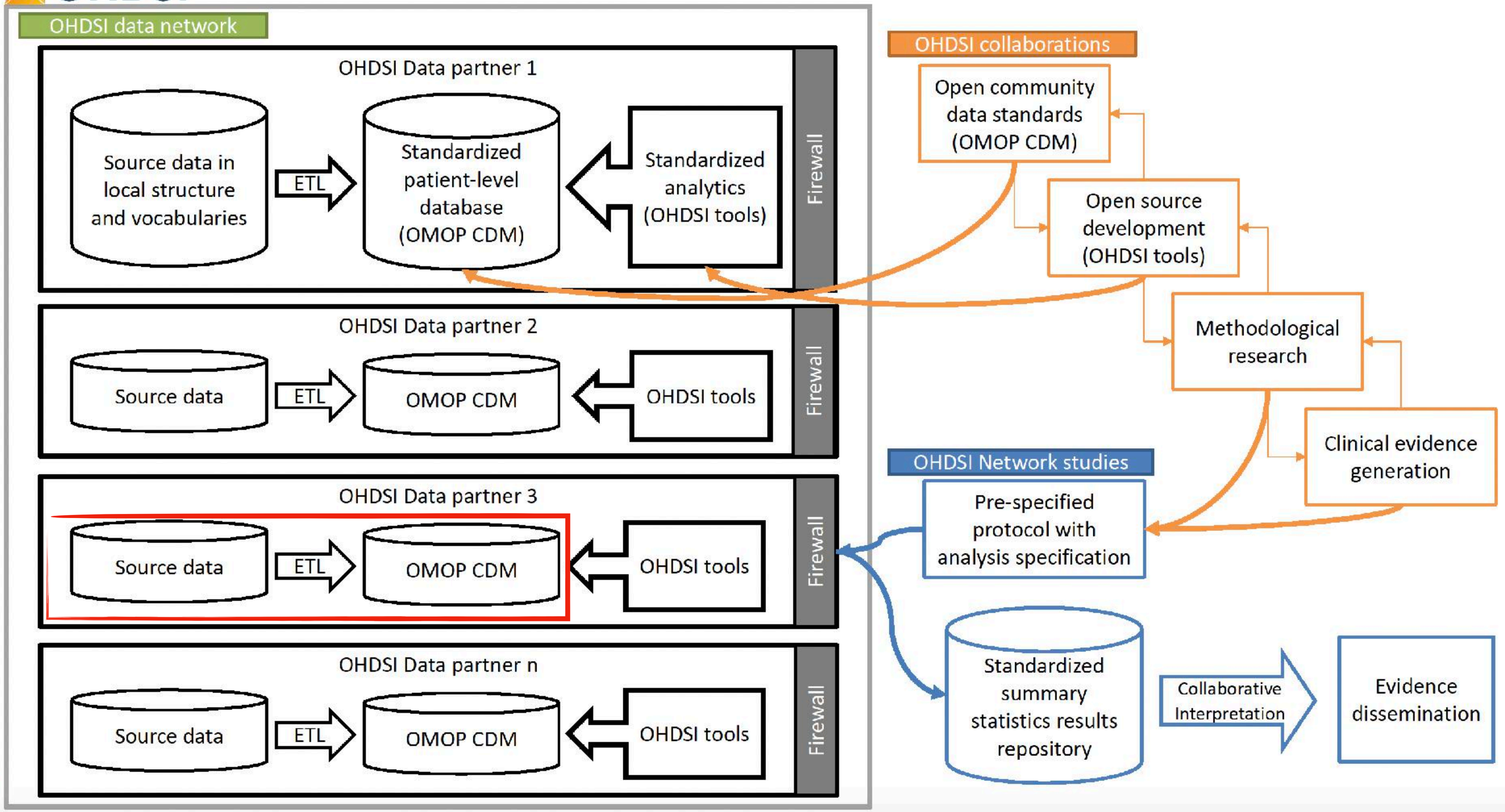
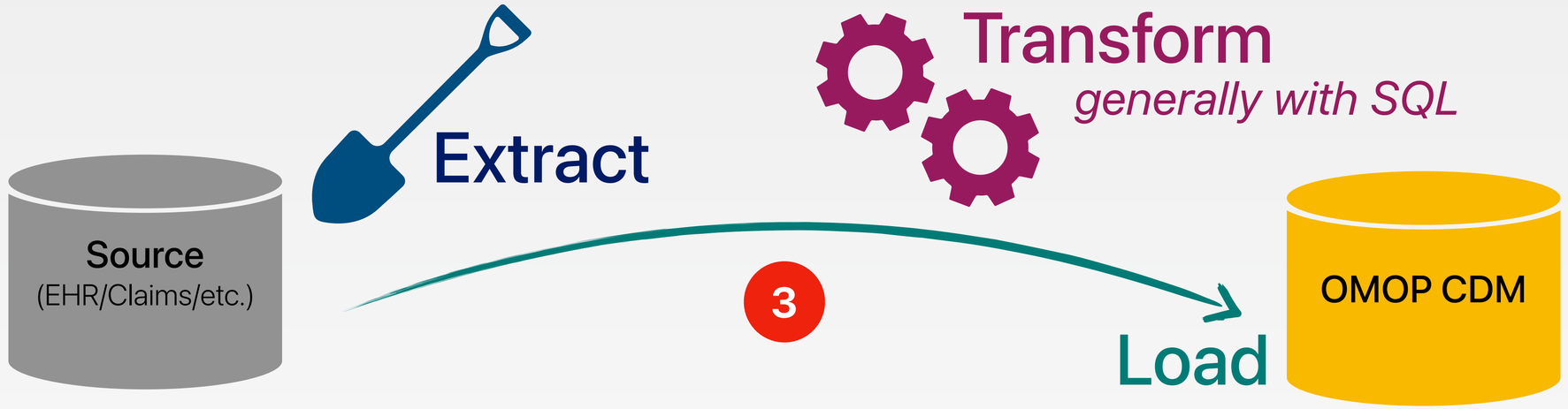
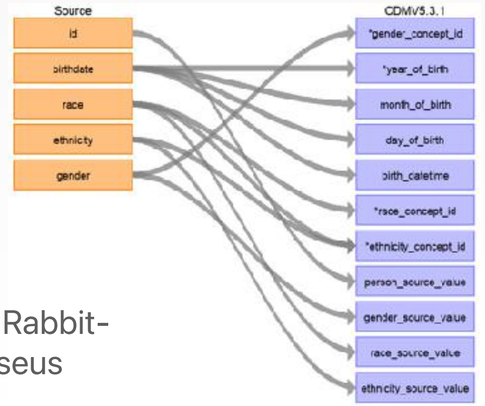


Extract Transform Load (ETL)



1

Data experts and CDM experts together design the ETL spec



OHDSI Tools: WhiteRabbit, Rabbit-In-a-Hat, Perseus

2

People with medical knowledge create the code mappings:
source -> standard
e.g., ICD-10 -> SNOMED*
TMT -> RxNorm
TMLT -> LOINC

*mapping table available

OHDSI Tools: Usagi

4

All are involved in quality control & regular updates

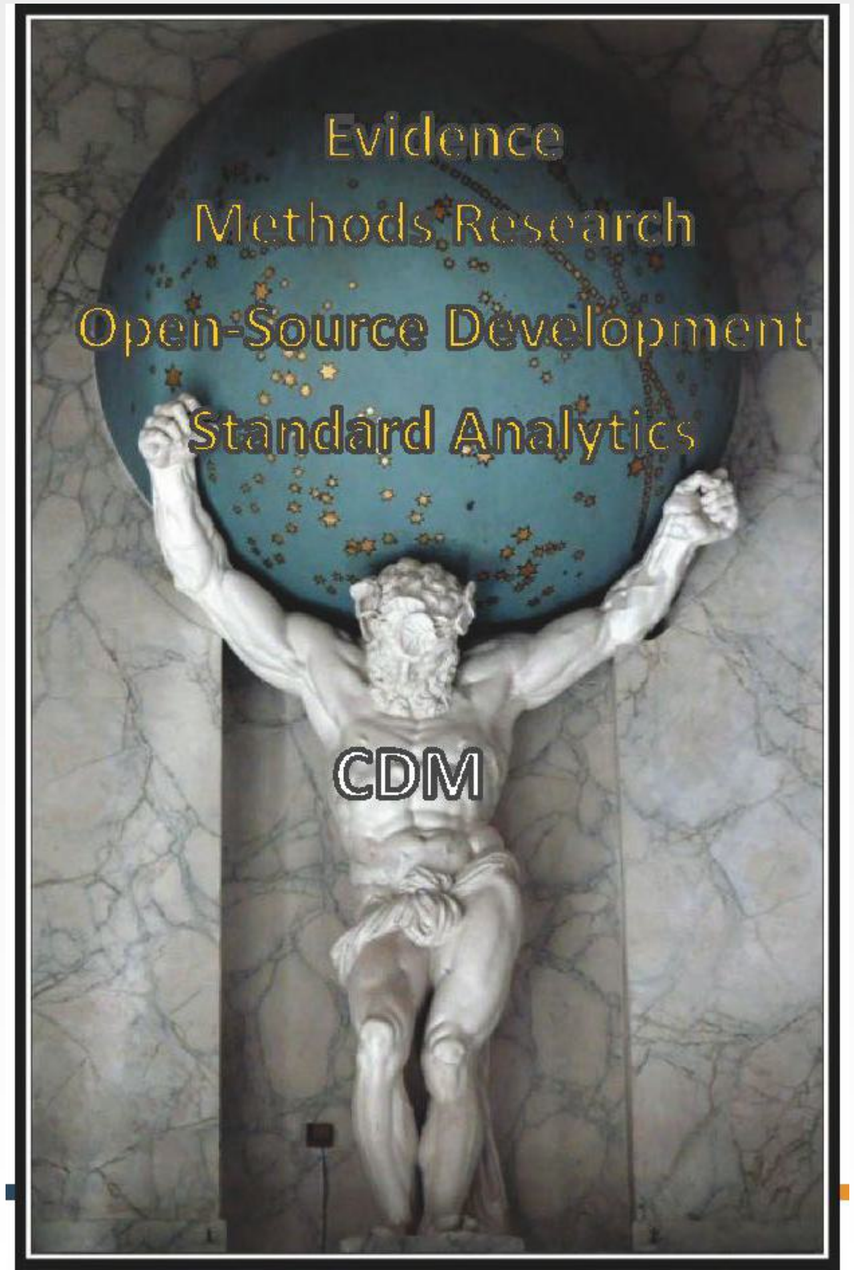
OHDSI Tools: DataQualityDashboard, Achilles

[https://ohdsi.github.io/TheBookOfOhdsi/ExtractTransformLoad.html]

OMOP CDM

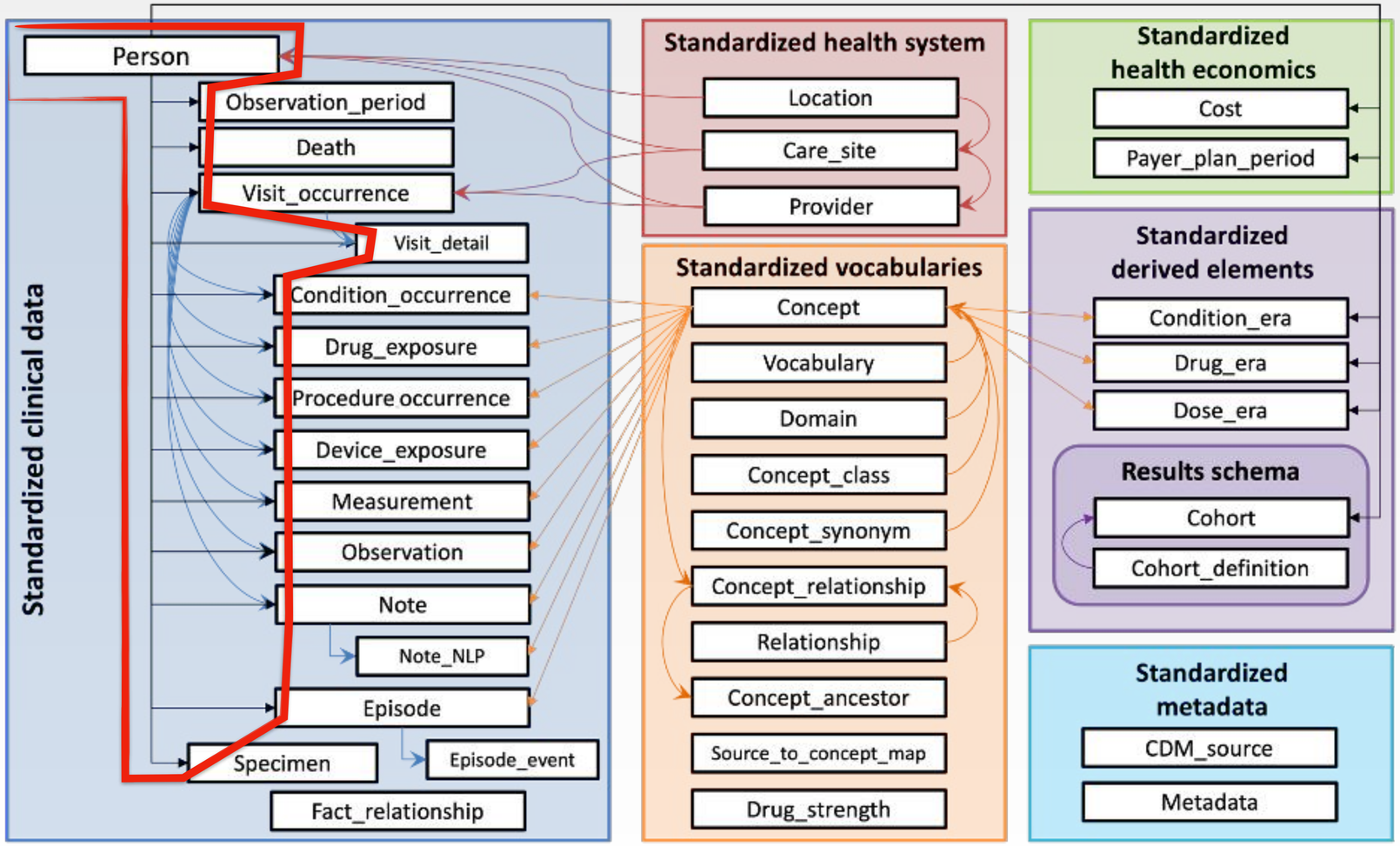
The OMOP CDM is **a system of tables, vocabularies, and conventions** that allow observational health data to be standardized.

It is this standard approach that facilitates rapid innovation in the areas of open-source development, methods research, and evidence generation.



General Conventions

The OMOP CDM is a Person centric model



General Conventions

- Required tables: **`person`** and **`observation_period`**
- Common fields:
  - **`[condition/procedure/drug_exposure/measurement]_id`** รหัส transaction ของแต่ละตาราง เป็น primary key
  - **`[…]_type_concept_id`** ประเภทที่มาข้อมูลเช่น EHR/Claims, IPD/OPD, Lab, Registry, Survey
  - **`[…]_source_value`** รหัสโรค/หัตถการ/ยา/แลป/อื่น ๆ ต้นทาง
  - **`[…]_source_concept_id`** รหัสโรค/หัตถการ/ยา/แลป/อื่น ๆ ต้นทาง ที่ mapped เป็น ID ของ OMOP
  - **`[…]_concept_id`** รหัสโรค/หัตถการ/ยา/แลป/อื่น ๆ standard ที่ mapped เป็น ID ของ OMOP

condition_source_value	condition_source_concept_id	condition_concept_id	*Standard Code*
I10 *(ICD10 for Essential (primary) Hypertension)*	45591453	320128	*59621000* *(SNOMED for Essential hypertension)*

Table/Field Conventions

https://ohdsi.github.io/CommonDataModel/cdm54.html

Clinical Data Tables

PERSON

Table Description

This table serves as the central identity management for all Persons in the database. It contains records that uniquely identify each person or patient, and some demographic information.

User Guide

All records in this table are independent Persons.

ETL Conventions

All Persons in a database needs one record in this table, unless they fail data quality requirements specified in the ETL. Persons with no Events should have a record nonetheless. If more than one data source contributes Events to the database, Persons must be reconciled, if possible, across the sources to create one single record per Person. The content of the BIRTH_DATETIME must be equivalent to the content of BIRTH_DAY, BIRTH_MONTH and BIRTH_YEAR.

CDM Field	User Guide	ETL Conventions	Datatype	Required	Primary Key	Foreign Key	FK Table	FK Domain
person_id	It is assumed that every person with a different unique identifier is in fact a different person and should be treated independently.	Any person linkage that needs to occur to uniquely identify Persons ought to be done prior to writing this table. This identifier can be the original id from the source data provided if it is an integer, otherwise it can be an autogenerated number.	integer	Yes	Yes	No		
gender_concept_id	This field is meant to capture the biological sex at birth of the Person. This field should not be used to study gender identity	Use the gender or sex value present in the data under the assumption that it is the biological sex at birth. If the source data captures gender identity it should be stored in the OBSERVATION table. Accepted gender concepts	integer	Yes	No	Yes	CONCEPT	Gender

แต่ละ Table มีหลักการเติมข้อมูลอย่างไร

แต่ละ Field มีหลักการเติมข้อมูลอย่างไร

OHDSI

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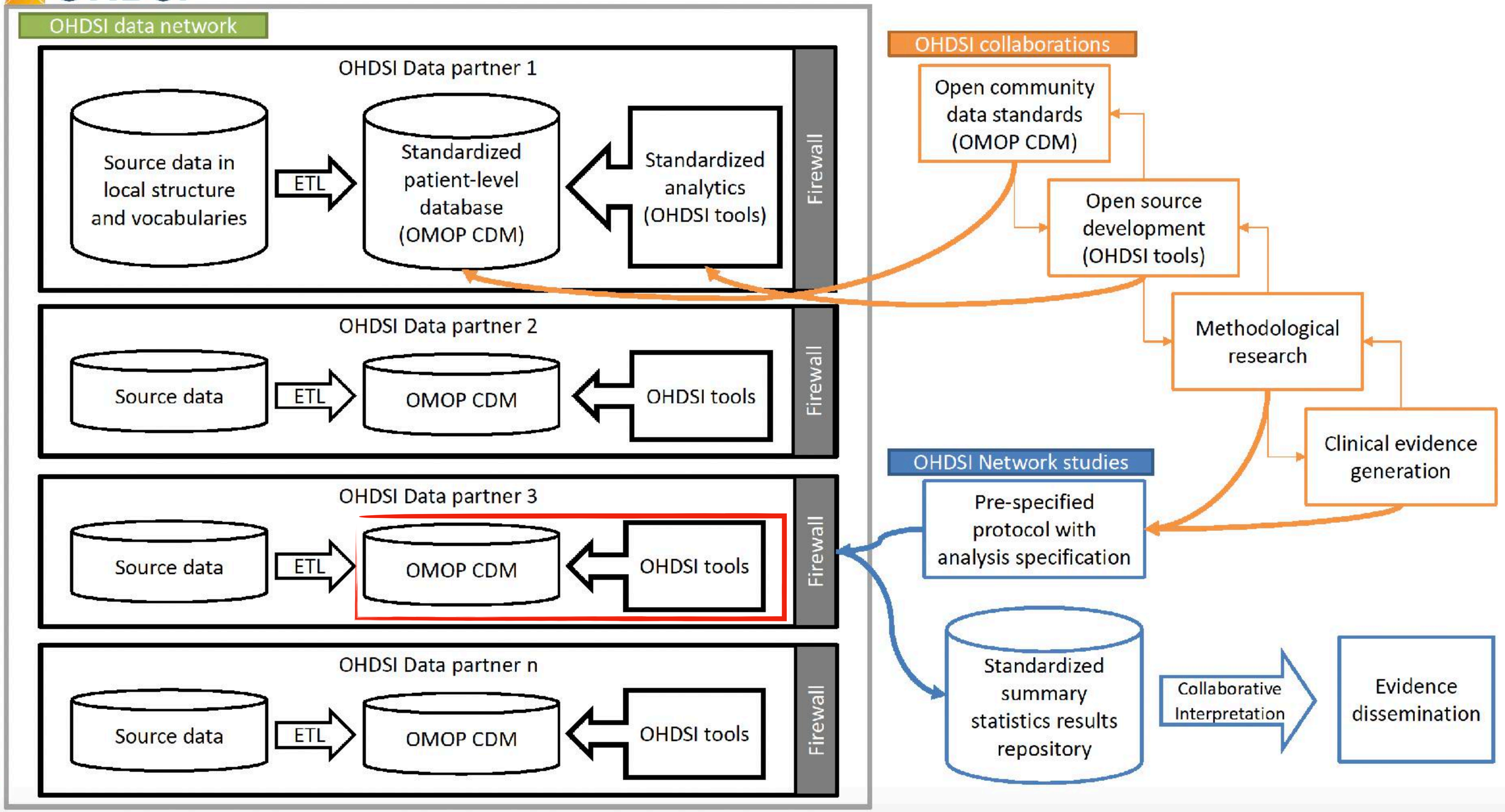
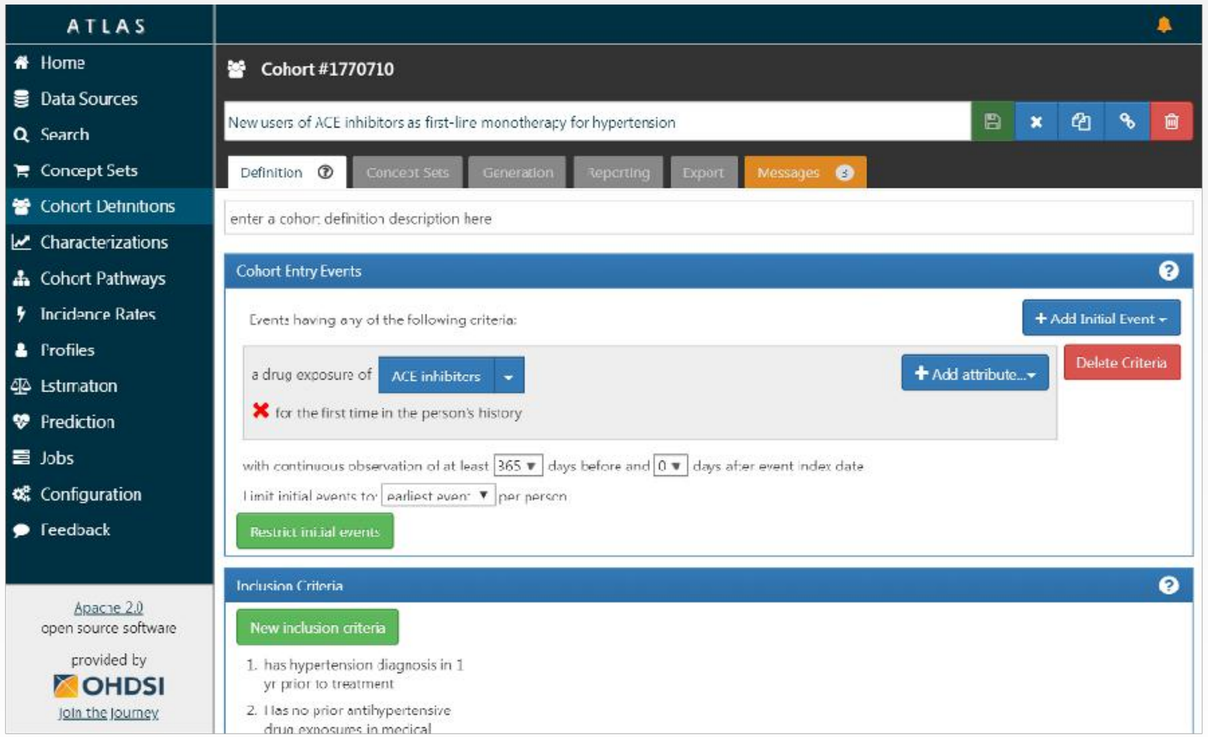


OHDSI Tools

Mahidol University
Faculty of Medicine
Siriraj Hospital

Web-based Tool: ATLAS



Code-based Tools: HADES

+Evidence Quality
+Cohort construction and evaluation
+Characterization
+Patient-level prediction
+Population-level estimation

HADES
HEALTH ANALYTICS DATA-TO-EVIDENCE SUITE

[https://ohdsi.github.io/Hades/packages.html]

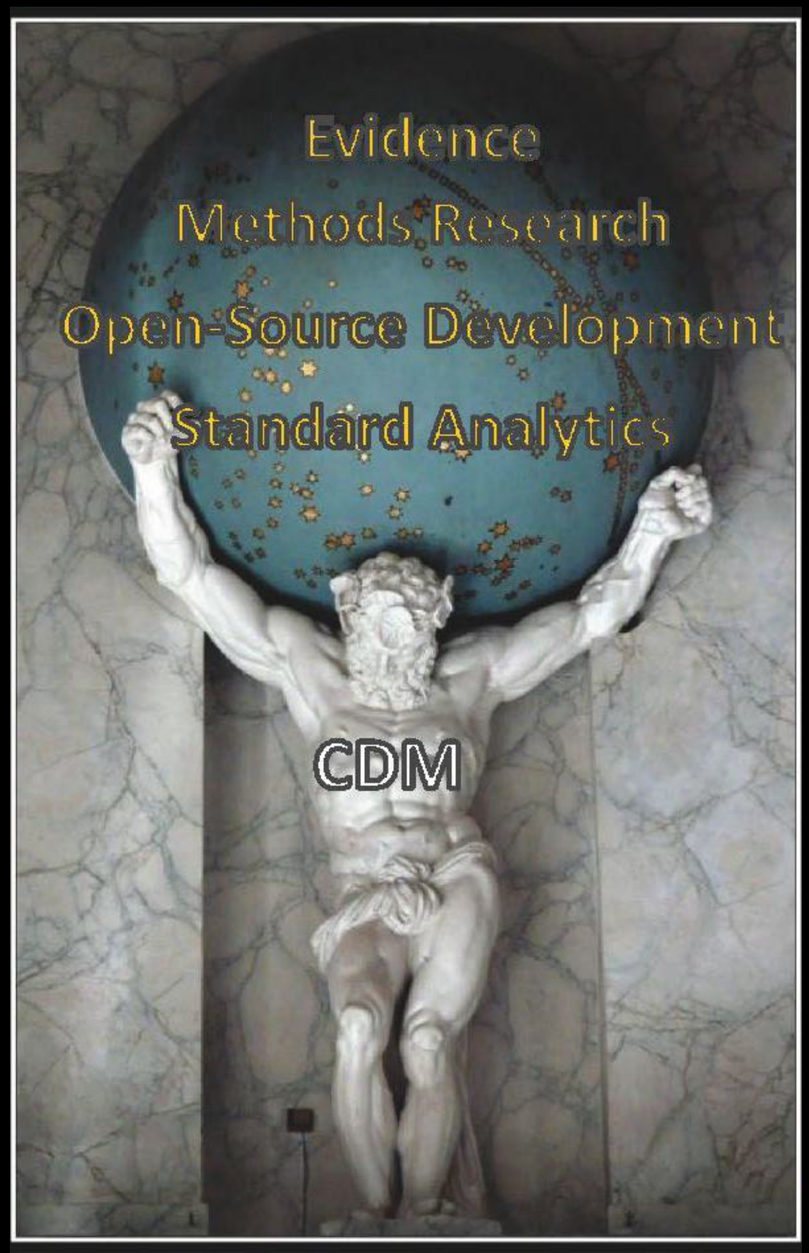
Atlas

In Greek mythology, the Titan Atlas was responsible for bearing the weight of the heavens on his shoulders, a burden given to him as punishment by Zeus for leading the Titans in their battle with the Olympian Gods for control of the heavens. Father of many stars and a protagonist in one of Hercules' famous labors, Atlas was also known as a wise man and the founder of astronomy.

[https://www.worldhistory.org/atlas]

The term Atlas has been used to describe a collection of maps since the 16th century when Flemish geographer Gerardus Mercator published his work in honor of the mythological Titan.

[https://en.wikipedia.org/wiki/Atlas_(mythology)]



Hades

Hades was both the name of the ancient Greek god of the underworld (Roman name: Pluto) and the name of the shadowy place below the earth which was considered the final destination for the souls of the dead.

Following the overthrow of first the Titans and then the Giants by the Olympian gods, Hades drew lots with his brothers Zeus and Poseidon to decide which part of the world each would rule. Zeus received the sky, Poseidon the seas, and Hades the underworld.

[https://www.worldhistory.org/Hades]

Aviad Bublil (CC BY-SA)

Where You Fit In

https://ohdsi.github.io/TheBookOfOhdsi/WhereToBegin.html

I am a clinical researcher looking to start a study. OHDSI loves to publish and has many resources available to expedite turning your research question into an analysis and a paper.

I want to read and consume the information the OHDSI community produces. Whether you're a patient, a practicing clinician or subject matter expertise in healthcare, OHDSI wants to provide you with high quality evidence to help you better understand health outcomes.

I work in a healthcare leadership role. I may be a data owner and/or represent one. I am evaluating the utility of the OMOP CDM and OHDSI analytical tools for my organization. More than 200 organizations around the world are collaborating in OHDSI, there's plenty of success stories to help showcase the value of this community.

I am a database administrator looking to ETL/convert my institution's data to the OMOP CDM. If you're just starting out on your ETL process, consult the OHDSI Community ETL Tutorial Slides or sign-up for the next offering at an upcoming OHDSI Symposium.

I am a biostatistician and/or methods developer interested in contributing to the OHDSI tool stack. You're savvy in R. You know how to commit to Git. Most of all, you're eager to bring your expertise to the OHDSI Methods Library and further develop these methodologies. We welcome your contributions!

I am a software developer interested in building a tool that complements the OHDSI tool stack. As part of the OHDSI mission, our tools are open source and governed under Apache licenses.

I am a consultant looking to advise the OHDSI Community. You're invited to join us at OHDSI Tutorials and consider giving back by contributing your expertise in the Symposium proceedings and OHDSI face-to-face meetings throughout the year.

I am a student looking to learn more about OHDSI. You're in the right place! Consider joining an OHDSI Community Call and introducing yourself. You are encouraged to delve into the OHDSI tutorials, attend OHDSI Symposiums and face-to-face meetings to learn more about the methods and tools the OHDSI community offers.

How Healthcare Systems Can Create Value by Adopting the OMOP CDM

John Methot, Melanie Philofsky, Brian J. Bush, Paul Nagy, Daniel Smith, Edward Smith
OHDSI Healthcare Systems Interest Group

Poster: https://www.ohdsi.org/2022showcase-78/

Background

In the OHDSI community there is wide belief that adoption of OHDSI has significant benefits for healthcare systems in both operations and research. However, that hypothesis is currently "expert opinion". We describe here our plan to gather evidence on cost savings and other benefits that healthcare systems can realize by adopting the OMOP CDM. Our results can be used by researchers and IT staff as business justification for OMOP adoption.

The benefits fall into these categories:

Methods

- A recent OHDSI-wide survey of organizations with OMOP CDMs revealed that approximately 250 respondents are healthcare organizations
- This ongoing project is an activity of the Healthcare Systems Interest Group. We surveyed members of the working group to collect and rank a set of realized and expected benefits.
- Our next step is to field a survey of OHDSI community members to identify healthcare systems that have adopted OMOP and collect quantitative estimates of associated cost savings across their activities.
- After collecting and analyzing survey data, we will author a publication containing quantitative evidence of cost savings and other benefits that healthcare organization can realize by adopting the OMOP CDM.

Top 10 Candidate Healthcare System Benefits of OMOP CDM Adoption

1. Common Data Model improves data analyst productivity by simplifying many representation decisions
2. Training materials are freely available and have been accessed by thousands of individuals who form a talent pool for recruiting
3. Reduce costly chart abstraction via automated mapping of EMR data
4. Rich environment of available open-source analysis tools, both web-based and R
5. Extensible for multi-model precision medicine research; can support EMRs, HIEs, Claims, Registries, IoT, etc.
6. All patient data remains local: OHDSI supports a federated analysis model in which analysis code is shared, not data
7. Supports reproducible research, based on CDM semantics and published analysis code
8. Ability to easily participate in collaborative studies; examples are All of Us, N3C, numerous OHDSI network studies
9. Easy deployment of the OHDSI technology stack on cloud infrastructure; supported by AWS, GCP and Microsoft Azure
10. An ecosystem of vendors exists with expertise in OMOP infrastructure, ETL, and study design

Do you represent a healthcare system? Please take our survey!

https://bit.ly/OMOPAdopt

Results and Conclusions

- We produced a list of the top 10 benefits we hypothesize healthcare systems can realize from OMOP CDM adoption.
- We designed and fielded a survey to more accurately characterize healthcare system benefits.
- We used this poster and the 2022 OHDSI Global Symposium to advertise the survey and recruit respondents.

- We will aggregate and summarize the survey findings
- We will author a publication describing actual benefits realized by healthcare systems, advancing the topic from expert opinion to published research
- We will publicize the paper and promote its use as business justification for researchers and informatics staff seeking financial support for OMOP CDM adoption at their institutions

Authors: John Methot[1], Melanie Philofsky[2], Brian J. Bush[3], Paul Nagy[4], Daniel Smith[5], Edward Smith[6]

[1]Dana-Farber Cancer Institute, [2]Odysseus Data Services, [3]Virginia Commonwealth University, [4]Johns Hopkins University, [5]Emory University, [6]University of Maryland Medical Center

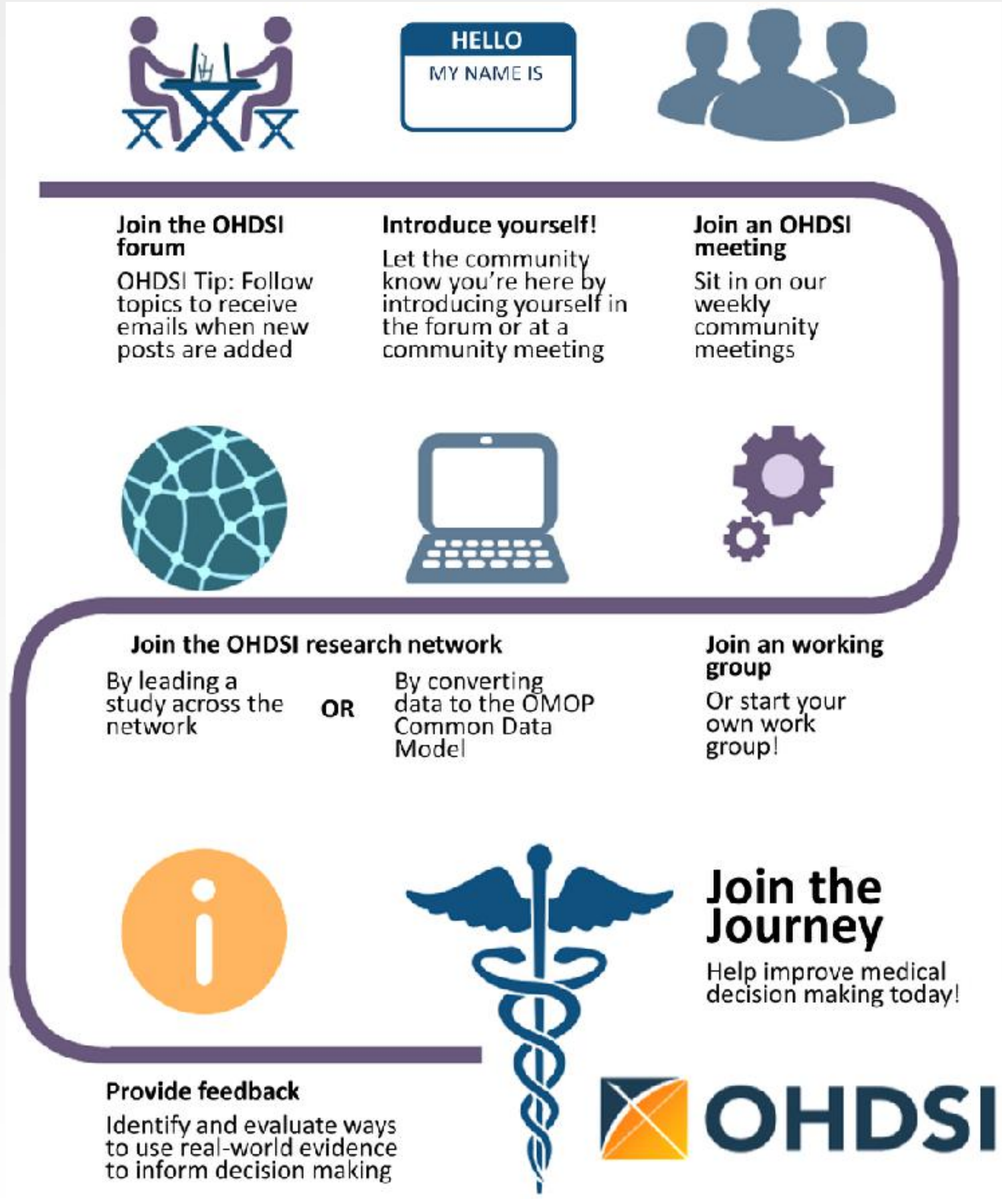
Contact: john_methot@dfci.harvard.edu

I work in a healthcare leadership role. I may be a data owner and/or represent one. I am evaluating the utility of the OMOP CDM and OHDSI analytical tools for my organization. More than 200 organizations around the world are collaborating in OHDSI, there's plenty of success stories to help showcase the value of this community.

[https://www.ohdsi.org/2022showcase-78/]

Resources

1. The Book of OHDSI: https://ohdsi.github.io/TheBookOfOhdsi
2. EHDEN Academy: https://academy.ehden.eu
3. OHDSI Past Events: https://www.ohdsi.org
4. OHDSI Community Calls: https://www.ohdsi.org/community-calls/
5. OHDSI Forums: http://forums.ohdsi.org
6. YouTube: https://www.youtube.com/@OHDSI
7. *Soon*, Intro to OMOP in Thai 🇹🇭: https://omop.sidata.plus



Siriraj Informatics and Data Innovation Center

OHDSI
OBSERVATIONAL HEALTH DATA SCIENCES AND INFORMATICS

Mahidol University
Faculty of Medicine
Siriraj Hospital

Inspiring Experience from Singapore

Asst. Prof. Mengling 'Mornin' Feng
National University of Singapore

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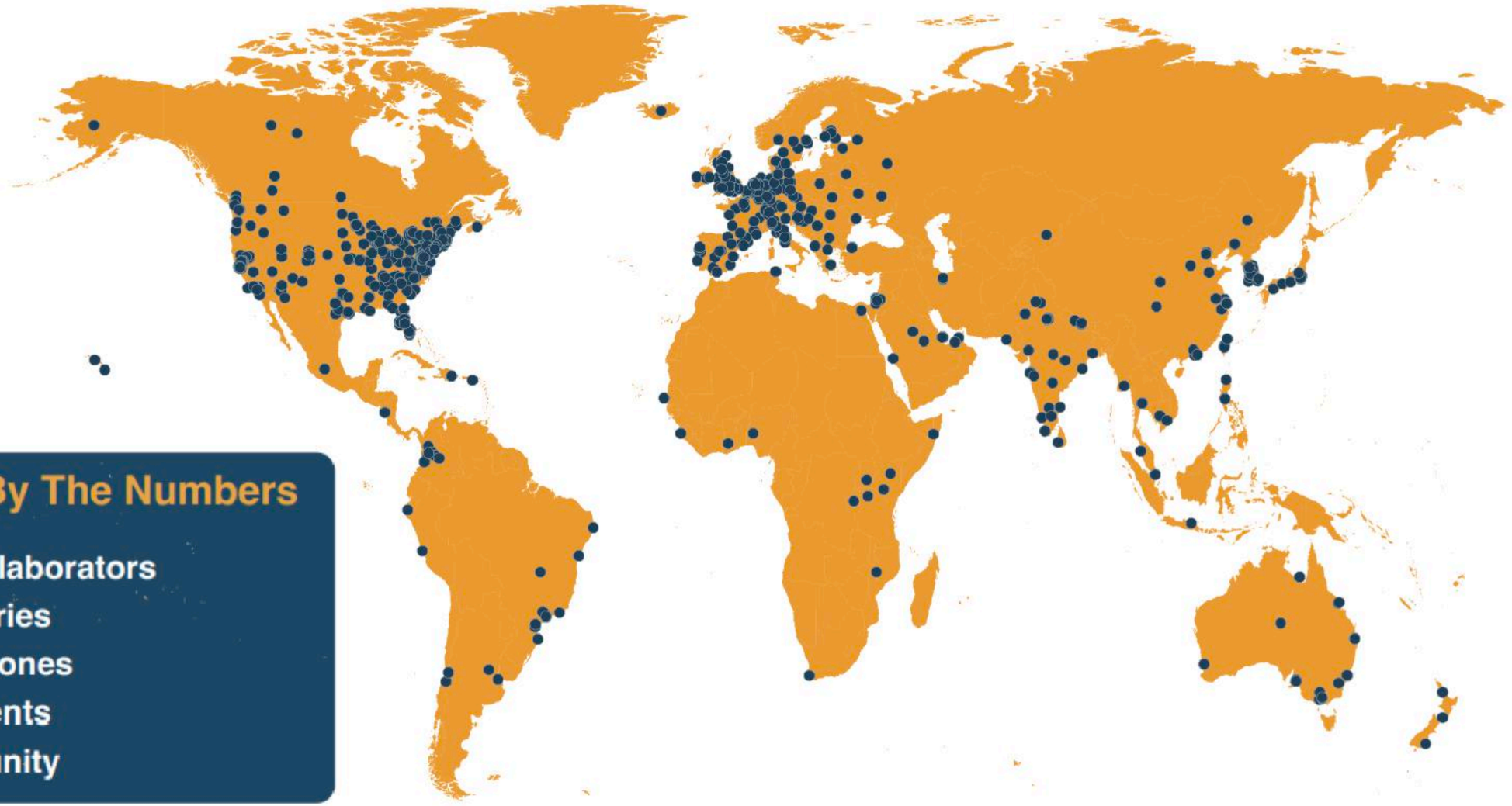
Session Overview

Inspiring Experience from Singapore @ 10:45 – 11:15 (30 min)

Why? Background & Questions	How? Methods & Materials	What? Objectives
☐ How do other countries/ systems adopt OMOP/ OHDSI? ☐ What are their research products?	⬟ Recorded talk from OHDSI Singapore Chapter Updates mid-2023 ⬟ Live Q&A session with Mornin	★ See Singapore's OMOP/ OHDSI adoption ★ Get inspired to further explore the global community and research opportunities

Map of collaborators



OHDSI By The Numbers

- 3,266 collaborators
- 80 countries
- 21 time zones
- 6 continents
- 1 community

[https://www.ohdsi.org/wp-content/uploads/2022/10/OHDSI-OurJourney-2022.pdf]

OHDSI APAC Local Chapters

OHDSI APAC - Our Asia-Pacific Community

OHDSI is a global, multi-stakeholder, interdisciplinary and open-science network that collaborates to bring out the value of health data through large-scale analytics. Our Asia-Pacific (APAC) community comprises seven regional chapters (Australia, China, India, Japan, Singapore, South Korea, Taiwan) and has led important OHDSI initiatives around the world.

OHDSI APAC Community in Teams

The APAC community has its own group in the OHDSI MS Teams environment to promote greater collaboration on our collaborative efforts. First, request access to our MS Teams Environment, then request access to our OHDSI APAC workgroup.

2023 Asia-Pacific Community Calls

Date	Topic
August 17	European and APAC Symposium Recap
September 21	Training Session #5
October 19	Training Session #6
November 16	Global Symposium Recap and Training Session #7
December 21	APAC 2023 Recap and Year Closing

@OHDSI www.ohdsi.org #JoinTheJourney ohdsi

APAC Monthly Community Call

Everybody is invited to the monthly OHDSI APAC community call, which takes place the third Thursday of each month at 12 pm Korea time. These calls are meant to provide updates, share research presentations, collaborate on topics of shared interest, and plenty more. The upcoming schedule is available to the right.

https://ohdsi.org/apac/

2023 APAC Symposium

July 13-14 · University of New South Wales · Sydney, Australia

The 2023 OHDSI APAC Symposium was held July 13-14 in Sydney, Australia at the University of New South Wales. Thank you to all the volunteers who helped put together this fantastic event. Videos of all presentations are included below, while videos from the tutorials are coming soon!

Symposium Presentations

Welcome, Keynote

Speakers: **Nicole Pratt** (President OHDSI Australia Chapter, University of South Australia) and **Patrick Ryan** (Vice President, Observational Health Data Analytics, Janssen Research and Development)

Transforming health: What do regulators, clinicians, and consumers really want to know about healthcare and how can OHDSI help

Speaker: **Asieh Golozar** (Vice President, Global Head of Data Science at Odysseus Data Services, Inc, Professor of the Practice & Director of Clinical Research at the OHDSI Center, Northeastern University)

https://ohdsi.org/2023apacsymposium/

OHDSI Singapore

OHDSI
OBSERVATIONAL HEALTH DATA SCIENCES AND INFORMATICS

Co-Chairs:

Dr. Mengling 'Mornin' Feng
Senior Assistant Director, National University Health System
Assistant Professor, National University of Singapore
ephfm@nus.edu.sg

Dr. Kee Yuan Ngiam
Group Chief Technology Officer
National University Health System

https://youtu.be/bFMgX6oUUa4?si=RZwAKxvr6oSluBR5&t=2166

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OHDSI Tools: Athena & Atlas

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หน่วยวิจัยเพื่อขับเคลื่อนนโยบายสุขภาพ
Siriraj Health Policy Unit

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สำนักงานหลักประกันสุขภาพแห่งชาติ

Session Overview

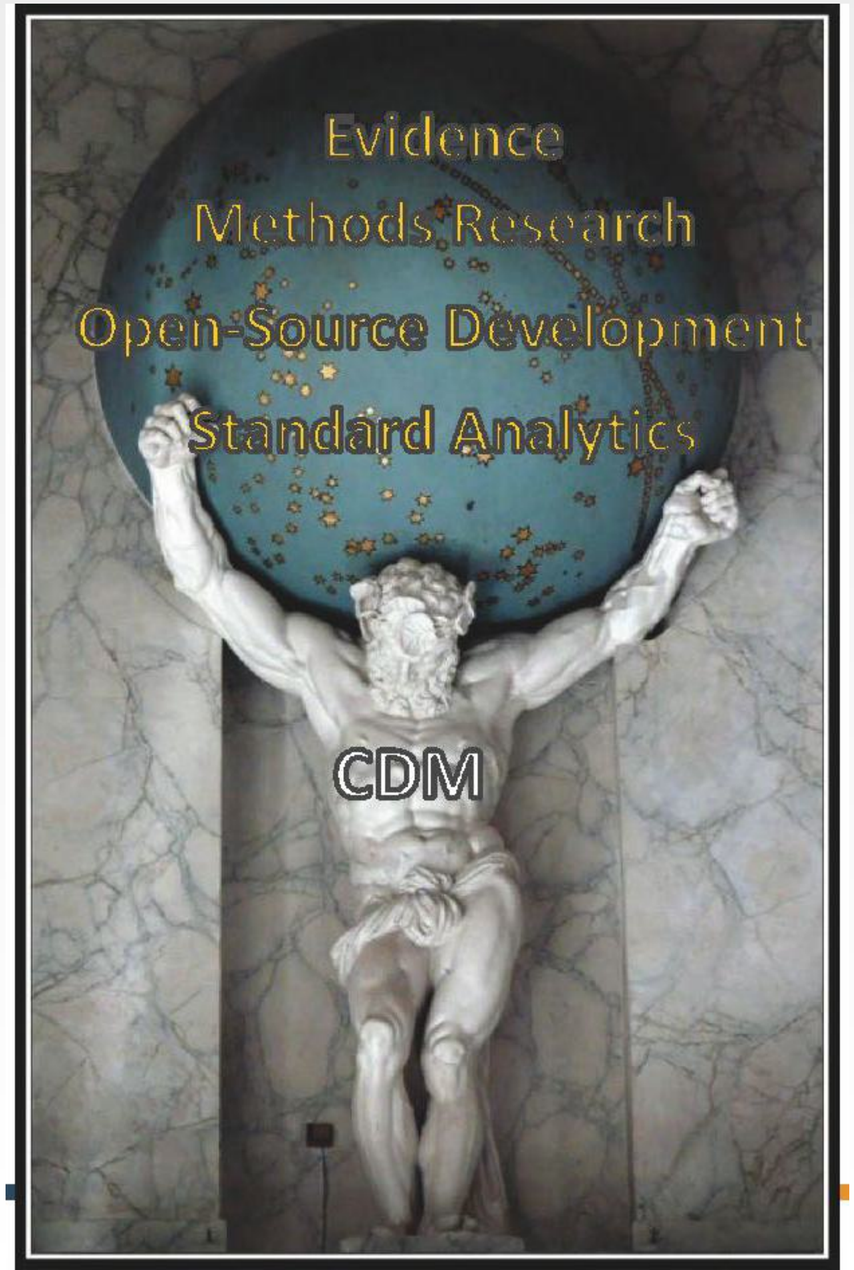
OHDSI Tools: Athena & Atlas @ 11:15 – 12:00 (45 min)

Why? Background & Questions	How? Methods & Materials	What? Objectives
☐ How do OMOP record medical concepts? ICD-10/ ICD-9? SNOMED? ☐ How can we browse standard codes on Athena? ☐ How can we use OMOP CDM via website, Atlas?	⬟ Overview of Standard Concepts ⬟ Features of Athena & Atlas ⬟ Hands-on: Vocabulary search in Athena ⬟ Hands-on: Log-in to Atlas	★ Learn how to navigate Athena & Atlas ★ Acquire practical experience through hands-on exercises

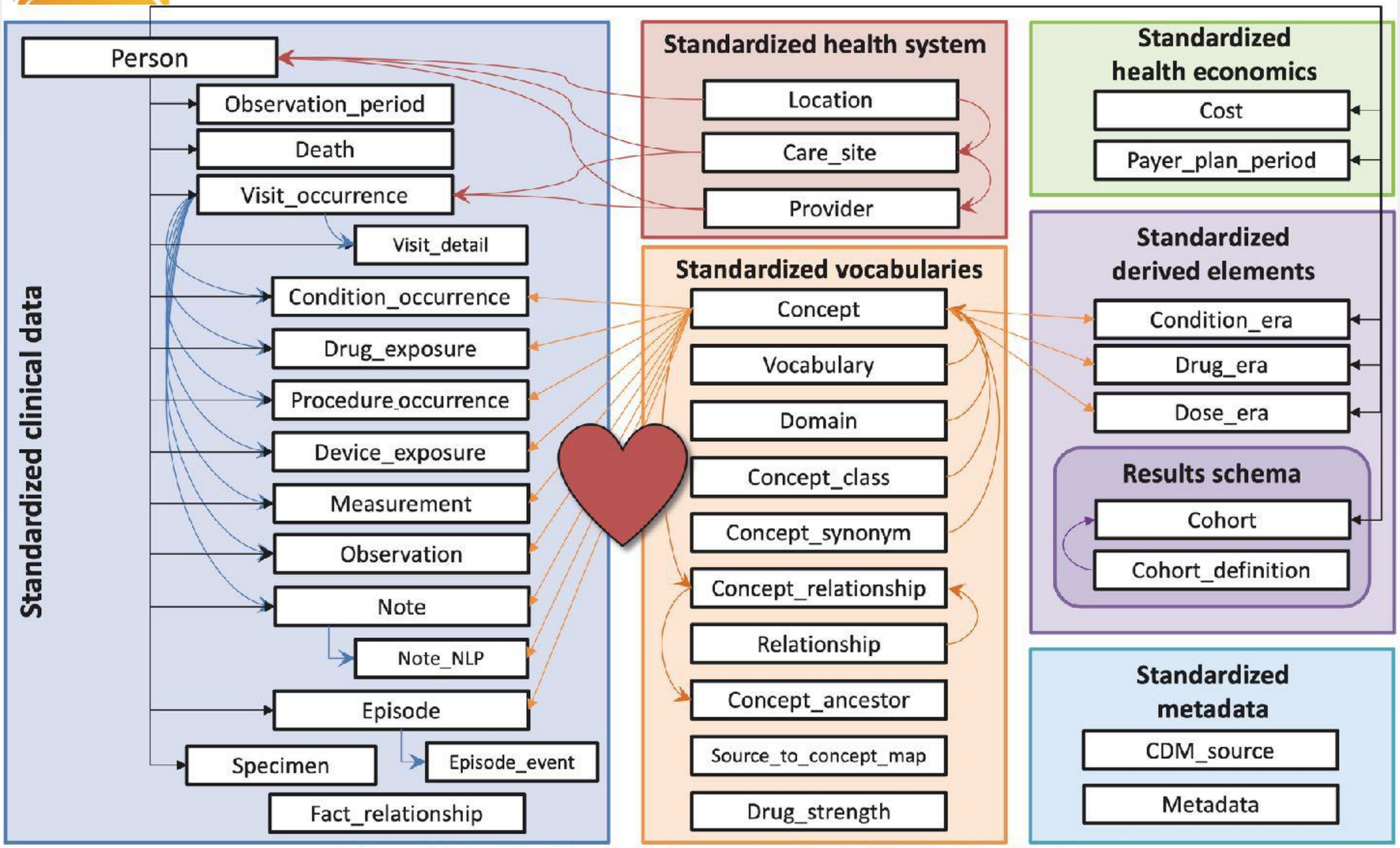
OMOP CDM

The OMOP CDM is **a system of tables, vocabularies, and conventions** that allow observational health data to be standardized.

It is this standard approach that facilitates rapid innovation in the areas of open-source development, methods research, and evidence generation.

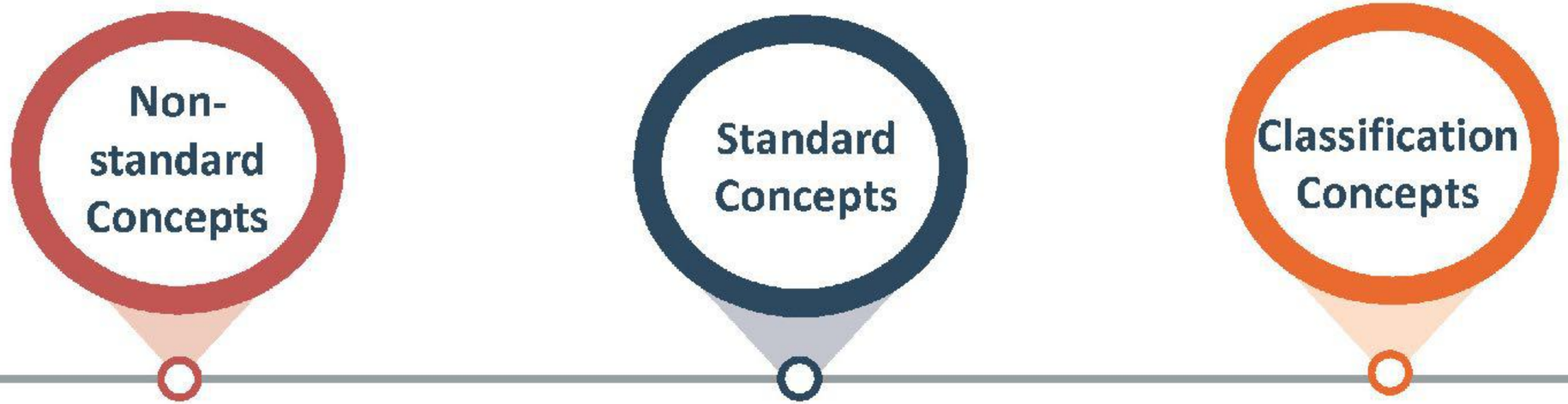


OMOP CDM & Vocabulary



https://ohdsi.github.io/CommonDataModel/index.html

Different Categories of Concepts



Function

Unique representation of a source code

e.g., ICD-10, TMT, TMLT

Function

Used for standardized analytics and by OHDSI tools

e.g., SNOMED, RxNorm, LOINC

Function

Used to perform hierarchical queries

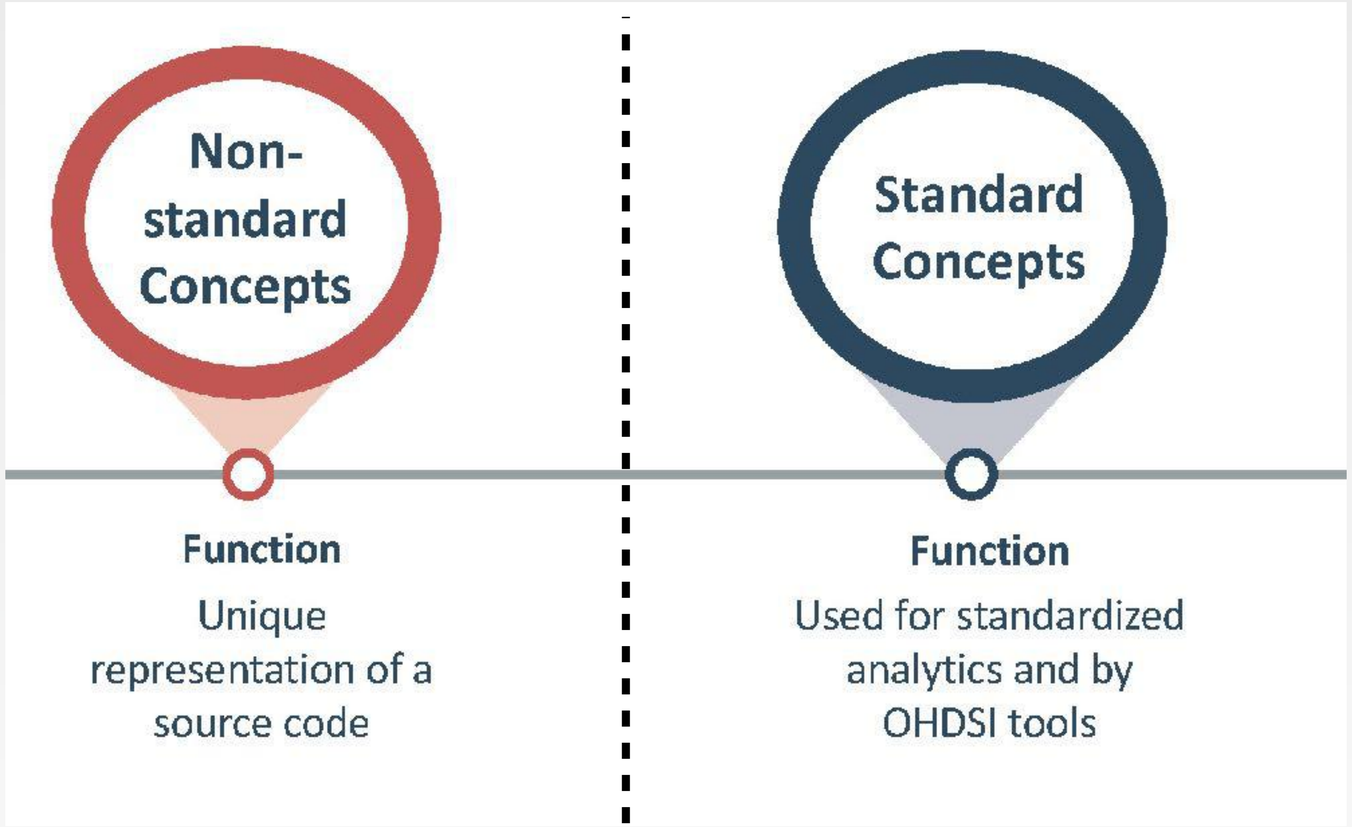
e.g., drug groups, dx groups

Standard Concepts

https://ohdsi.github.io/TheBookOfOhdsi/StandardizedVocabularies.html

Table 5.2: List of vocabularies to utilize for Standard/non-standard/classification concept assignments.

Domain	for Standard Concepts	for source concepts	for classification concepts
Condition	SNOMED, ICDO3	SNOMED Veterinary	MedDRA
Procedure	SNOMED, CPT4, HCPCS, ICD10PCS, ICD9Proc, OPCS4	SNOMED Veterinary, HemOnc, NAACCR	None at this point
Measurement	SNOMED, LOINC	SNOMED Veterinary, NAACCR, CPT4, HCPCS, OPCS4, PPI	None at this point
Drug	RxNorm, RxNorm Extension, CVX	HCPCS, CPT4, HemOnc, NAAACCR	ATC
Device	SNOMED	Others, currently not normalized	None at this point
Observation	SNOMED	Others	None at this point
Visit	CMS Place of Service, ABMT, NUCC	SNOMED, HCPCS, CPT4, UB04	None at this point

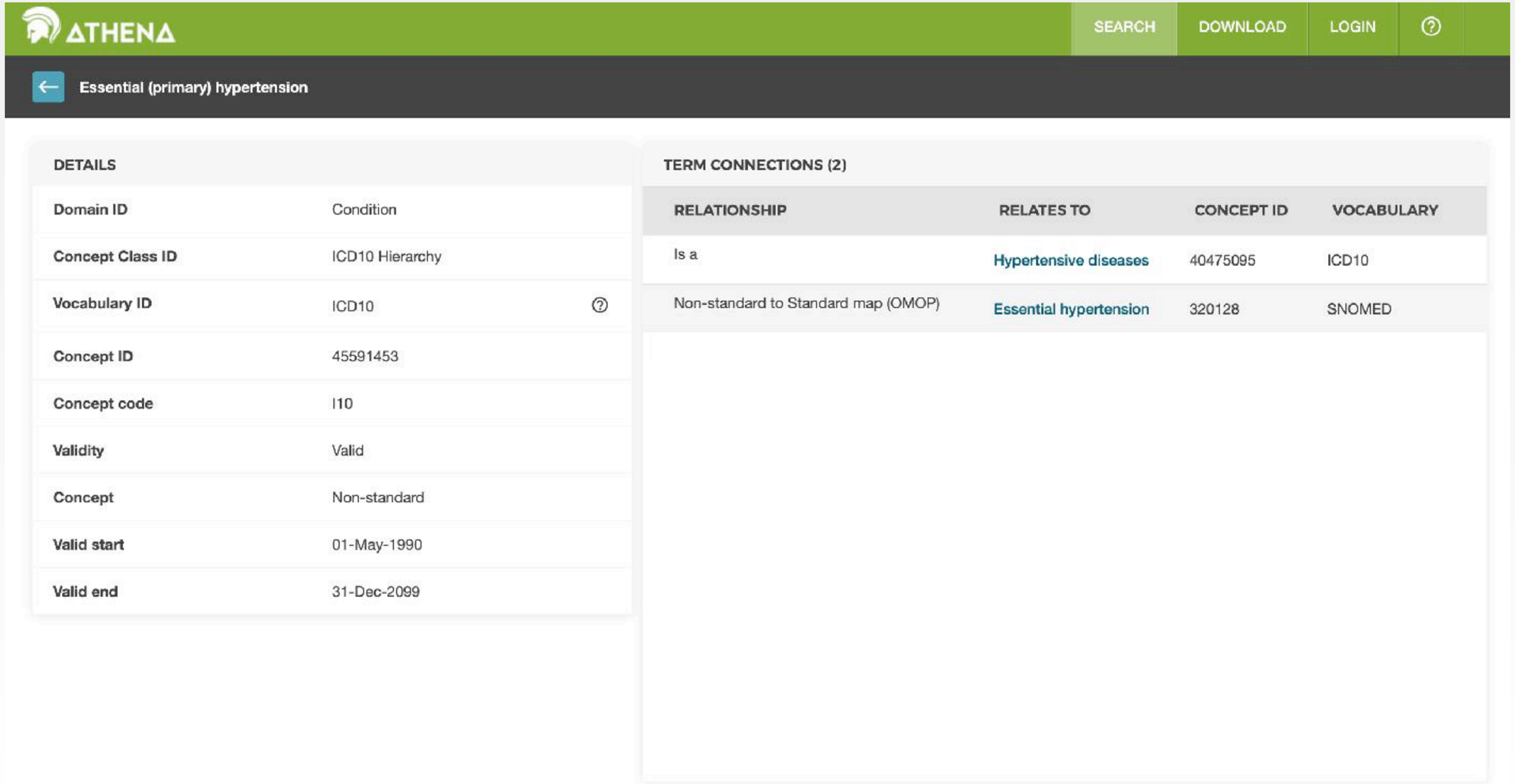


condition_source_value	condition_source_concept_id	condition_concept_id	*Standard Code*
I10 *(ICD10 for Essential (primary) Hypertension)*	45591453	320128	*59621000 (SNOMED for Essential hypertension)*

- **_source_value** รหัสโรค/หัตถการ/ยา/แลป/อื่น ๆ ต้นทาง
- **_source_concept_id** รหัสโรค/หัตถการ/ยา/แลป/อื่น ๆ ต้นทาง ที่ mapped เป็น ID ของ OMOP
- **_concept_id** รหัสโรค/หัตถการ/ยา/แลป/อื่น ๆ standard ที่ mapped เป็น ID ของ OMOP

Demo: I10 Hypertension

https://athena.ohdsi.org/search-terms/terms/45591453



Hands-on: Find standard concept for I48 Atrial Fibrillation

https://athena.ohdsi.org

Mahidol University
Faculty of Medicine
Siriraj Hospital

ATHENA

SEARCH | DOWNLOAD | LOGIN

SEARCH BY KEYWORD: i48

i48 ×

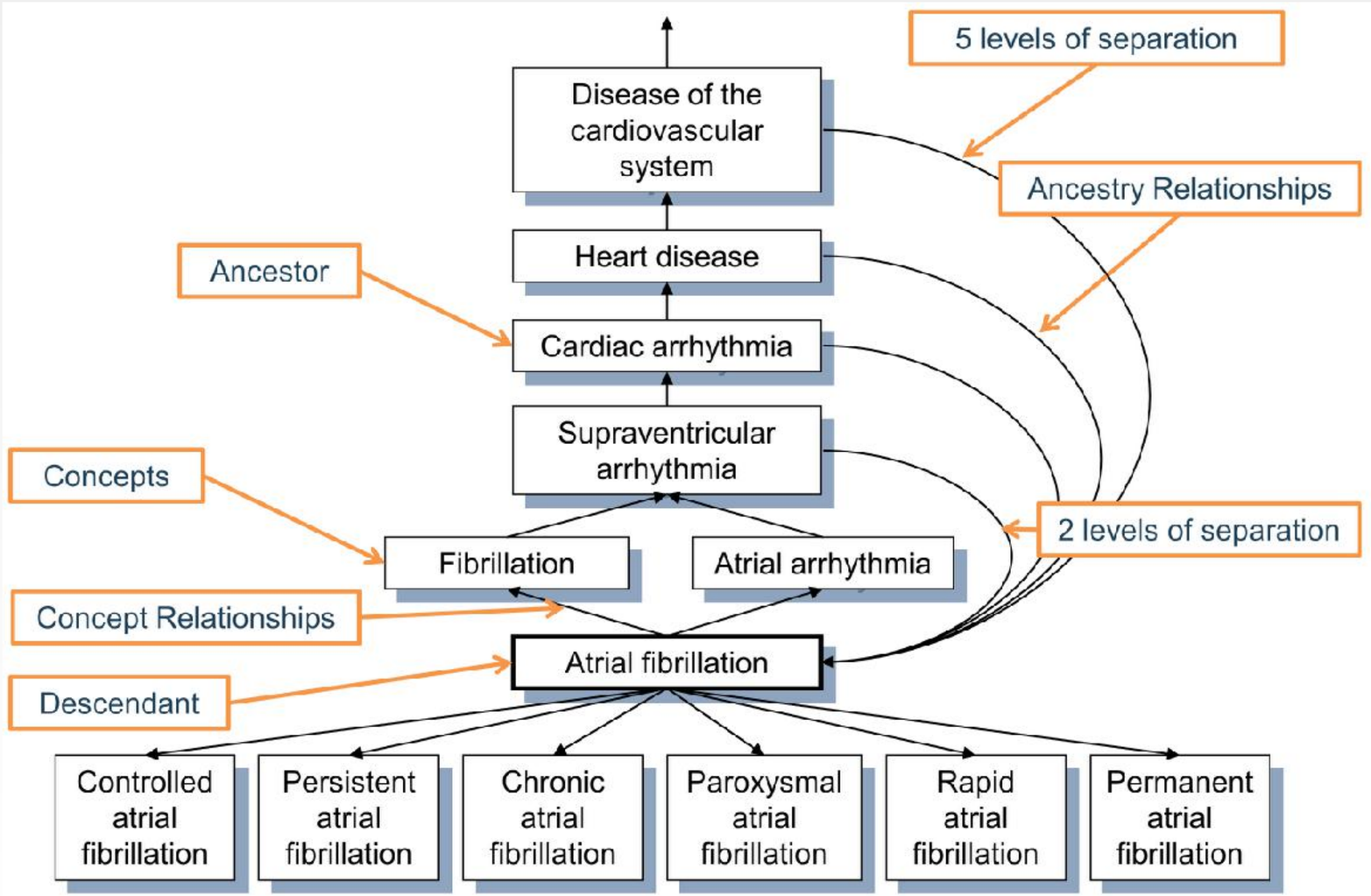
DOWNLOAD RESULTS

Show by 15 items | Total 6 items

- DOMAIN
- CONCEPT
- CLASS
- VOCAB
- VALIDITY

ID	CODE	NAME	CLASS	CONCEPT	VALIDITY	DOMAIN	VOCAB
45596206	I48	Atrial fibrillation and flutter	ICD10 Hierarchy	Non-standard	Valid	Condition	ICD10
1569170	I48	Atrial fibrillation and flutter	3-char nonbill code	Non-standard	Valid	Condition	ICD10CM
1414209	I48	Atrial fibrillation and flutter	ICD10 Hierarchy	Non-st			ICD10CN
37084653	I48	Atrial fibrillation and flutter	ICD10 Hierarchy	Non-st			ICD10GM
42488510	I48	Atrial fibrillation and flutter	KCD7 code	Non-st			KCD7
37613128	I48	Atrial fibrillation and flutter	ICD10 Hierarchy	Non-st			CIM10

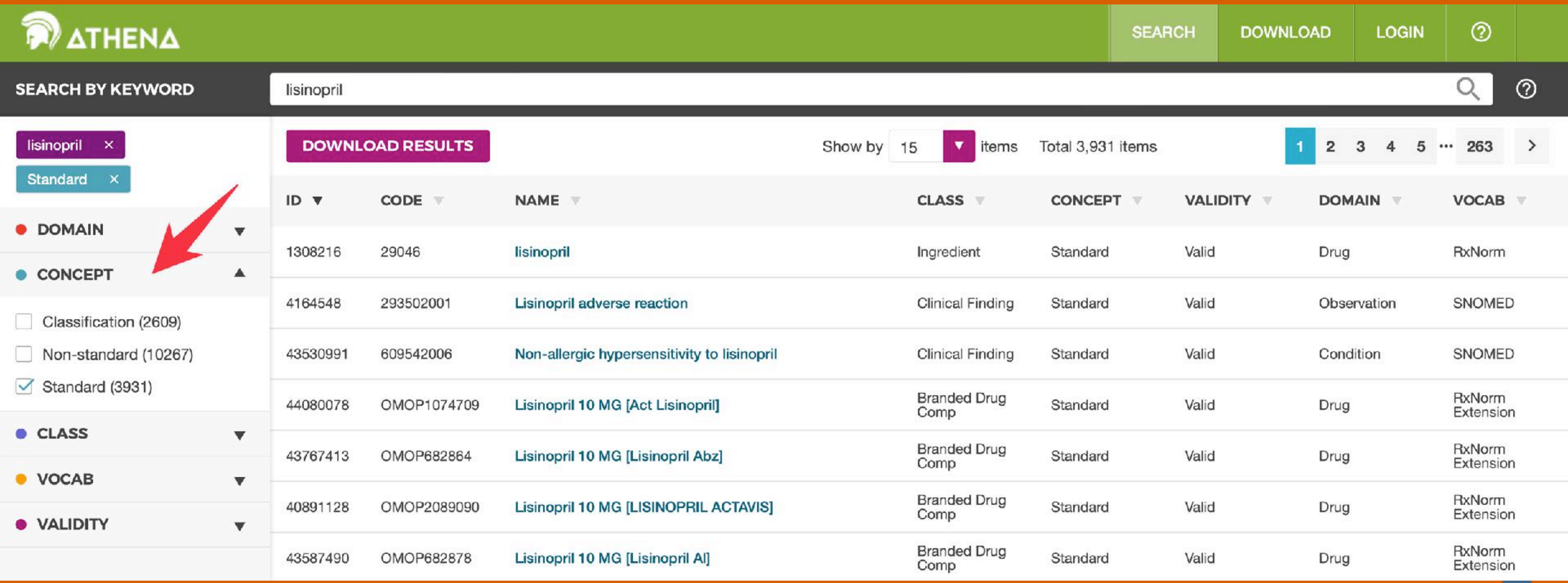
Hierarchy



[https://ohdsi.github.io/TheBookOfOhdsi/StandardizedVocabularies.html]

Hands-on: Find standard concept for Lisinopril*

https://athena.ohdsi.org — Hint: filter only standard concept on the left panel



ID	CODE	NAME	CLASS	CONCEPT	VALIDITY	DOMAIN	VOCAB
1308216	29046	lisinopril	Ingredient	Standard	Valid	Drug	RxNorm
4164548	293502001	Lisinopril adverse reaction	Clinical Finding	Standard	Valid	Observation	SNOMED
43530991	609542006	Non-allergic hypersensitivity to lisinopril	Clinical Finding	Standard	Valid	Condition	SNOMED
44080078	OMOP1074709	Lisinopril 10 MG [Act Lisinopril]	Branded Drug Comp	Standard	Valid	Drug	RxNorm Extension
43767413	OMOP682864	Lisinopril 10 MG [Lisinopril Abz]	Branded Drug Comp	Standard	Valid	Drug	RxNorm Extension
40891128	OMOP2089090	Lisinopril 10 MG [LISINOPRIL ACTAVIS]	Branded Drug Comp	Standard	Valid	Drug	RxNorm Extension
43587490	OMOP682878	Lisinopril 10 MG [Lisinopril Al]	Branded Drug Comp	Standard	Valid	Drug	RxNorm Extension

*Lisinopril is an ACE inhibitor.

Athena

Athena was the goddess of wisdom, war, and the crafts. She was the favorite daughter of Zeus and was, perhaps, the wisest, most courageous, and certainly the most resourceful of the Olympian gods.

Athena is credited with giving Odysseus the idea of the Wooden Horse in the Trojan War.

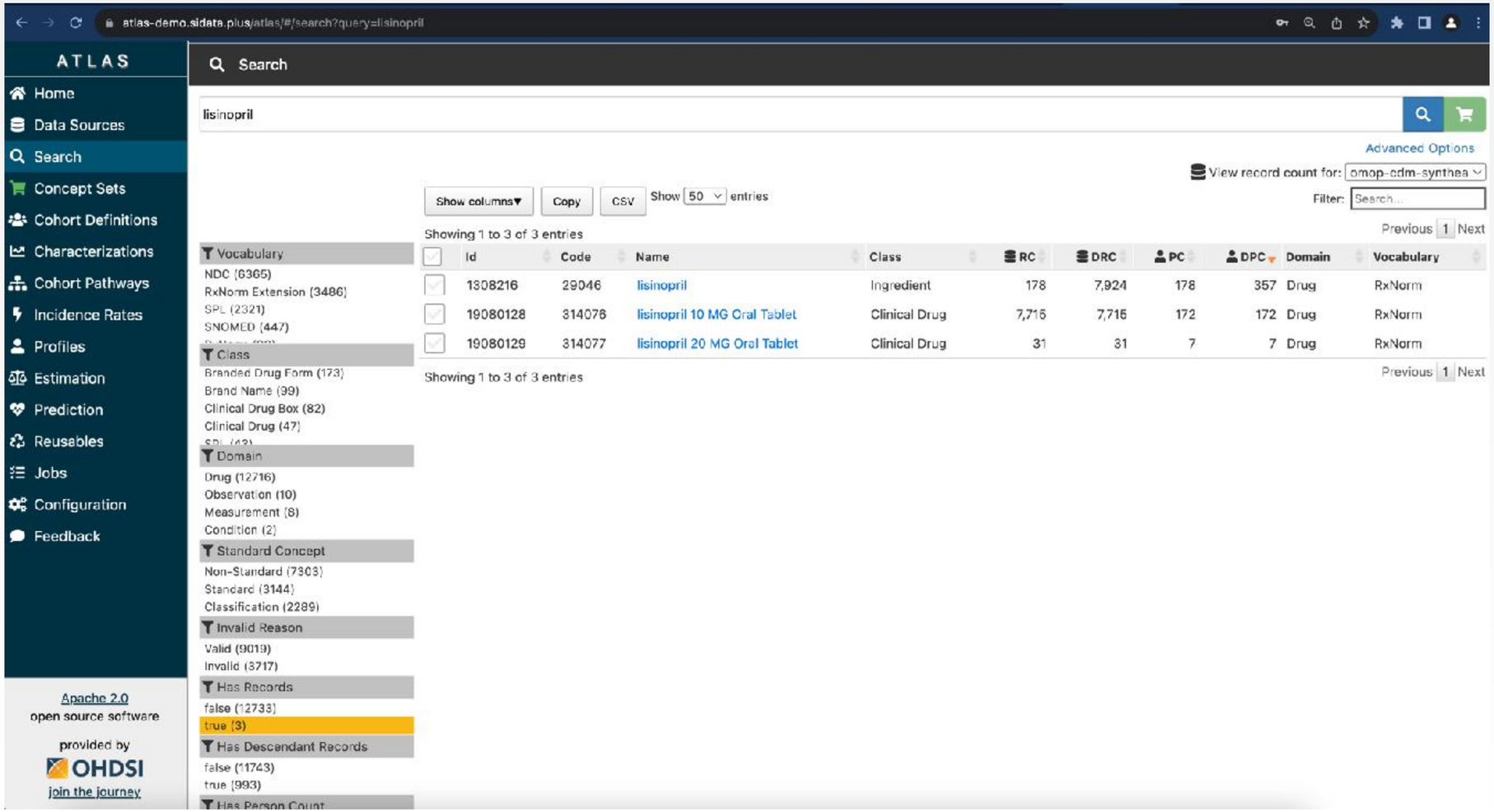
Carole Raddato (CC BY-SA)

[https://www.worldhistory.org/athena/]

Demo: Find Lisinopril on Atlas

https://atlas-demo.sidata.plus/atlas

backup: https://atlas-demo.ohdsi.org/, https://atlas.ohdsi.org



Concept Set Expressions

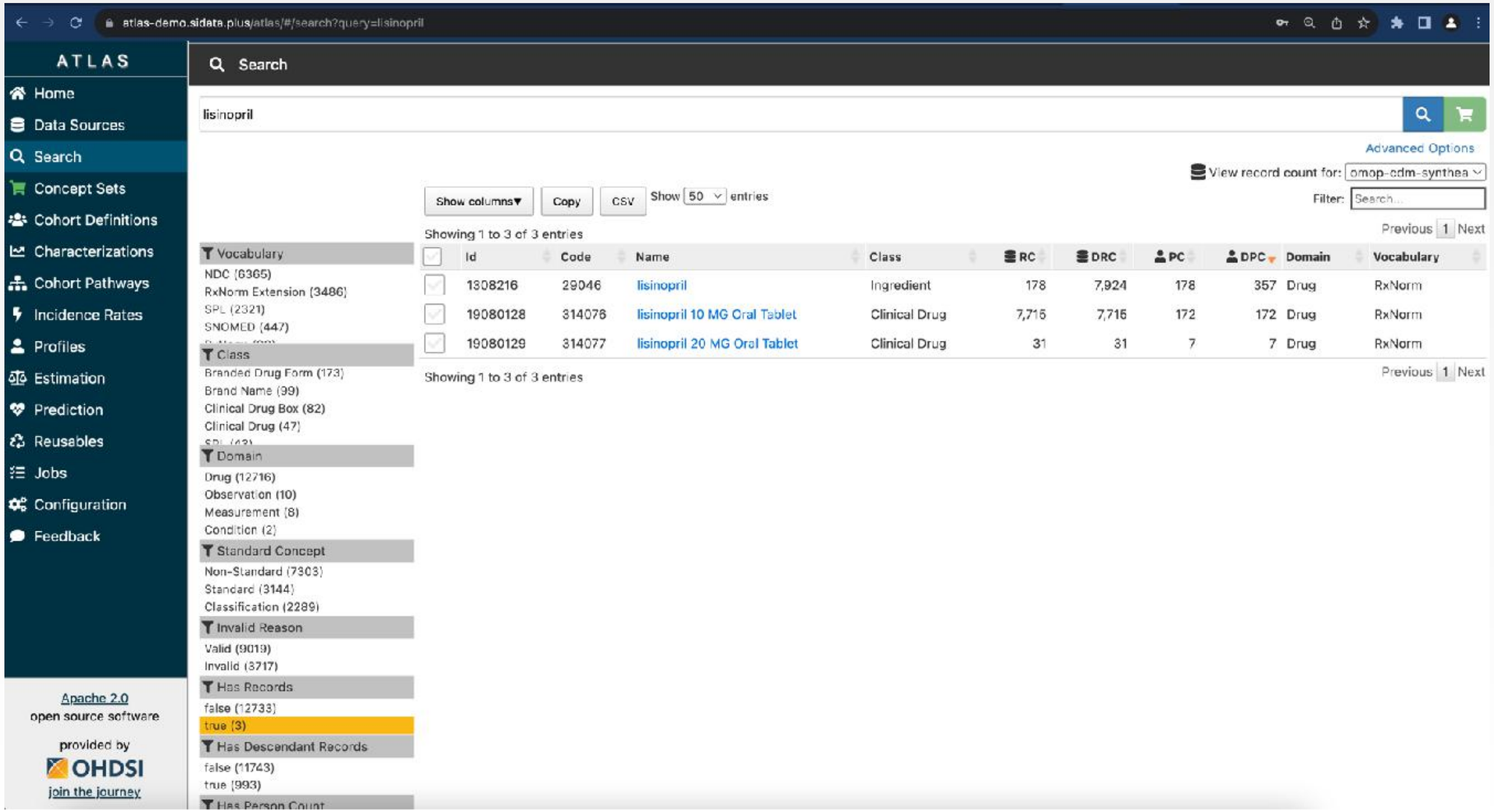
- **Concept Set:** logical expression to represent a list of concepts in the OHDSI vocabularies encompassing a clinical entity of interest
  - List of one or more concepts
  - Optional operator for each concepts in the list:
    - **Exclude**: Exclude this concept (and any of its descendants if selected) from the concept set.
    - **Descendants**: Consider not only this concept, but also all of its descendants.
    - **Mapped**: Allow to search for non-standard concepts.

- **Concept Set** can be thought of as a standardized, computer-executable equivalent of the code lists often used in observational studies.
- A concept set expression can be materialized into a list of concepts using any instance of the OHDSI vocabularies
  - JSON expression executed via webAPI into standard SQL query

Demo: Create concept set for Lisinopril

https://atlas-demo.sidata.plus/atlas

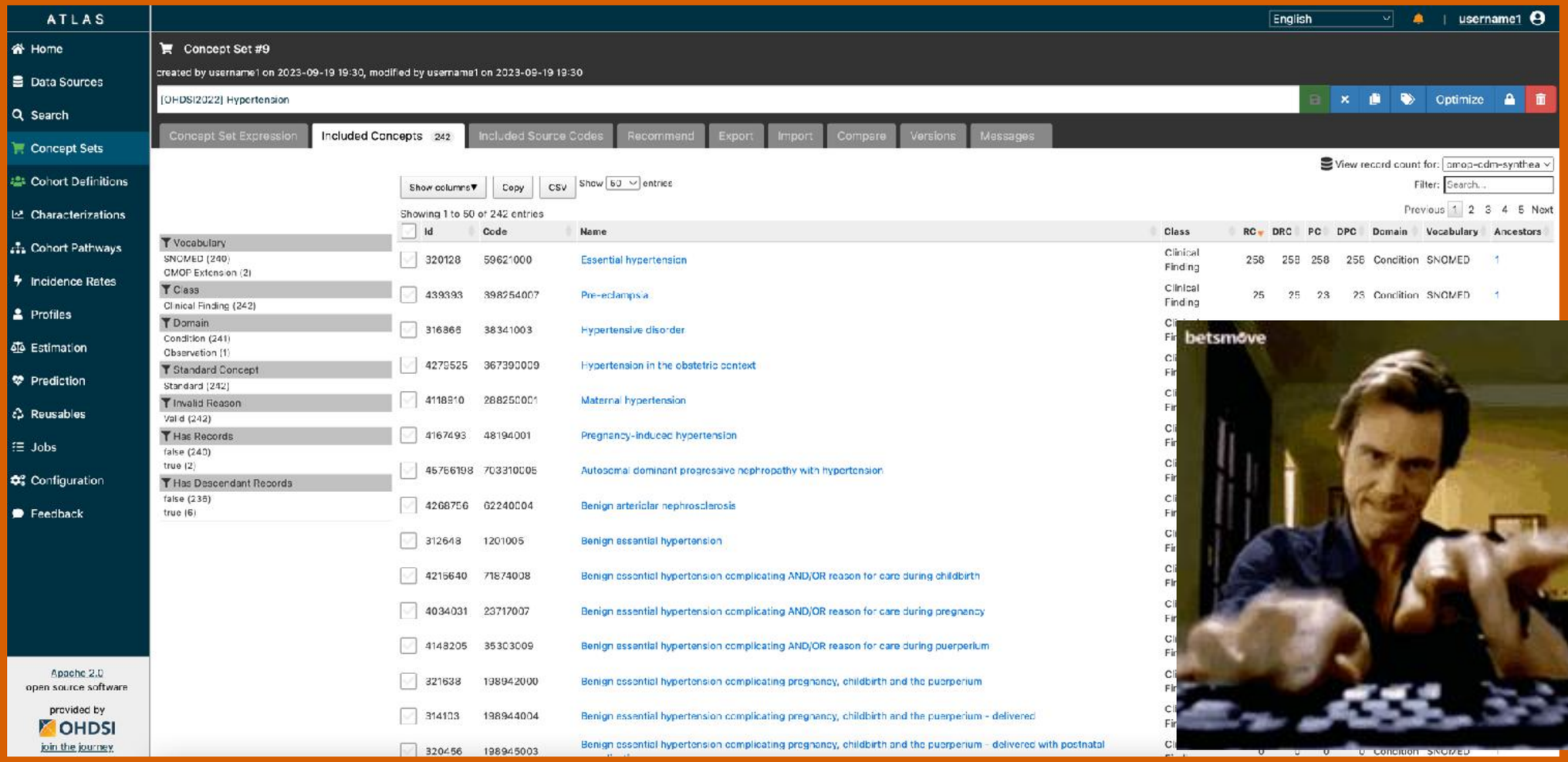
backup: https://atlas-demo.ohdsi.org/, https://atlas.ohdsi.org



Hands-on: Create concept set for Hypertension

https://atlas-demo.sidata.plus/atlas

backup: https://atlas-demo.ohdsi.org/, https://atlas.ohdsi.org



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OHDSI Tools:
Cohort Definition & Characterization

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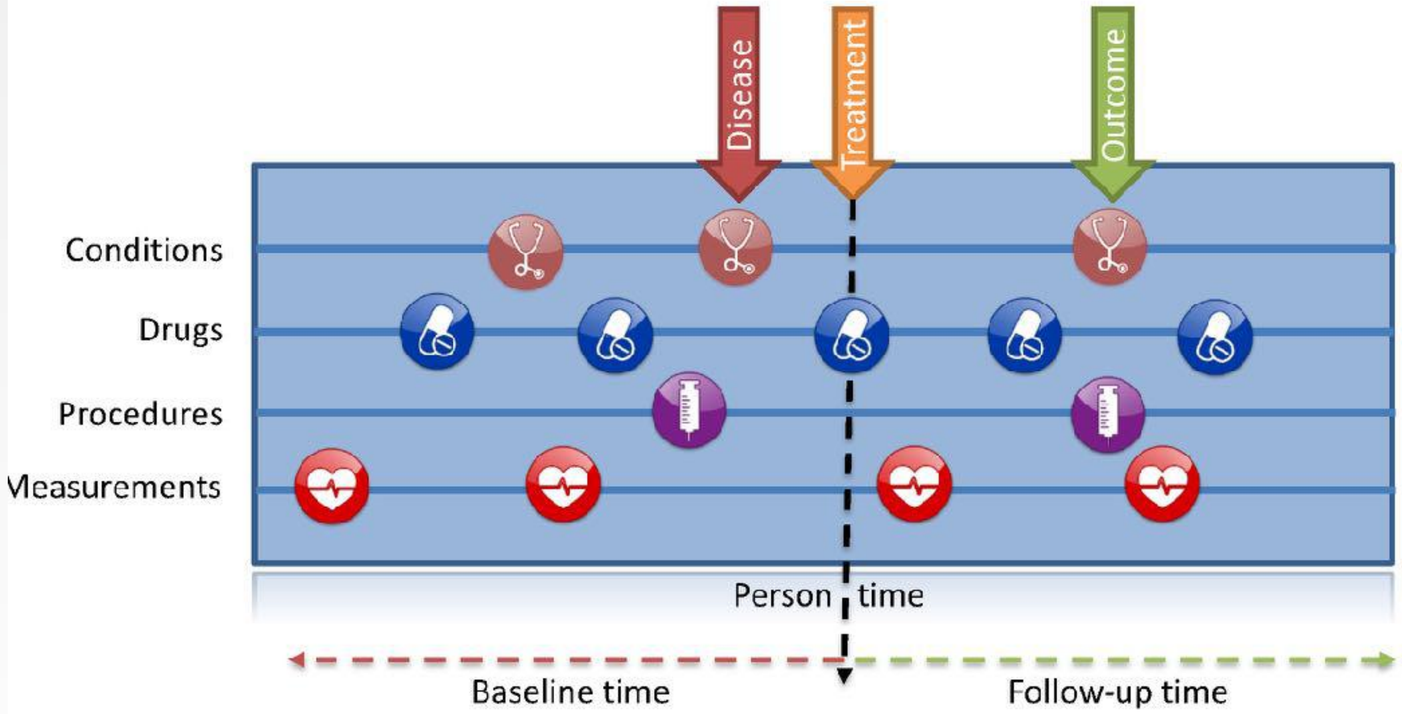
Session Overview

OHDSI Tools: Cohort Definition & Characterization @ 13:00 – 14:30 (90 min)

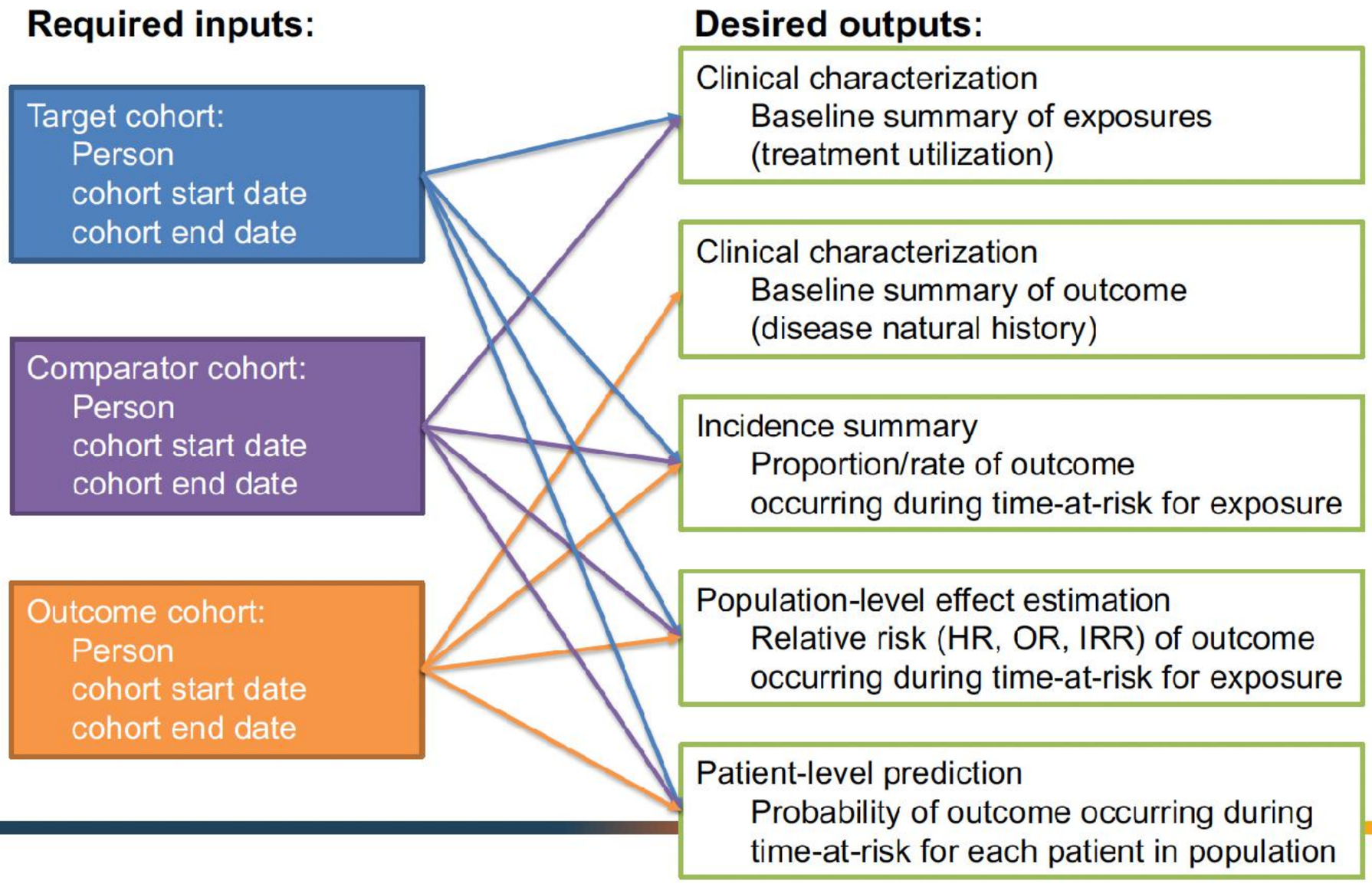
Why? Background & Questions	How? Methods & Materials	What? Objectives
☐ What is a cohort? ☐ How can we specify research cohorts on Atlas? using Phenotype? ☐ Can we do basic descriptive statistical analyses on cohorts?	⬟ Basics of cohort definition, phenotype ⬟ Hands-on: Defining a cohort using Atlas ⬟ Hands-on: Cohort characterization with Atlas ⬟ Most of slides from OHDSI2022 Tutorial sessions 3–5: https://www.ohdsi.org/ohdsi2022-tutorial/	★ Grasp the principles of cohort definition and characterization ★ Practical exercise in defining and characterizing cohorts using Atlas ★ Take home: Importance and practical know-how of cohort analytics

Data are Like Lego Bricks for Phenotyping



- **Conditions**
- **Drugs**
- **Procedures**
- **Measurements**
- **Observations**
- **Visits**

The common building block of all observational analysis: cohorts



Defining ‘phenotype’

Journal of the American Medical Informatics Association, 0(0), 2017, 1–6
doi: 10.1093/jamia/ocx110
Perspective

Perspective

High-fidelity phenotyping: richness and freedom from bias

George Hripcsak[1] and David J Albers[1]

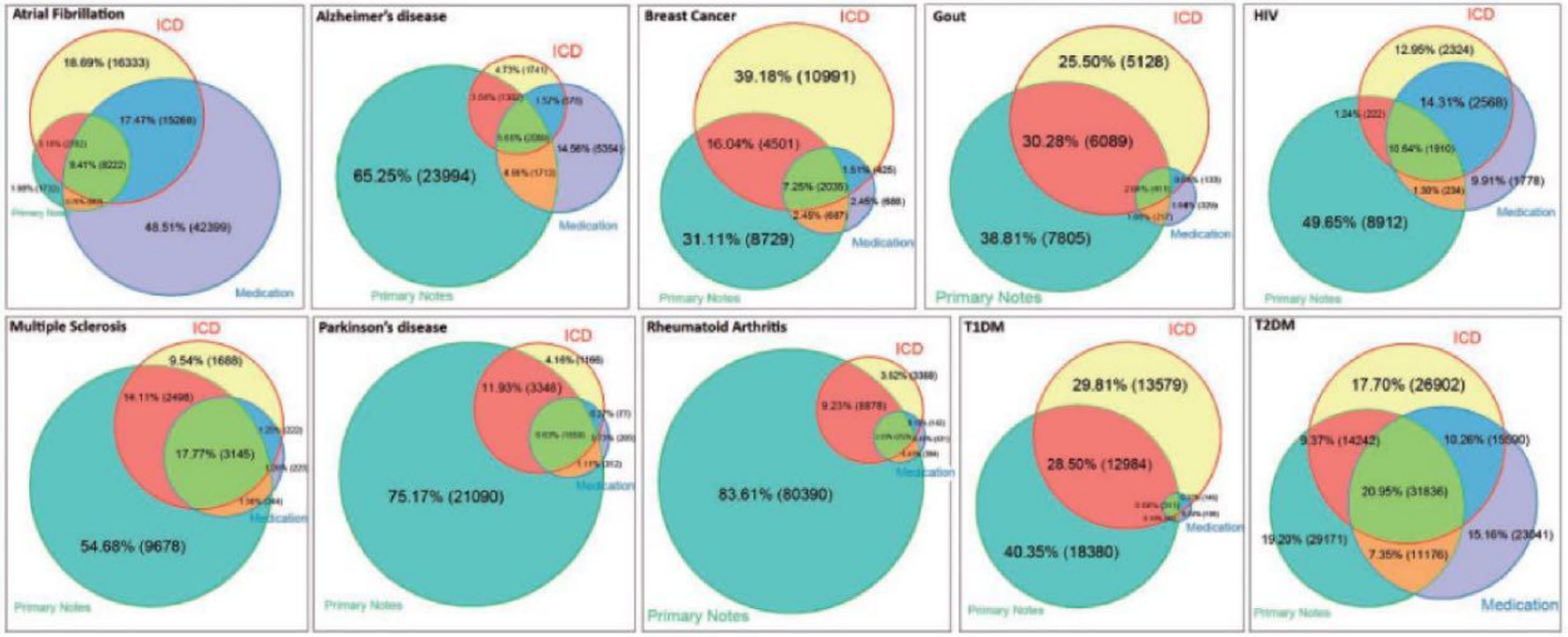
- A phenotype is a specification of an observable, potentially changing state of an organism (as distinguished from the genotype, derived from genetic makeup).
- The term phenotype can be applied to patient characteristics inferred from electronic health record (EHR) data.
- The goal is to draw conclusions about a target concept based on raw EHR data, claims data, or other clinically relevant data.
- Phenotype algorithms – ie, algorithms that identify or characterize phenotypes – may be generated by domain exerts and knowledge engineers, or through diverse forms of machine learning to generate novel representations of data.

Combining billing codes, clinical notes, and medications from electronic health records provides superior phenotyping performance

RECEIVED 8 January 2015
REVISED 14 July 2015
ACCEPTED 15 July 2015
PUBLISHED ONLINE FIRST 2 September 2015

Wei-Qi Wei[1], Pedro L Teixeira[1], Huan Mo[1], Robert M Cronin[1,2], Jeremy L Warner[1,2], Joshua C Denny[1,2]

Figure 1: Weighted Venn diagrams of the distributions of patients with ICD-9, primary notes, and specific medications. Each color represents a resource. Different area colors represent the number of patients that were found within intersecting resources.



OHDSI Phenotype Phebruary

https://www.ohdsi.org/phenotype-phebruary-2023/

Feb. 1 • Type 2 Diabetes Mellitus
Feb. 2 • Type 1 Diabetes Mellitus
Feb. 3 • Atrial Fibrillation
Feb. 4 • Multiple Myeloma
Feb. 5 • Alzheimer's Disease
Feb. 6 • Hemorrhagic Events
Feb. 7 • Neutropenia
Feb. 8 • Kidney Stones
Feb. 9 • Delirium
Feb. 10 • Systemic Lupus Erythematosus
Feb. 11 • Suicide Attempts
Feb. 12 • Parkinson's Disease and Parkinsonism
Feb. 13 • Attention Deficit Hyperactivity Disorder
Feb. 14 • Hypertension *(Video Description)*
Feb. 15 • Acute Myocardial Infarction
Feb. 16 • Heart Failure
Feb. 17 • Cardiomyopathy
Feb. 18 • Multiple Sclerosis
Feb. 19 • Triple Negative Breast Cancer
Feb. 20 • Pulmonary Hypertension
Feb. 21 • Prostate Cancer
Feb. 22 • HIV
Feb. 23 • Hidradenitis Suppurativa
Feb. 24 • Anaphylaxis
Feb. 25 • Depression
Feb. 26 • Non-Small-Cell Lung Cancer
Feb. 27 • Drug-Induced Liver Injury
Feb. 28 • Severe Visual Impairment And Blindness
Bonus • Acute Kidney Injury

Phenotype Phebruary 2023: How To Join The Effort

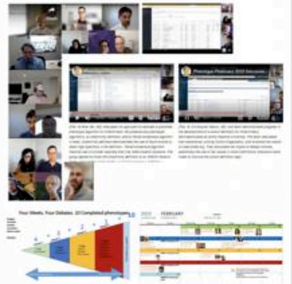
"Phenotype Phebruary" was a community-wide initiative to both develop and evaluate phenotypes for health outcomes that could be investigated by the community.

This is the second year of Phenotype Phebruary in the OHDSI community (look back at Year 1 here). It was introduced during the Jan. 31 community call (watch here), and went on throughout the month. This year, the leadership team of **Gowtham Rao** and **Azza Shoaibi** helped identify 11 phenotypes that are being investigated throughout the month. Though the month has ended, the work continues. If you would like to join the discussions around any of the phenotypes, please visit the appropriate links below, which will take you to the proper threads on the OHDSI forums.

What Did We Accomplish?

Phenotype Phebruary 2023 **in numbers**

- **11** phenotypes discussed in the forums
  - **5** phenotypes finished peer review --> library
  - **5** phenotypes developed, evaluated and on their way to peer review
- **4** debates/discussions addressed
- **7** shiny apps on data.ohdsi.org
- **32** collaborators interacted in the forums or attended calls
- **9 Publications**
  - **8 applied** publications planned
  - **1 methods** publication

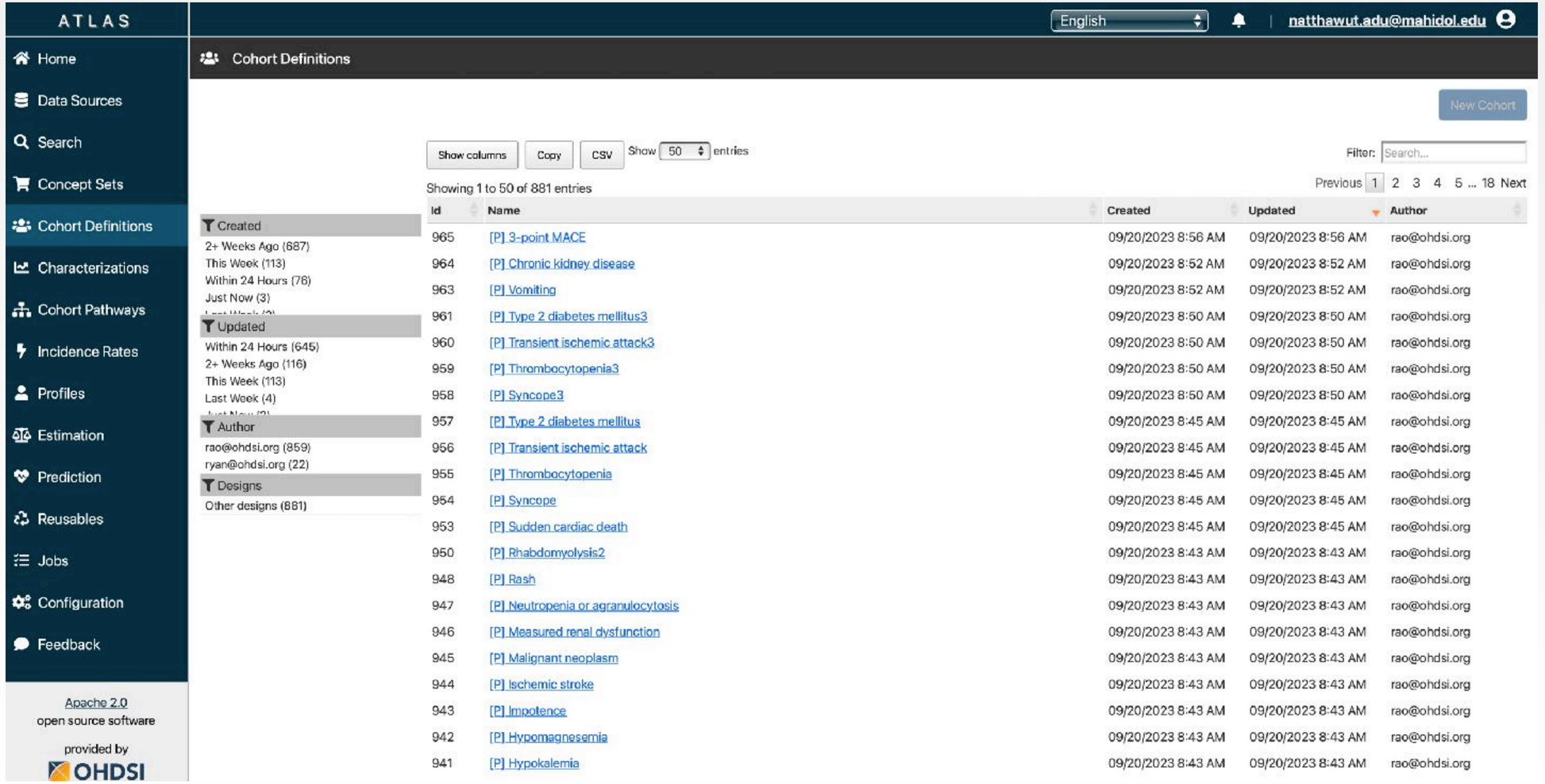


Join Our Community Efforts Around Any Of These Phenotypes

Announcements and Meeting/Workshop Links	Acute Pancreatitis	Anaphylaxis	Appendicitis
Acquired Neutropenia	Systemic Lupus Erythematosus	Acute Hepatic Failure	Idiopathic Inflammatory Myopathies
Parkinson's Disease	ST Elevation Myocardial Infarction	Neonatal Hypoxic Ischemic Encephalopathy	Neurofibromatosis type 1 with Optical Pathway Glioma

OHDSI Phenotype Library on Atlas

https://atlas-phenotype.ohdsi.org/



Cohorts: The common building block of all observational analysis

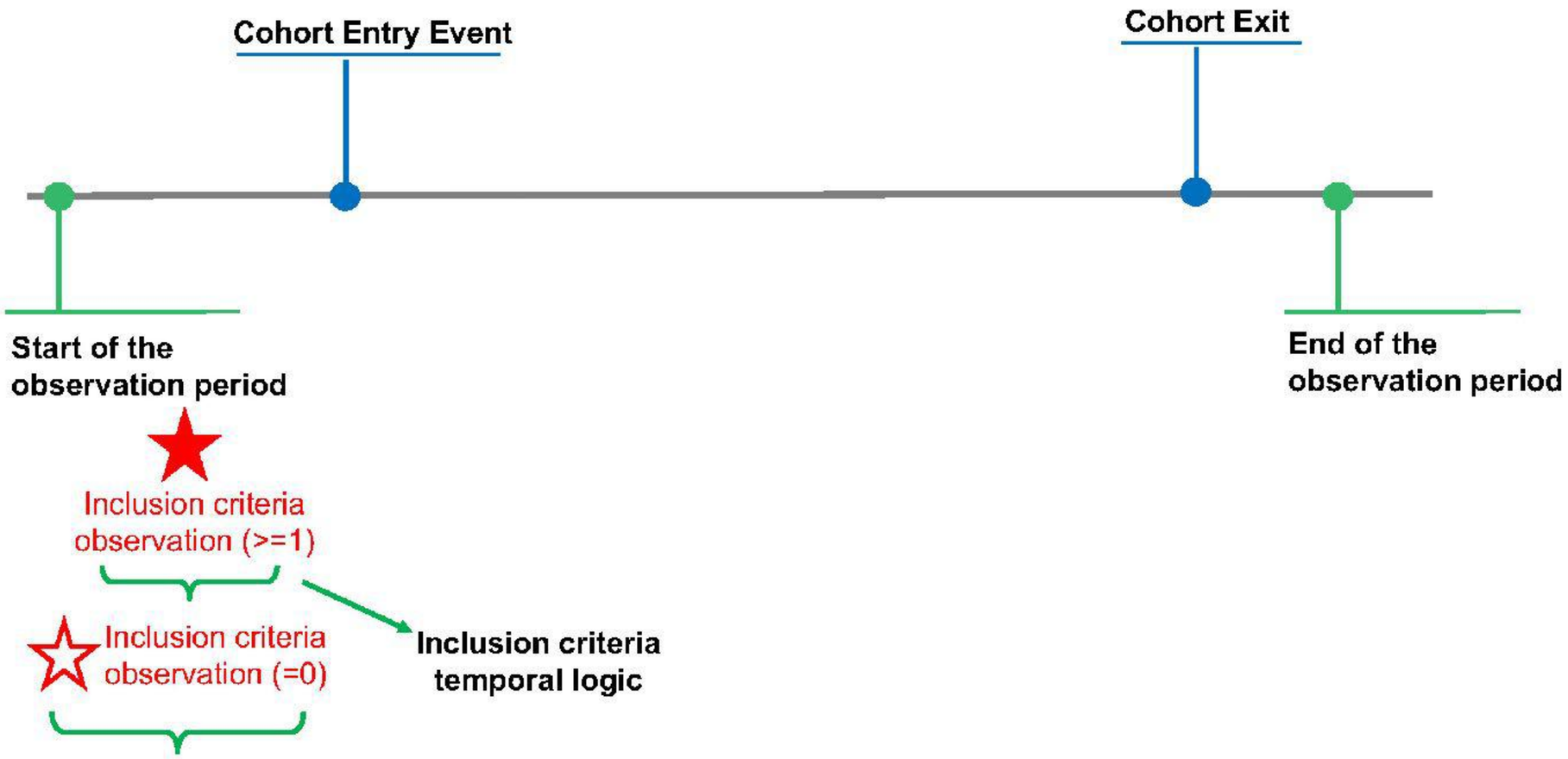
- **OHDSI's definition of 'cohort':** Cohort is a set of persons who satisfy one or more inclusion criteria for a duration of time
- **Cohort era:** a continuous period during which a person has satisfied a cohort's inclusion criteria
- **Cohort definition:** the specification for how to identify a cohort

Objective consequences based on this cohort definition:

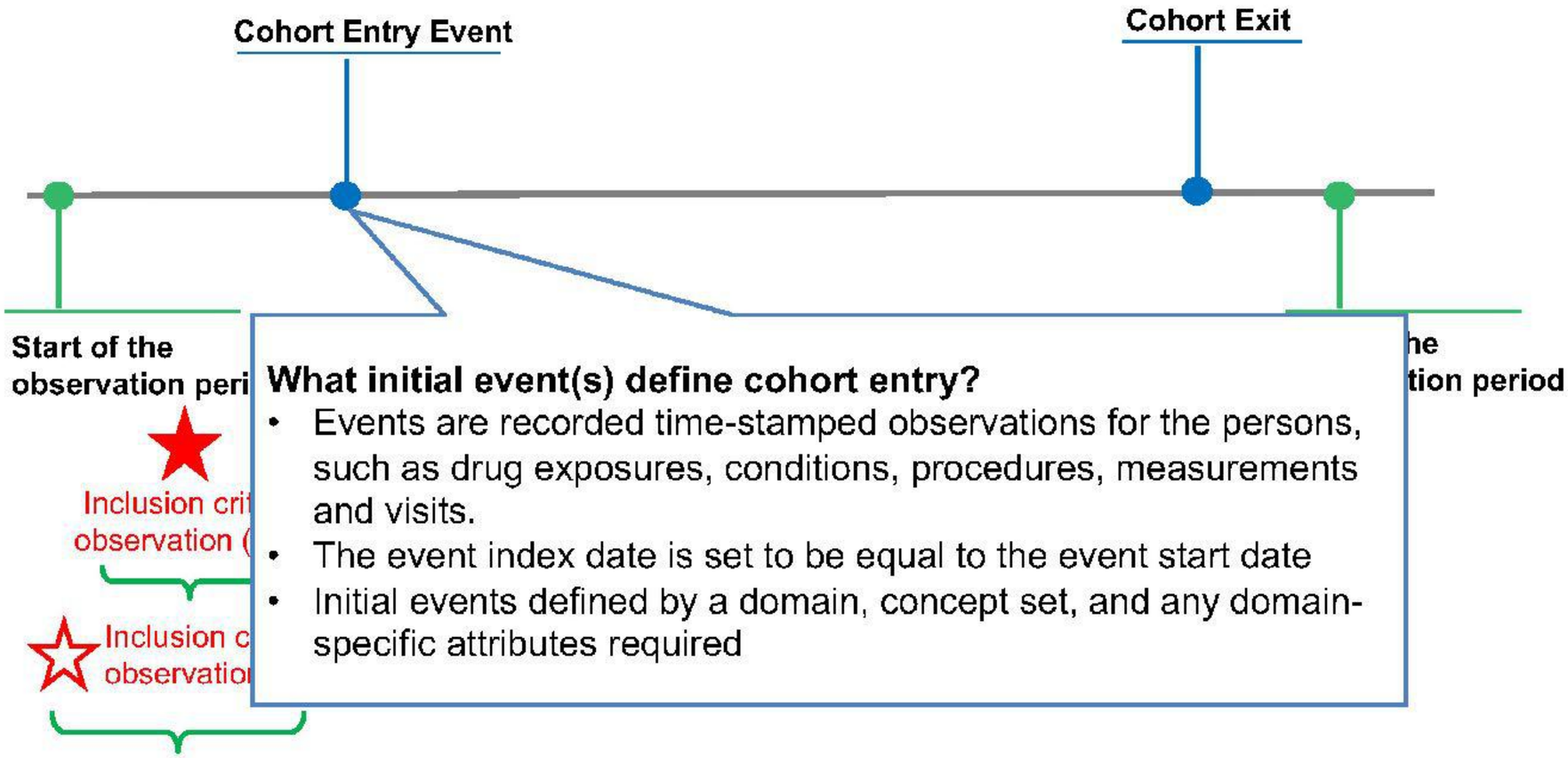
- One person may belong to multiple cohorts
- One person may belong to the same cohort at multiple different time periods
- One person may not belong to the same cohort multiple times during the same period of time
- One cohort may have **zero or more** members
- A codeset is **NOT** a cohort…

…logic for how to use the codeset in a criteria is required

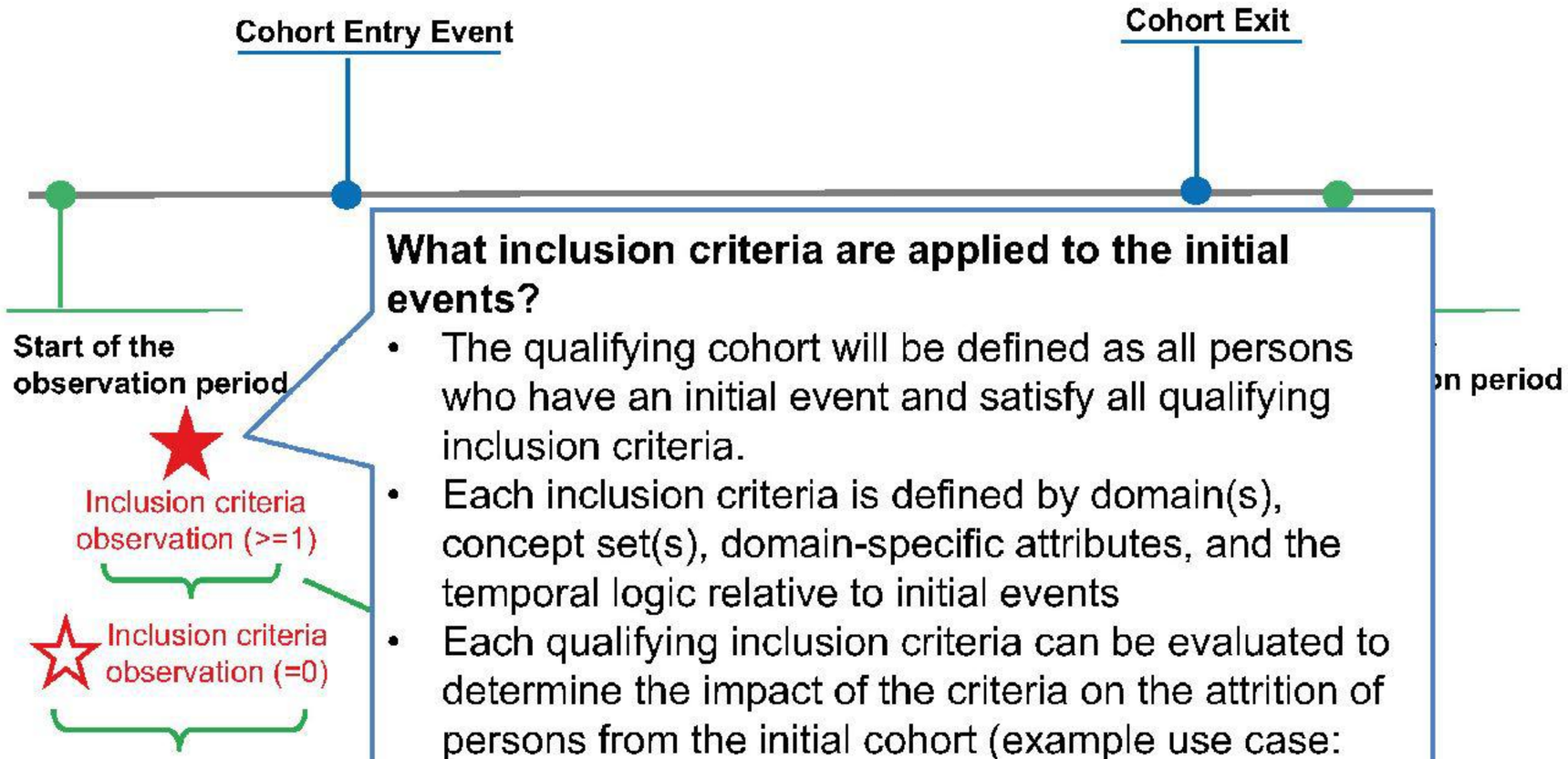
The Anatomy of a Cohort Definition



The Anatomy of a Cohort Definition



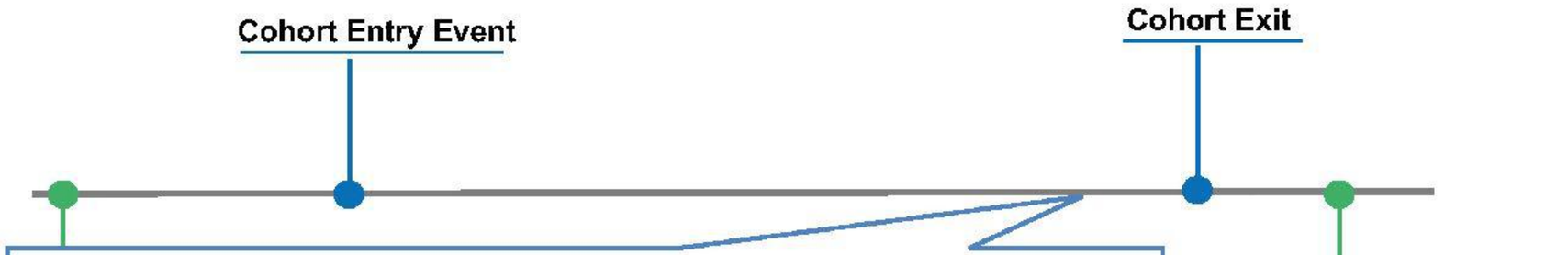
The Anatomy of a Cohort Definition



What inclusion criteria are applied to the initial events?

- The qualifying cohort will be defined as all persons who have an initial event and satisfy all qualifying inclusion criteria.
- Each inclusion criteria is defined by domain(s), concept set(s), domain-specific attributes, and the temporal logic relative to initial events
- Each qualifying inclusion criteria can be evaluated to determine the impact of the criteria on the attrition of persons from the initial cohort (example use case: clinical trial feasibility)

The Anatomy of a Cohort Definition



What defines a person's cohort exit?

- Cohort exit signifies when a person no longer qualifies for cohort membership
- Cohort exit can be defined in multiple ways:
  - End of observation period
  - Fixed time interval relative to initial event
  - Last event in a sequence of related observations (ex: persistent drug exposure)
  - Censoring observations
- Cohort exit strategy will impact whether a person can belong to the cohort multiple times during different time intervals

Phenotype development and evaluation workflow

Concept set expressions

Cohort definition logic

Initial events

Conceptsets

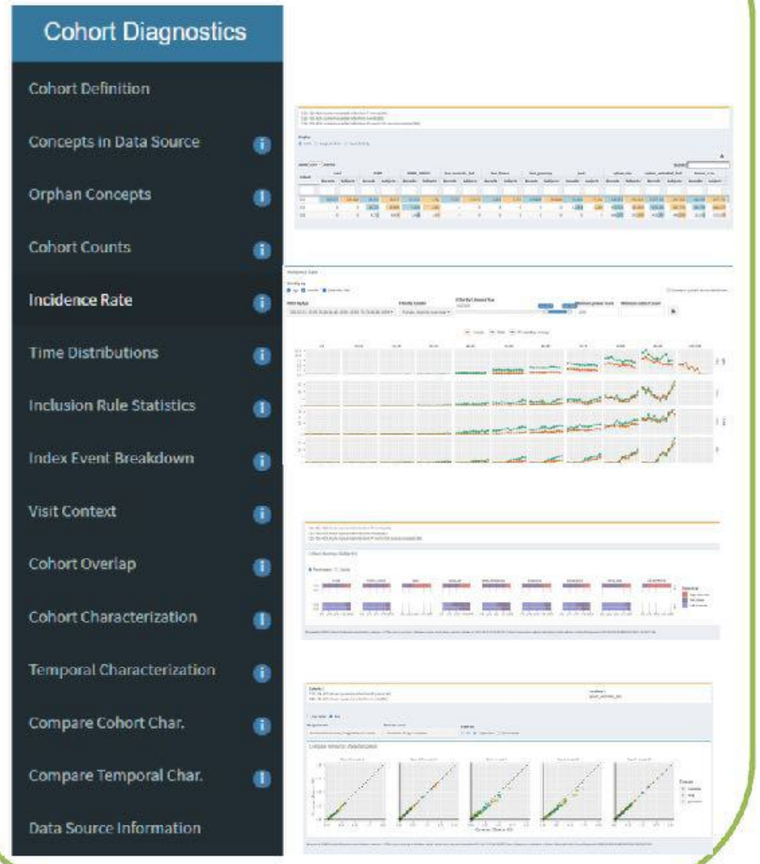
Inclusion criteria

Conceptsets

Exit strategy

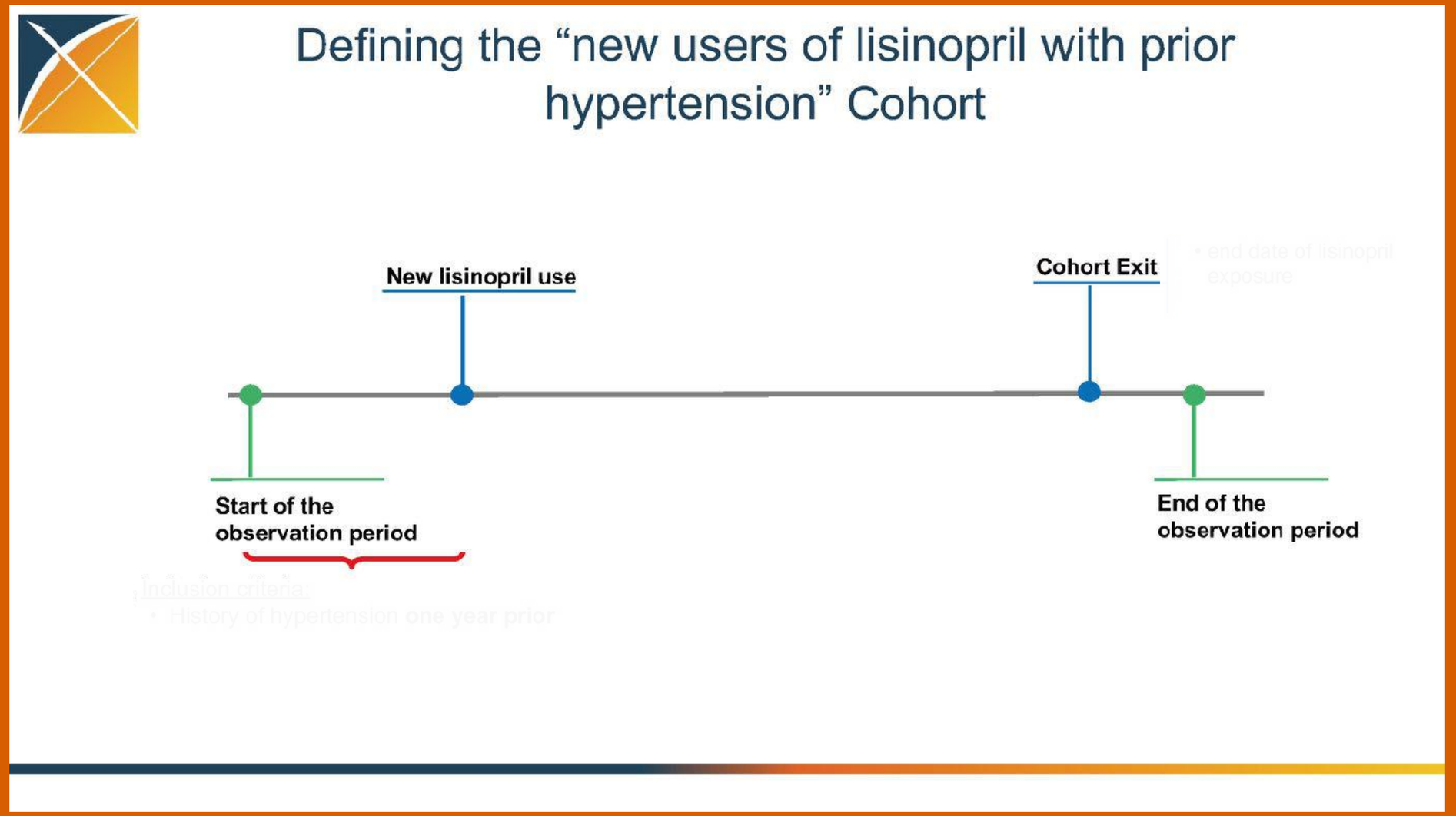
Conceptsets

Cohort diagnostics

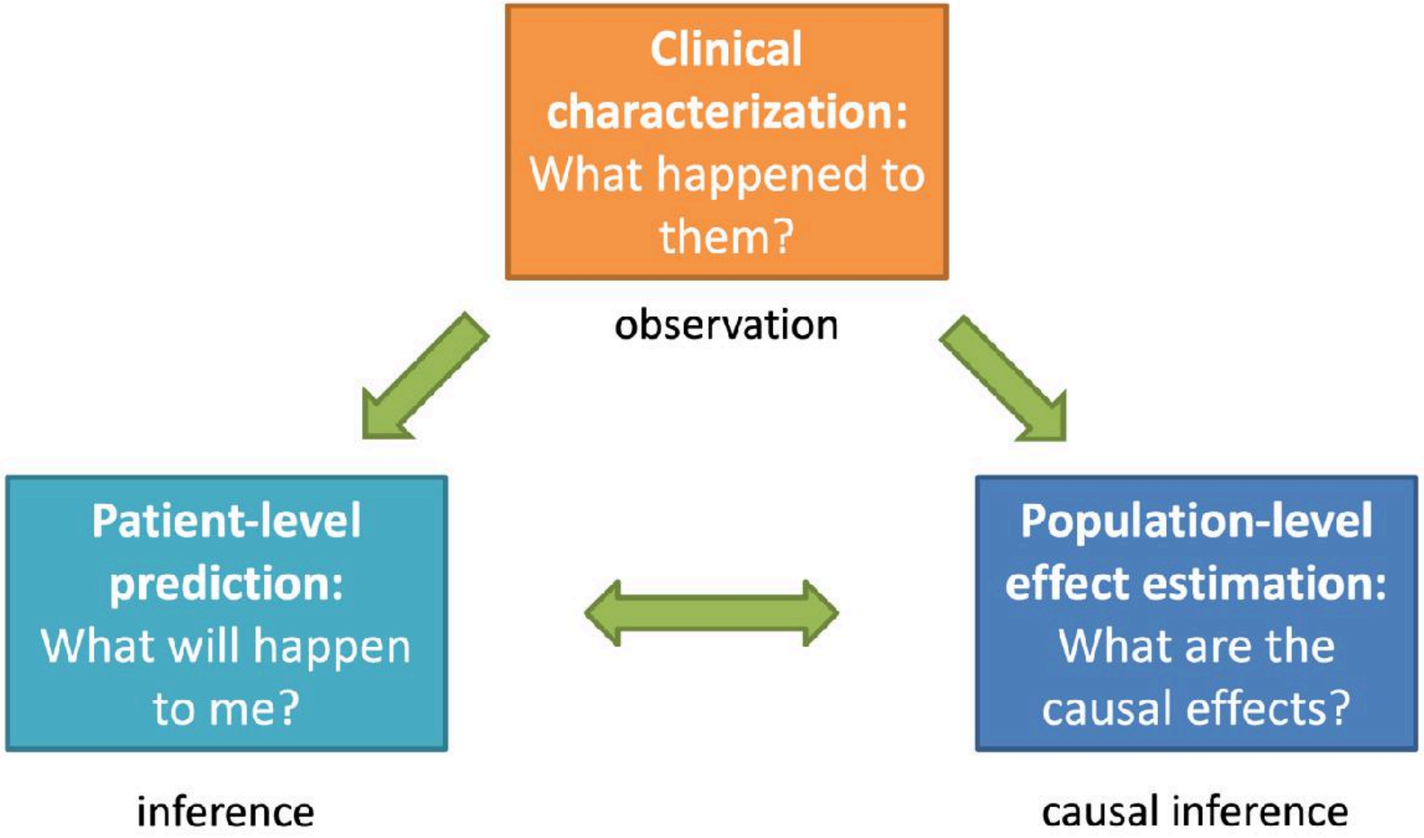


Hands-on Practice: New Users of Lisinopril with prior Hypertension

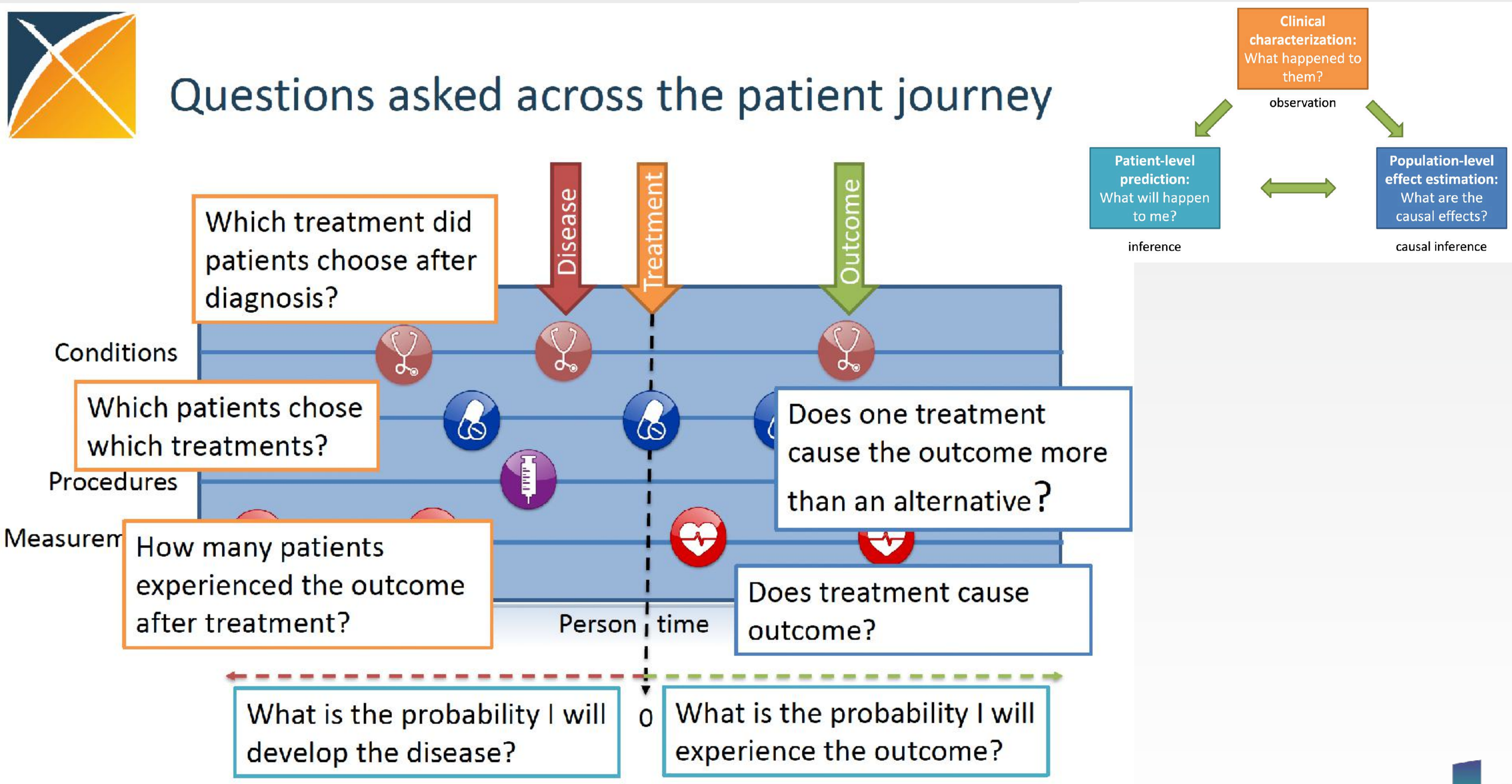
on slide & on Atlas: https://atlas-demo.sidata.plus/atlas



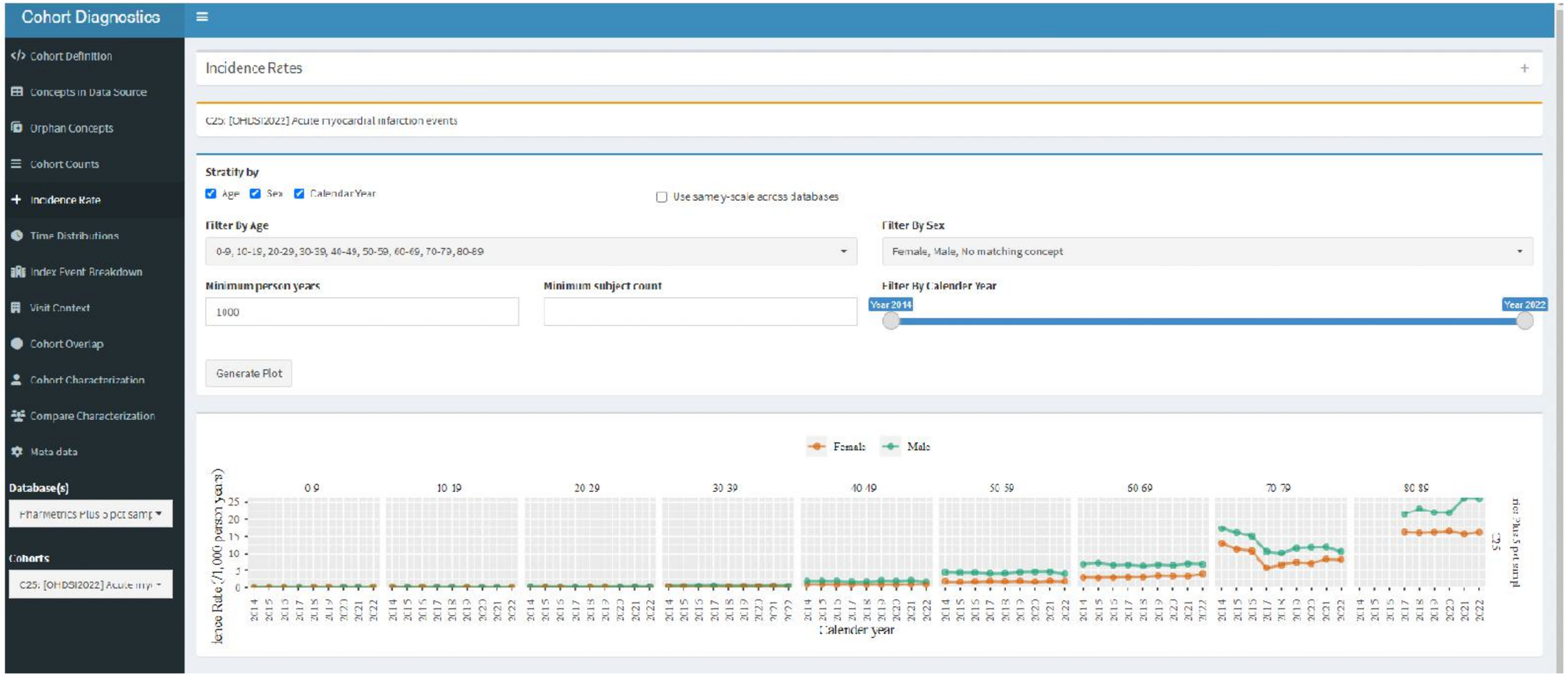
Complementary evidence to inform the patient journey



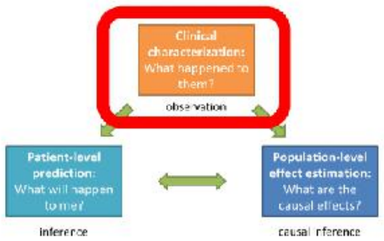
Questions asked across the patient journey



Cohort Diagnostics – Incidence Rate



OHDSI Characterization Framework



- Target cohort: who do you want to study?
- Stratification (pre-index): what subgroups do you want to study?
- Features of interest: what attributes do you want to look at and describe differences in?
- Time-at-risk: what windows of time do you want to describe features in?

OHDSI in action: Clinical characterization

PNAS

COLLOQUIUM PAPER

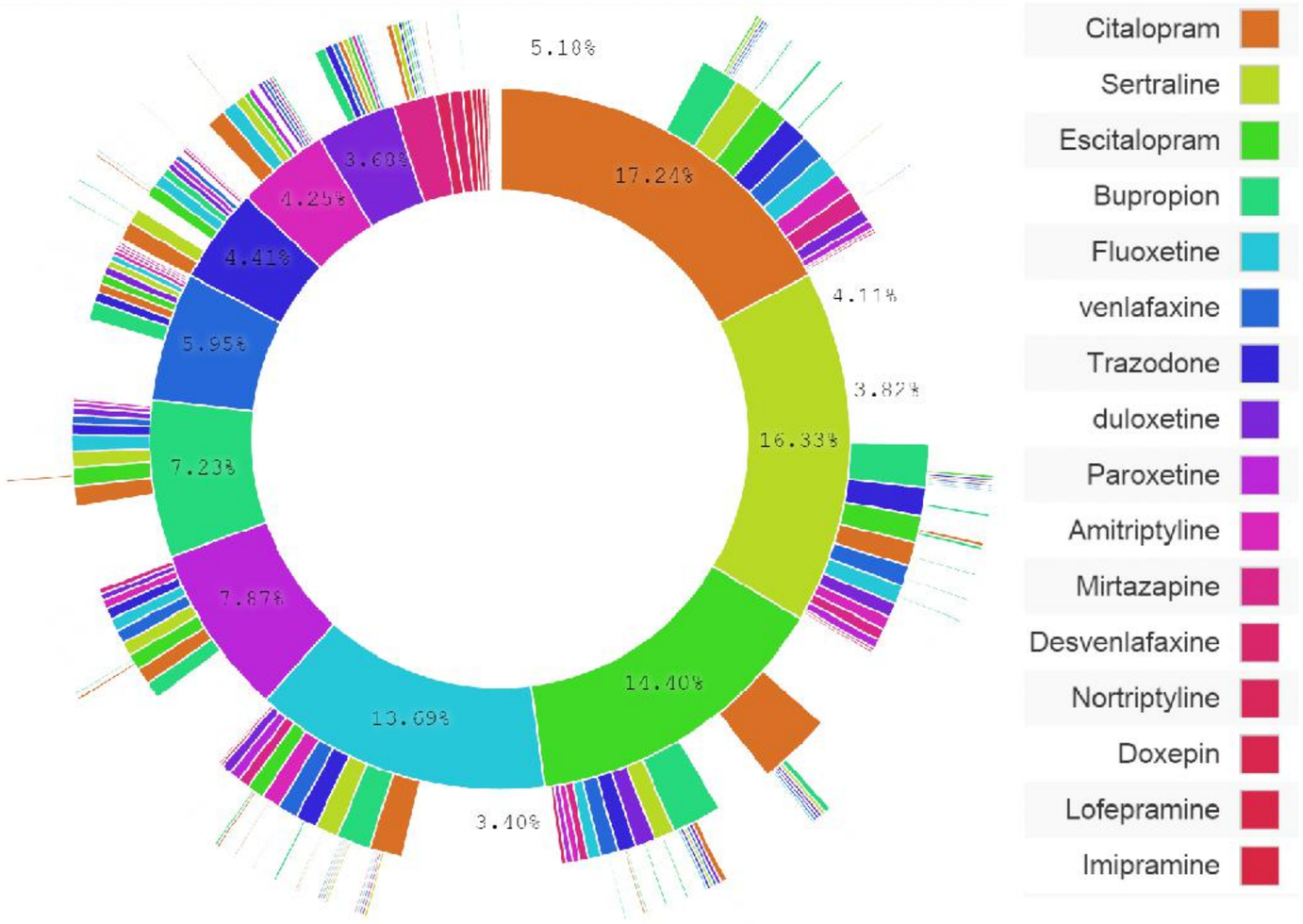
Characterizing treatment pathways at scale using the OHDSI network

George Hripcsak[a,b,c,1], Patrick B. Ryan[c,d], Jon D. Duke[c,e], Nigam H. Shah[c,f], Rae Woong Park[c,g], Vojtech Huser[c,h], Marc A. Suchard[c,i,j,k], Martijn J. Schuemie[c,d], Frank J. DeFalco[c,d], Adler Perotte[a,c], Juan M. Banda[c,f], Christian G. Reich[c,l], Lisa M. Schilling[c,m], Michael E. Matheny[c,n,o], Daniella Meeker[c,p,q], Nicole Pratt[c,r], and David Madigan[c,s]

[a]Department of Biomedical Informatics, Columbia University Medical Center, New York, NY 10032; [b]Medical Informatics Services, NewYork-Presbyterian Hospital, New York, NY 10032; [c]Observational Health Data Sciences and Informatics, New York, NY 10032; [d]Epidemiology Analytics, Janssen Research and Development, Titusville, NJ 08560; [e]Center for Biomedical Informatics, Regenstrief Institute, Indianapolis, IN 46205; [f]Center for Biomedical Informatics Research, Stanford University, CA 94305; [g]Department of Biomedical Informatics, Ajou University School of Medicine, Suwon, South Korea, 443-380; [h]Lister Hill National Center for Biomedical Communications (National Library of Medicine), National Institutes of Health, Bethesda, MD 20894; [i]Department of Biomathematics, University of California, Los Angeles, CA 90095; [j]Department of Biostatistics, University of California, Los Angeles, CA 90095; [k]Department of Human Genetics, University of California, Los Angeles, CA 90095; [l]Real World Evidence Solutions, IMS Health, Burlington, MA 01809; [m]Department of Medicine, University of Colorado School of Medicine, Aurora, CO 80045; [n]Department of Biomedical Informatics, Vanderbilt University Medical Center, Nashville, TN 37212; [o]Geriatric Research, Education and Clinical Center, VA Tennessee Valley Healthcare System, Nashville, TN 37212; [p]Department of Preventive Medicine, University of Southern California, Los Angeles, CA 90089; [q]Department of Pediatrics, University of Southern California, Los Angeles, CA 90089; [r]Division of Health Sciences, University of South Australia, Adelaide, SA, Australia 5001; and [s]Department of Statistics, Columbia University, New York, NY 10027

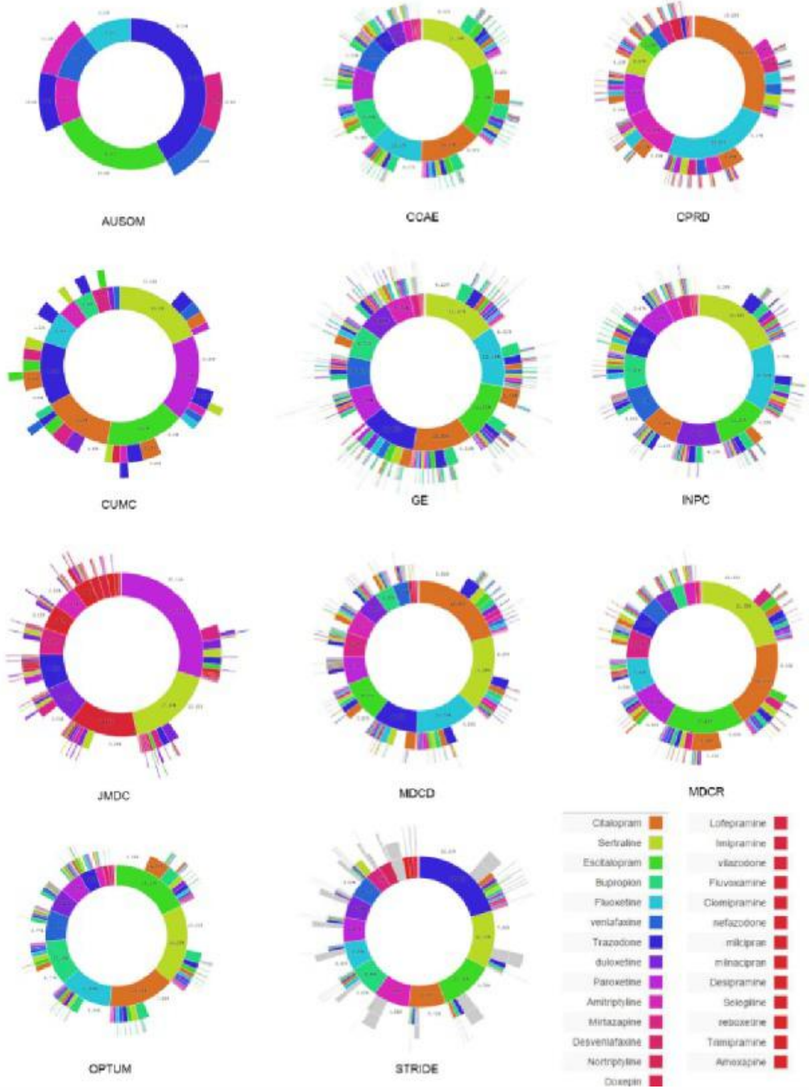
Edited by Richard M. Shiffrin, Indiana University, Bloomington, IN, and approved April 5, 2016 (received for review June 14, 2015)

How are patients with major depressive disorder *ACTUALLY* treated?



Hripcsak et al, PNAS, 2016

How are patients with major depressive disorder *ACTUALLY* treated?

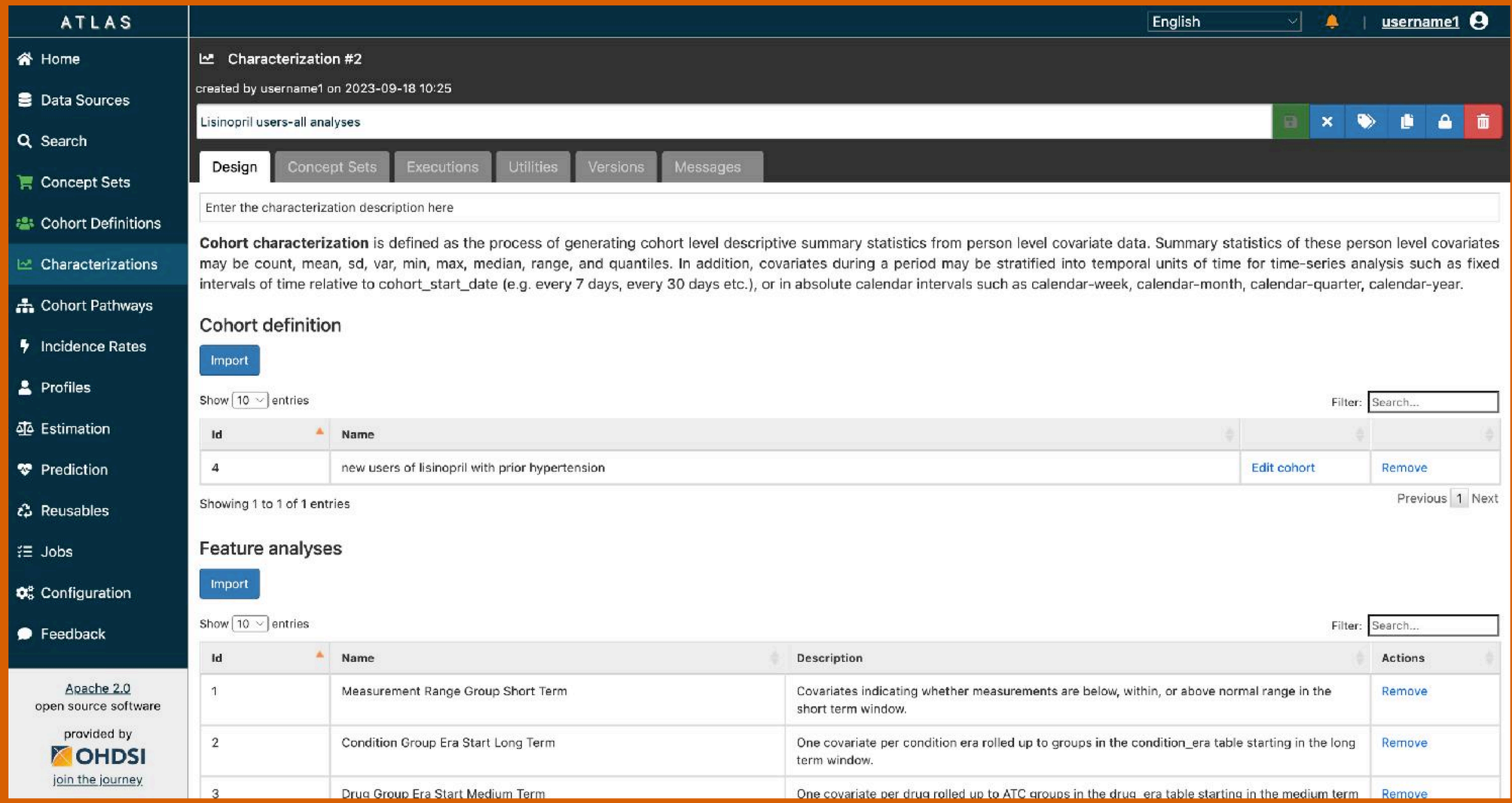


- Substantial variation in treatment practice across data sources, health systems, geographies, and over time
- Consistent heterogeneity in treatment choice as no source showed one preferred first-line treatment
- 11% of depressed patients followed a treatment pathway that was shared with no one else in any of the databases

Hripcsak et al, PNAS, 2016

Hands-on: Characterization of Lisinopril users

on Atlas https://atlas-demo.sidata.plus/atlas



Siriraj Informatics and Data Innovation Center

OHDSI
OBSERVATIONAL HEALTH DATA SCIENCES AND INFORMATICS

Mahidol University
Faculty of Medicine
Siriraj Hospital

OHDSI Tools: Patient-level Prediction

Supported by

ศูนย์ความเป็นเลิศด้านชีววิทยาศาสตร์ (องค์การมหาชน)
Thailand Center of Excellence for Life Sciences
(Public Organization)

SiHP
หน่วยวิจัยเพื่อขับเคลื่อนนโยบายสุขภาพ
Siriraj Health Policy Unit

สปสช.
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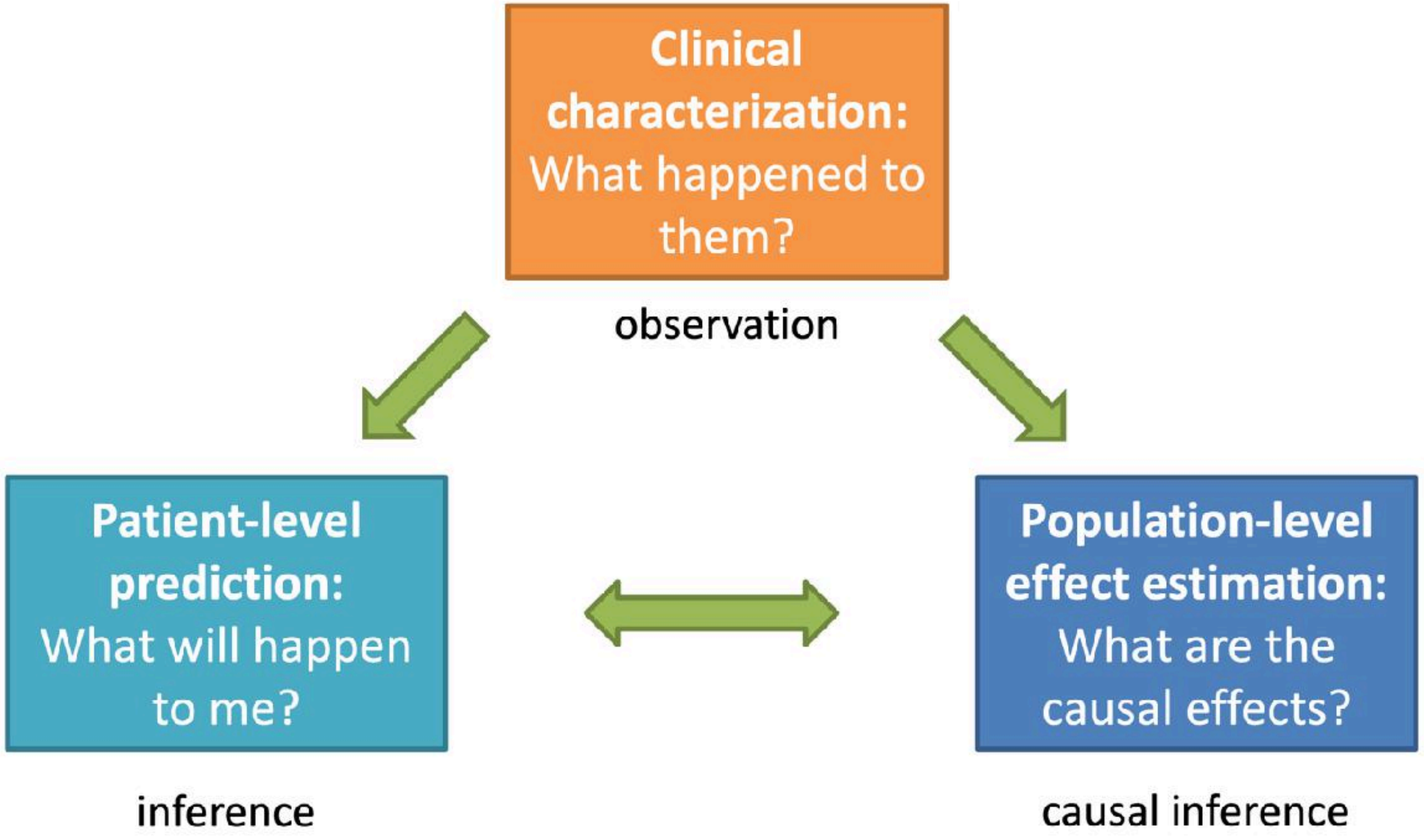
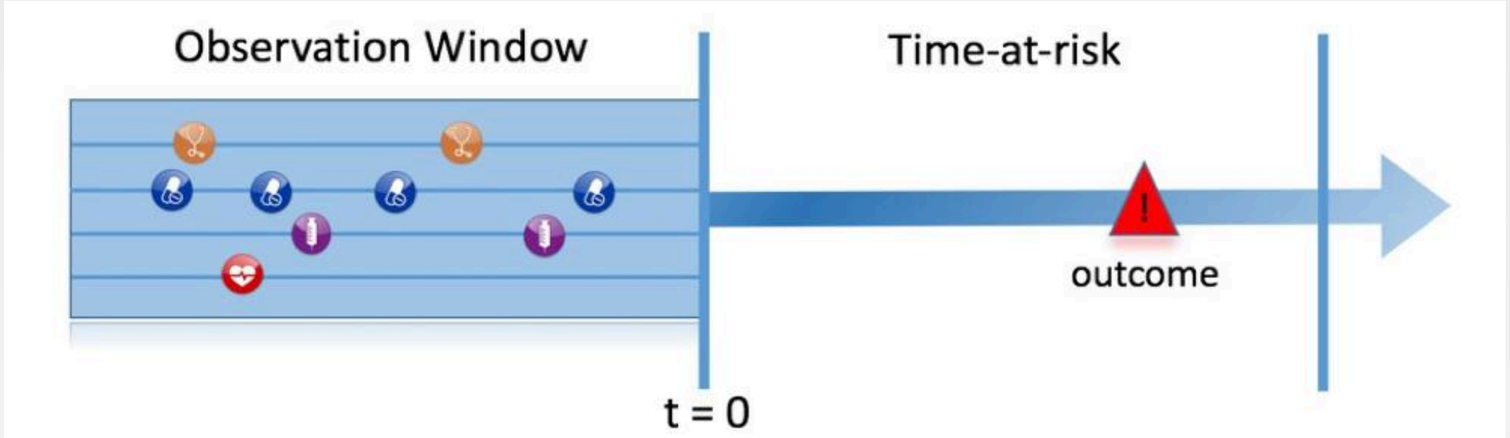
Session Overview

OHDSI Tools: Patient-level Prediction @ 14:45 – 15:45 (60 min)

Why? Background & Questions	How? Methods & Materials	What? Objectives
☐ How can we make a prediction at patient-level?	⬟ Introduce types of predictive models ⬟ OHDSI tools for patient-level prediction ⬟ Hands-on: Develop a simple prediction model in Atlas ⬟ Most of slides from OHDSI2022 Tutorial session 7: https://www.ohdsi.org/ohdsi2022-tutorial/	★ Understand different types of prediction models ★ Acquire hands-on experience in developing a predictive model using Atlas

Complementary evidence to inform the patient journey





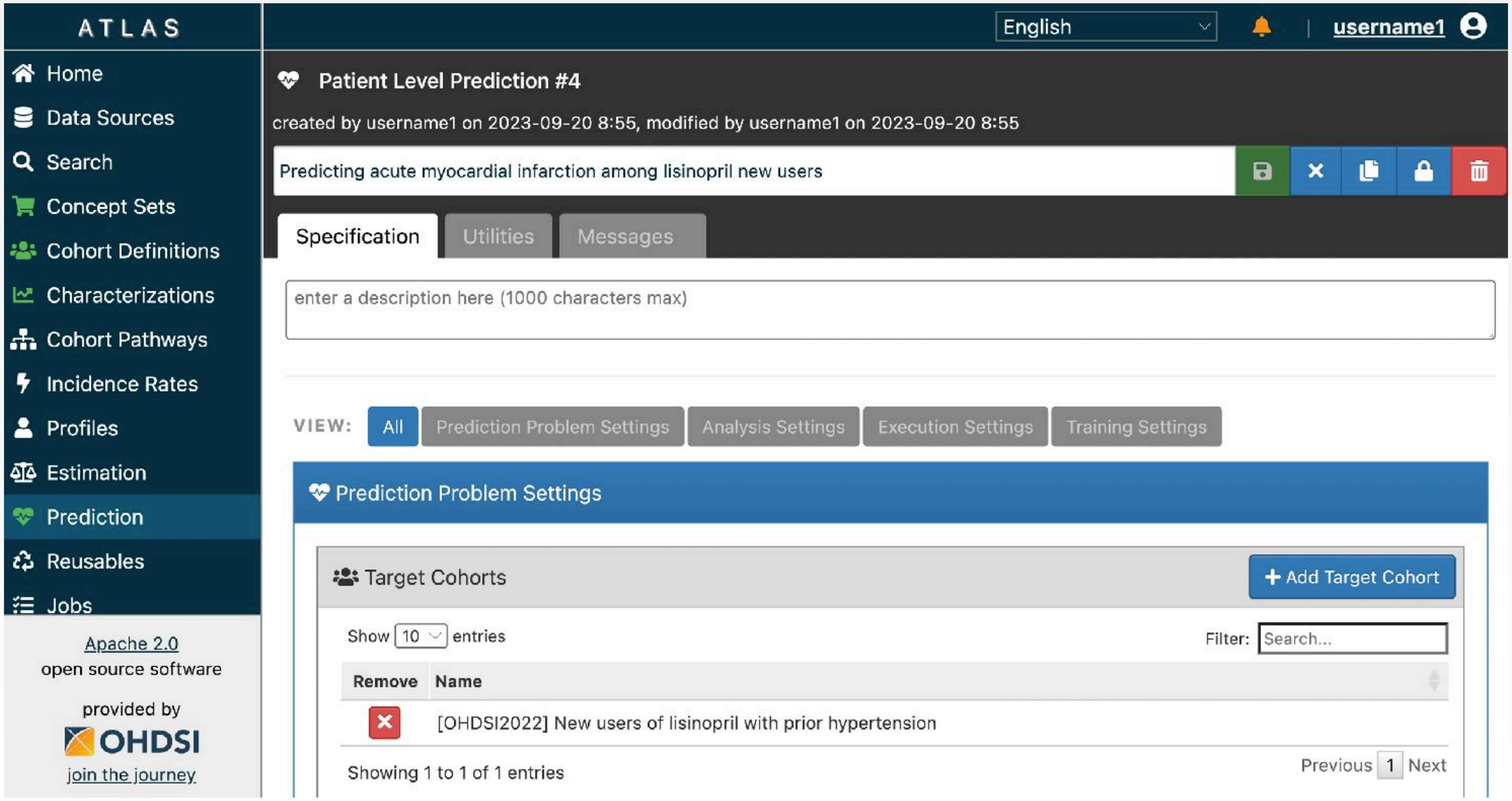
Type	Structure	Example
Disease onset and progression	Amongst patients who are newly diagnosed with **<insert your favorite disease>**, which patients will go on to have **<another disease or related complication>** within <time horizon from diagnosis>?	Among newly diagnosed AFib patients, which will go onto to have ischemic stroke in next 3 years?
Treatment choice	Amongst patients with **<indicated disease> who are treated with either <treatment 1> or <treatment 2>**, which patients were treated with **<treatment 1>** (on day 0)?	Among AFib patients who took either warfarin or rivaroxaban, which patients got warfarin? (as defined for propensity score model)
Treatment response	Amongst patients who are new users of **<insert your favorite chronically-used drug>**, which patients will **<insert desired effect>** in <time window>?	Which patients with T2DM who start on metformin stay on metformin after 3 years?
Treatment safety	Amongst patients who are new users of **<insert your favorite drug>**, which patients will experience **<insert your favorite known adverse event from the drug profile>** within <time horizon following exposure start>?	Among new users of warfarin, which patients will have GI bleed in 1 year?
Treatment adherence	Amongst patients who are new users of **<insert your favorite chronically-used drug>**, which patients will achieve **<adherence metric threshold>** at <time horizon>?	Which patients with T2DM who start on metformin achieve >=80% proportion of days covered at 1 year?

Prediction task specification

Component	Description
Target population (T):	Who do you want to do the prediction for?
Outcome (O):	What are you predicting?
Time-at-risk (TAR):	When are you predicting?

Demo: Patient-level Prediction

Predicting acute myocardial infarction among lisinopril new users



Best Practice Research

Jenna Reps, Peter R. Rijnbeek

2023-08-28

Source: `vignettes/BestPractices.rmd`

Contents

Best practice publications using the OHDSI PatientLevelPrediction framework

Topic	Research Summary	Link
Problem Specification	When is prediction suitable in observational data?	Guidelines needed
Data Creation	Comparison of cohort vs case-control design	Journal of Big Data
Data Creation	Addressing loss to follow-up (right censoring)	BMC medical informatics and decision makingk
Data Creation	Investigating how to address left censoring in features construction	BMC Medical Research Methodology
Data Creation	Impact of over/under-sampling	Study being developed
Data Creation	Impact of phenotypes	Study Done - Paper submitted
Model development	How much data do we need for prediction - Learning curves at scale	Preprint link
Model development	What impact does test/train/validation design have on model performance	BMJ Open
Model development	What is the impact of the classifier	JAMIA

Siriraj Informatics and Data Innovation Center

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Siriraj Hospital

Data Governance for Research

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Thailand Center of Excellence for Life Sciences
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SiHP
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Siriraj Health Policy Unit

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Session Overview

Data Governance for Research @ 15:45 – 16:15 (30 min)

Why? Background & Questions	How? Methods & Materials	What? Objectives
☐ What are the ethical considerations for data in healthcare? ☐ How does governance impact data quality and research integrity?	⬟ Principles of Data Governance ⬟ OMOP/OHDSI compliant governance practices	★ Comprehend the criticality of data governance in healthcare research ★ Understand how OMOP/ OHDSI complies with data governance norms

Data Governance

2 Prongs

Promotion

Support and Enhance Data Uses

What are the data we have?

Where are the data?

How are the data collected and used?

Whose data is it?

How can we improve data quality?

How can we make the data more valuable?

Deliverables

Policies, Procedures,
Data Catalog,
Metadata,
Data Lineage,
Data Quality Assurance

Regulation

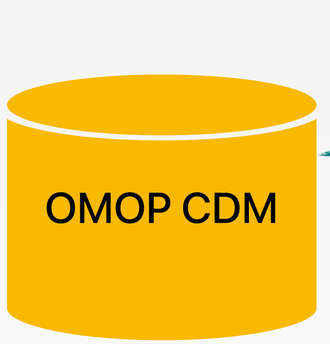
Govern and Take Care of Data Uses

How can we use the data given legal regulations & ethics guidelines?

How can we facilitate external parties' usage of our data assets given intellectual property & legal considerations?

OHDSI Data Quality Dashboard

https://ohdsi.github.io/DataQualityDashboard/



SYNTHEA SYNTHETIC HEALTH DATABASE

OVERVIEW

METADATA

RESULTS

ABOUT

DATA QUALITY ASSESSMENT

SYNTHEA SYNTHETIC HEALTH DATABASE

DataQualityDashboard Version: 2.0.0.100
Results generated at 2022-10-12 10:45:28 in 15 mins

	Verification				Validation				Total			
	Pass	Fail	Total	% Pass	Pass	Fail	Total	% Pass	Pass	Fail	Total	% Pass
Plausibility	2179	36	2215	98%	287	0	287	100%	2466	36	2502	99%
Conformance	996	11	1007	99%	180	0	180	100%	1176	11	1187	99%
Completeness	415	33	448	93%	12	4	16	75%	427	37	464	92%
Total	3590	80	3670	98%	479	4	483	99%	4069	84	4153	**98%**

2752 out of 4069 passed checks are Not Applicable, due to empty tables or fields.
1 out of 84 failed checks are SQL errors.
Corrected pass percentage for NA and Errors: 94% (1317/1400).

eGEMs
Generating Evidence & Methods to improve patient outcomes

A Harmonized Data Quality Assessment Terminology and Framework for the Secondary Use of Electronic Health Record Data

Michael G. Kahn, MD, PhD;[i] Tiffany J. Callahan, MPH;[i] Juliana Barnard, MA;[i] Alan E. Bauck;[ii] Jeff Brown, PhD;[iii] Bruce N. Davidson, PhD;[iv] Hossein Estiri, PhD;[v] Carsten Goerg, PhD;[i] Erin Holve, PhD, MPH, MPP;[vi] Steven G. Johnson, MS;[vii] Siaw-Teng Liaw, MBBS, PhD, FRACGP, FACHI;[viii] Marianne Hamilton-Lopez, PhD, MPA;[ix] Daniella Meeker, PhD;[x] Toan C. Ong, PhD;[xi] Patrick Ryan, PhD;[xii] Ning Shang, PhD;[xiii] Nicole G. Weiskopf, PhD;[xiv] Chunhua Weng, PhD, FACMI;[xiii] Meredith N. Zozus, PhD;[xv] Lisa Schilling, MD[xi]

ABSTRACT

Objective: Harmonized data quality (DQ) assessment terms, methods, and reporting practices can establish a common understanding of the strengths and limitations of electronic health record (EHR) data for operational analytics, quality improvement, and research. Existing published DQ terms were harmonized to a comprehensive unified terminology with definitions and examples and organized into a conceptual framework to support a common approach to defining whether EHR data is 'fit' for specific uses.

[Kahn, M. G., Callahan, T. J., Barnard, J., Bauck, A. E., Brown, J., Davidson, B. N., Estiri, H., Goerg, C., Holve, E., Johnson, S. G., Liaw, S.-T., Hamilton-Lopez, M., Meeker, D., Ong, T. C., Ryan, P., Shang, N., Weiskopf, N. G., Weng, C., Zozus, M. N., & Schilling, L. (2016). A Harmonized Data Quality Assessment Terminology and Framework for the Secondary Use of Electronic Health Record Data. In eGEMs (Generating Evidence & Methods to improve patient outcomes) (Vol. 4, Issue 1, p. 18). Ubiquity Press, Ltd. https://doi.org/10.13063/2327-9214.1244]

Table 1. Harmonized DQ Terms, Definitions, and Examples: Organized by Verification and Validation Contexts Within Categories and Subcategories

VERIFICATION		VALIDATION	
DEFINITION	**EXAMPLE**	**DEFINITION**	**EXAMPLE**
CONFORMANCE: DO DATA VALUES ADHERE TO SPECIFIED STANDARDS AND FORMATS?			
VALUE CONFORMANCE			
a. Data values conform to internal formatting constraints. b. Data values conform to allowable values or ranges.	a. Sex is only one ASCII character. b. Sex only has values "M," "F," or "U."	a. Data values conform to representational constraints based on external standards.	a. Values for primary language conform to ISO standards.
RELATIONAL CONFORMANCE			
a. Data values conform to relational constraints. b. Unique (key) data values are not duplicated. c. Changes to the data model or data model versioning.	a. Patient medical record number links to other tables as required. b. A medical record number is assigned to a single patient. c. Version 1 data does not include medical discharge hour.	a. Data values conform to relational constraints based on external standards.	a. Data values conform to all not-NULL requirements in a common multi-institutional data exchange format.
COMPUTATIONAL CONFORMANCE			
a. Computed values conform to computational or programming specifications.	a. Database- and hard-calculated Body Mass Index (BMI) values are identical.	a. Computed results based on published algorithms yield values that match validation values provided by external source.	a. Computed BMI percentiles yield identical values compared to test results and values provided by the CDC.
COMPLETENESS: ARE DATA VALUES PRESENT?			
a. The absence of data values at a single moment in time agrees with local or common expectations. b. The absence of data values measured over time agrees with local or common expectations.	a. The encounter ID variable has missing values. b. Gender should not be null. c. Medical discharge time is missing for three consecutive days.	a. The absence of data values at a single moment in time agrees with trusted reference standards or external knowledge. b. The absence of data values measured over time agrees with trusted reference standards or external knowledge.	a. The current encounter ID variable is missing twice as many values as the institutionally validated database. b. A drop in ICD-9CM codes matches implementation of ICD-10CM
PLAUSIBILITY: ARE DATA VALUES BELIEVABLE?			
UNIQUENESS PLAUSIBILITY			
a. Data values that identify a single object are not duplicated.	a. Patients from a single institution do not have multiple medical record numbers.	a. Data values that identify a single object in an external source are not duplicated.	a. An institution's CMS facility identifier does not refer to a multiple institutions.

[Kahn, M. G., et al. (2016). https://doi.org/10.13063/2327-9214.1244]

Table 1. Harmonized DQ Terms, Definitions, and Examples: Organized by Verification and Validation Contexts Within Categories and Subcategories (Cont'd)

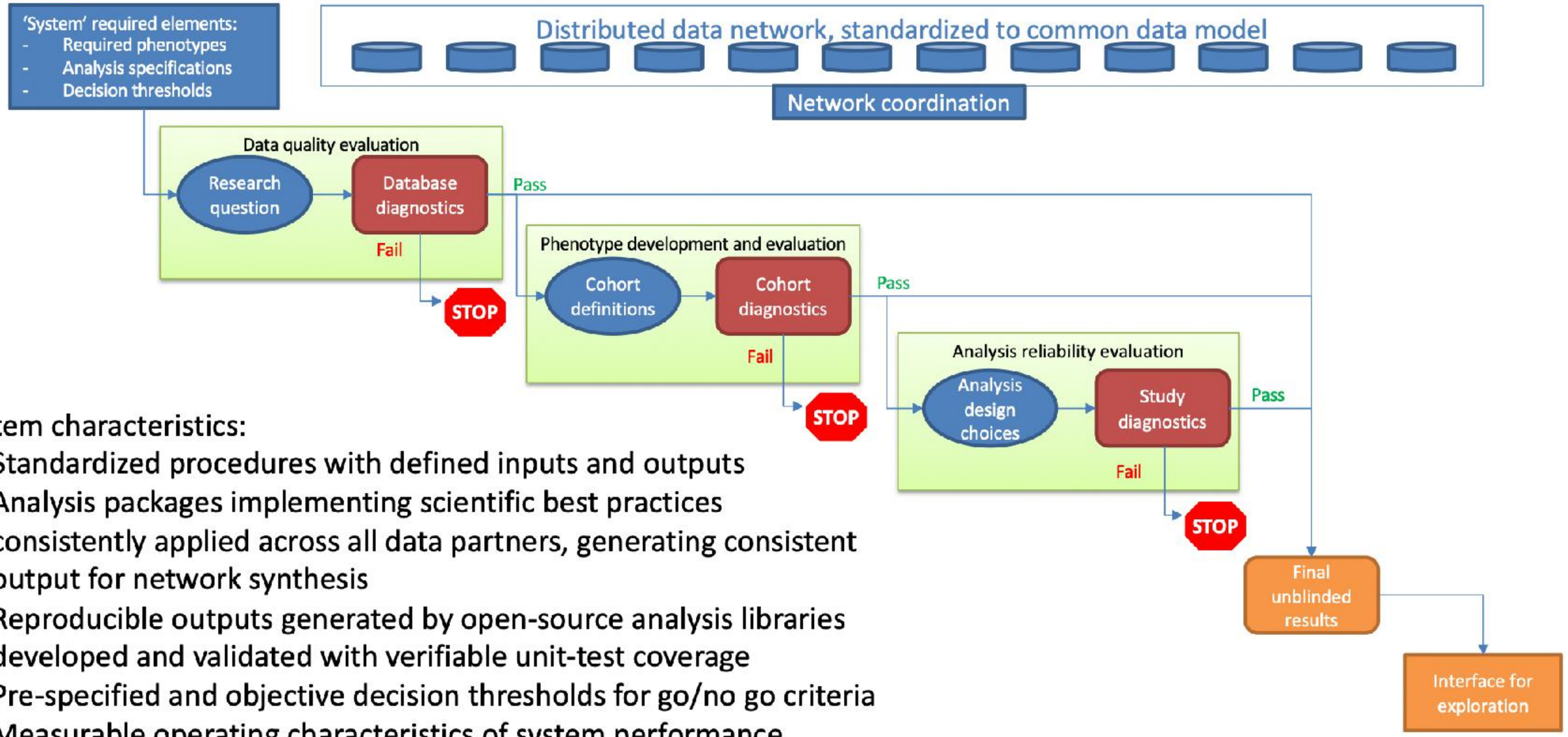
VERIFICATION		VALIDATION	
DEFINITION	**EXAMPLE**	**DEFINITION**	**EXAMPLE**
ATEMPORAL PLAUSIBILITY			
a. Data values and distributions agree with an internal measurement or local knowledge. b. Data values and distributions for independent measurements of the same fact are in agreement. c. Logical constraints between values agree with local or common knowledge (includes "expected" missingness). d. Values of repeated measurement of the same fact show expected variability.	a. Height and weight values are positive. a. Counts of unique patients by diagnoses are as expected a. Distribution of encounters per patient or medications per encounter distributions are as expected b. Serum glucose measurement is similar to finger stick glucose measurement. b. Oral and axillary temperatures are similar. c. Sex values agree with sex-specific contexts (pregnancy, prostate cancer). d. Height values are similar when taken by two separate nurses within the same facility using the same equipment.	a. Data values and distributions (including subgroup distributions) agree with trusted reference standards or external knowledge. b. Similar values for identical measurements are obtained from two independent databases representing the same observations with equal credibility. c. Two dependent databases (e.g., database 1 abstracted from database 2) yield similar values for identical variables.	a. HbA1c values from hospital and national reference lab are statistically similar under the same conditions. a. Distribution of patients with cardiovascular disease diagnoses are similar to CDC rates for the same age and sex groups a. Readmission rates by age groups for Medicare patients agree with CMS values b. Diabetes ICD-9CM and CPT codes are similar between two independent claims databases serving similar populations. c. Recorded date of birth is consistent between EHR data and registry data for the same patient.
TEMPORAL PLAUSIBILITY			
a. Observed or derived values conform to expected temporal properties. b. Sequences of values that represent state transitions conform to expected properties. c. Measures of data value density against a time-oriented denominator are expected *based on internal knowledge*.	a. Admission date occurs before discharge date. b. Date of an initial immunization precedes date of a booster immunization. c. Similar counts of patient observations between extraction-transformation-load cycles. c. Counts of emergency room visits by month shows expected spike during flu season. c. Medications per patient-day are as expected	a. Observed or derived values have similar temporal properties across one or more external comparators or gold standards. b. Sequences of values that represent state transitions are similar to external comparators or gold standards. c. Measures of data value density against a time-oriented denominator are expected *based on external knowledge*.	a. Length of stay by outpatient procedure types conforms to Medicare data for similar populations. b. Immunization sequences match the CDC recommendations. c. Counts of emergency room visits by month shows spike during flu season that are similar to local health department reports. c. Medications per patient-day matches claims data.

Notes: The lettering in each column can be used to map each definition to its corresponding example. Not every definition has a corresponding example.

Extract, Transform, Load ETL (ETL); International Organization for Standardization (ISO); Electronic Health Record (EHR) Data; International Classification of Diseases, Ninth and Tenth Revisions (ICD-9CM and ICD-10CM); Current Procedural Terminology (CPT); Centers for Medicare & Medicaid Services (CMS); Centers for Disease Control and Prevention (CDC).

[Kahn, M. G., et al. (2016). https://doi.org/10.13063/2327-9214.1244]

Engineering open science systems that build trust into the real-world evidence generation and dissemination process



System characteristics:

- Standardized procedures with defined inputs and outputs
- Analysis packages implementing scientific best practices consistently applied across all data partners, generating consistent output for network synthesis
- Reproducible outputs generated by open-source analysis libraries developed and validated with verifiable unit-test coverage
- Pre-specified and objective decision thresholds for go/no go criteria
- Measurable operating characteristics of system performance

from 11Jan2022 OHDSI ca

[https://www.ohdsi.org/wp-content/uploads/2022/10/OHDSI2022-Plenary-ObjectiveDiagnostics-Schuemie-Ryan.pdf]
[https://www.youtube.com/watch?v=DJZP5z6r-QE]

Secondary Use of Health Data

European review by Open Data Institute

[https://secondary-use-health-data.theodi.org]

Secondary Use of Health Data

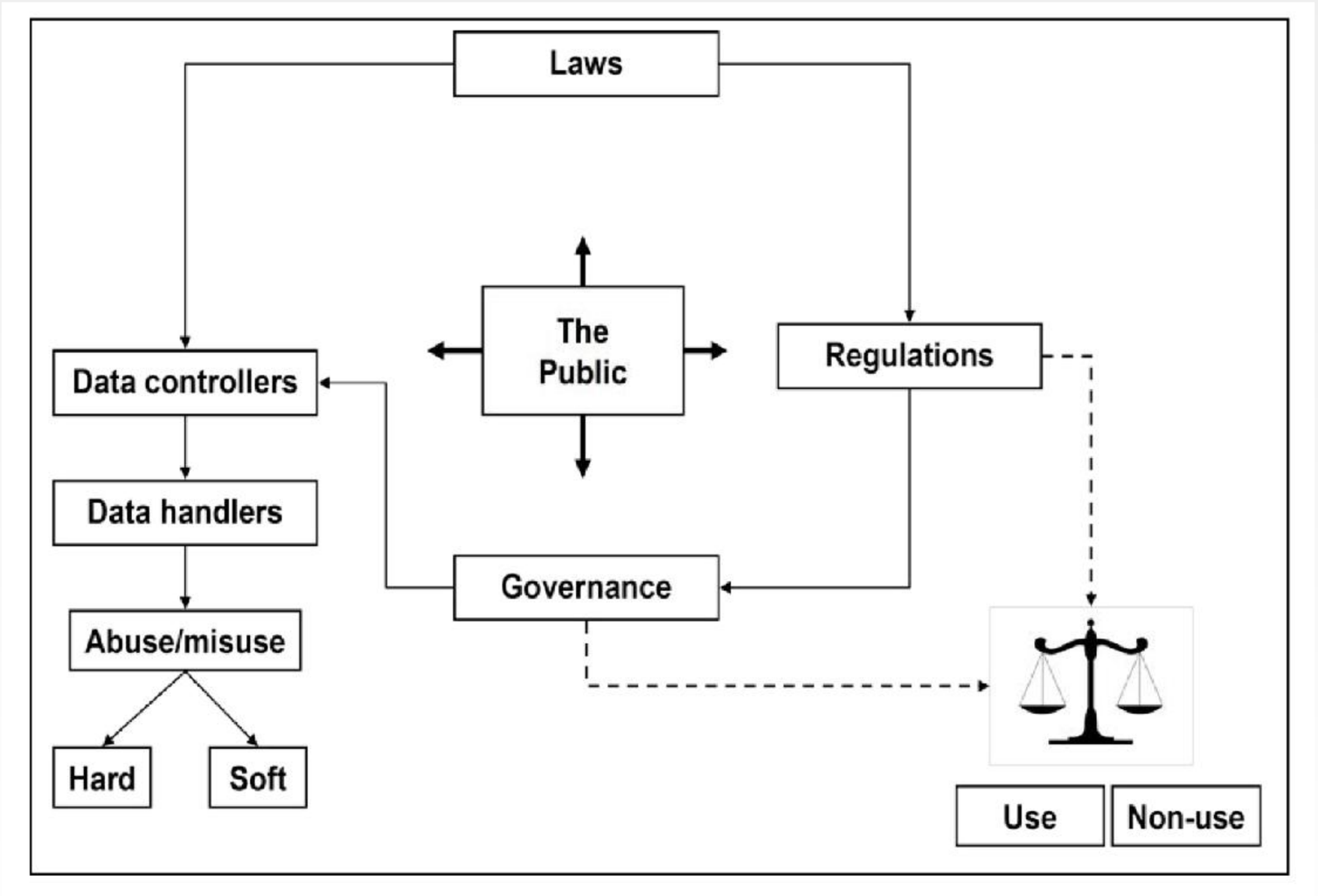
National example from UK

ในสหราชอาณาจักร เมื่อปี 2022 กระทรวง Health and Social Care ได้จัดทำการศึกษาและสรุปคำแนะนำการใช้ข้อมูลสุขภาพเพื่อการวิเคราะห์และวิจัยในสหราชอาณาจักร ชื่อว่า “Better, broader, safer: using health data for research and analysis” หรือเรียกอย่างไม่เป็นทางการว่า Goldacre Review ตามชื่อของประธานคณะศึกษา Professor Ben Goldacre จากมหาวิทยาลัย Oxford โดยแบ่งคำแนะนำไว้เป็น 6 ด้าน

1. Platforms and security
2. Modern, open working methods for NHS data
3. Data curation and knowledge management
4. NHS data analysts
5. Governance
6. Approaches and strategy

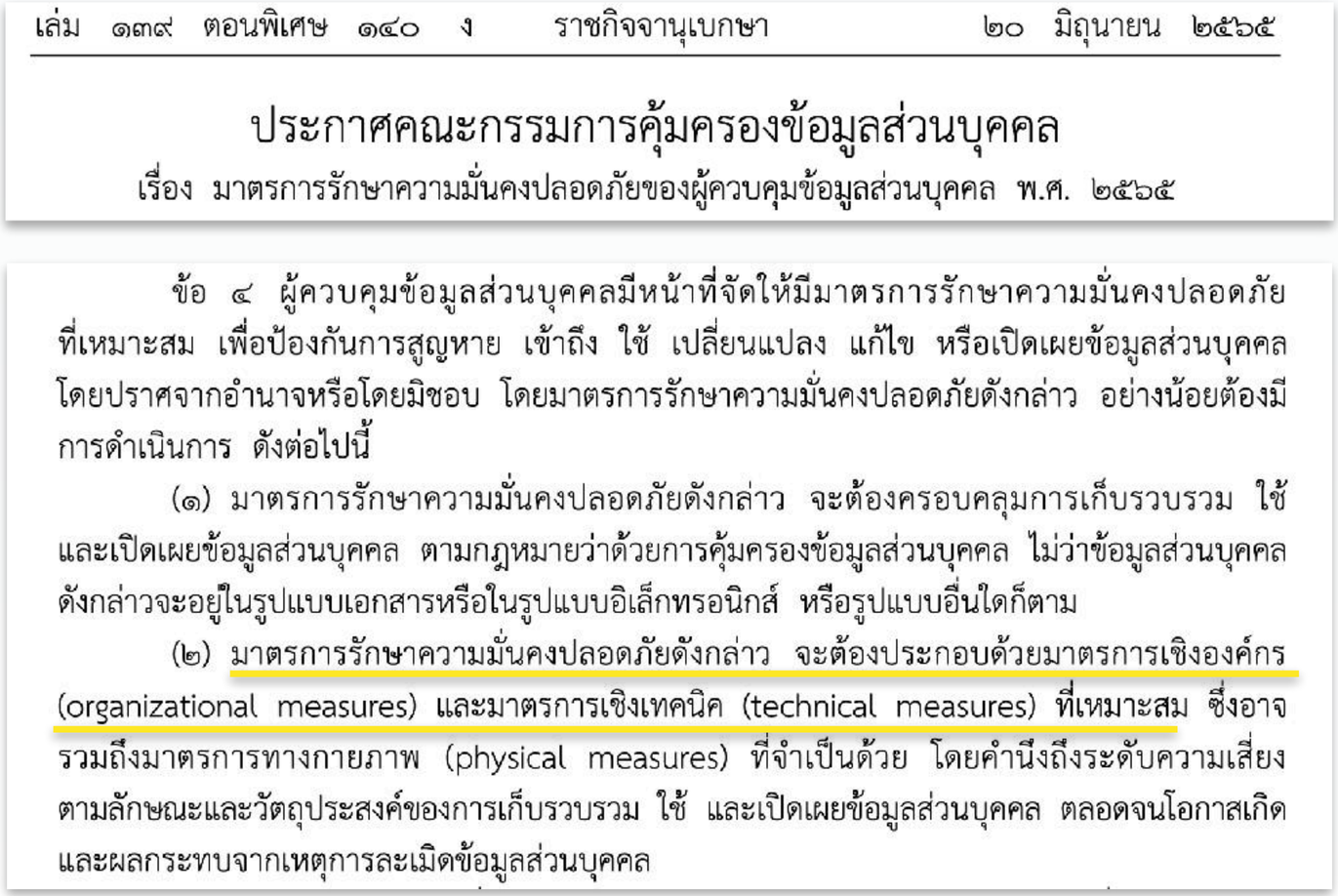
[https://www.goldacrereview.org]

Secondary Use of Health Data Governance



[Laurie, G., Stevens, L., Jones, K. H., & Dobbs, C. (2014). A Review of Evidence Relating to Harm Resulting from Uses of Health and Biomedical Data. Nuffield Council on Bioethics.]

Data Protection Measures



เล่ม ๑๓๙ ตอนพิเศษ ๑๔๐ ง ราชกิจจานุเบกษา ๒๐ มิถุนายน ๒๕๖๕

ประกาศคณะกรรมการคุ้มครองข้อมูลส่วนบุคคล

เรื่อง มาตรการรักษาความมั่นคงปลอดภัยของผู้ควบคุมข้อมูลส่วนบุคคล พ.ศ. ๒๕๖๕

ข้อ ๔ ผู้ควบคุมข้อมูลส่วนบุคคลมีหน้าที่จัดให้มีมาตรการรักษาความมั่นคงปลอดภัยที่เหมาะสม เพื่อป้องกันการสูญหาย เข้าถึง ใช้ เปลี่ยนแปลง แก้ไข หรือเปิดเผยข้อมูลส่วนบุคคลโดยปราศจากอำนาจหรือโดยมิชอบ โดยมาตรการรักษาความมั่นคงปลอดภัยดังกล่าว อย่างน้อยต้องมีการดำเนินการ ดังต่อไปนี้

(๑) มาตรการรักษาความมั่นคงปลอดภัยดังกล่าว จะต้องครอบคลุมการเก็บรวบรวม ใช้ และเปิดเผยข้อมูลส่วนบุคคล ตามกฎหมายว่าด้วยการคุ้มครองข้อมูลส่วนบุคคล ไม่ว่าข้อมูลส่วนบุคคลดังกล่าวจะอยู่ในรูปแบบเอกสารหรือในรูปแบบอิเล็กทรอนิกส์ หรือรูปแบบอื่นใดก็ตาม

(๒) มาตรการรักษาความมั่นคงปลอดภัยดังกล่าว จะต้องประกอบด้วยมาตรการเชิงองค์กร (organizational measures) และมาตรการเชิงเทคนิค (technical measures) ที่เหมาะสม ซึ่งอาจรวมถึงมาตรการทางกายภาพ (physical measures) ที่จำเป็นด้วย โดยคำนึงถึงระดับความเสี่ยงตามลักษณะและวัตถุประสงค์ของการเก็บรวบรวม ใช้ และเปิดเผยข้อมูลส่วนบุคคล ตลอดจนโอกาสเกิดและผลกระทบจากเหตุการละเมิดข้อมูลส่วนบุคคล

1. **Organizational Measures, e.g.,**
   1.1. CIOMS Guideline 2016
   1.2. Declaration of Taipei 2016
   1.3. PDPA 2019
   1.4. IRB
2. **Technical Measures, e.g.,**
   2.1. Shift and Truncate for De-identification
   2.2. Secure Remote Research Environment
   2.3. Conventional security settings

THE COUNCIL FOR INTERNATIONAL ORGANIZATIONS OF MEDICAL SCIENCES (CIOMS) International Ethical Guidelines for Health-related Research Involving Humans (2016), GUIDELINE 12: COLLECTION, STORAGE AND USE OF DATA IN HEALTH-RELATED RESEARCH

	สิ่งที่ต้องกำหนดตาม Commentary Guideline 12	สรุปใจความสำคัญ
1	to which legal entity the material is entrusted	นิติบุคคลที่ได้รับมอบหมายให้จัดการข้อมูล
2	how authorization from the donor is obtained	วิธีการได้มาซึ่งการอนุญาตให้ใช้ข้อมูลจากผู้ให้ข้อมูล
3	how the donor can retract this authorization	วิธีการยกเลิกการอนุญาตโดยผู้ให้ข้อมูล
4	in which circumstances donors need to be recontacted	เมื่อเกิดเหตุการณ์ใดจึงจะต้องติดต่อผู้ให้ข้อมูล
5	a procedure for determining whether unsolicited findings should be disclosed, and if so, how they should be managed	กระบวนการพิจารณาว่าควรเปิดเผยผลการค้นพบที่ไม่ได้ร้องขอหรือไม่ หากใช่ ควรจัดการอย่างไร
6	how the quality of the data collection is controlled	วิธีการควบคุมคุณภาพการเก็บรวบรวมข้อมูล
7	how confidentiality of the link between collected data and personal identifiers of the donors is maintained	วิธีการรักษาความลับระหว่างข้อมูลที่เก็บและตัวบ่งชี้ส่วนบุคคลของผู้ให้ข้อมูล
8	who may have access to the data for future research, and under what circumstances	ใครสามารถเข้าถึงข้อมูลเพื่อการวิจัยในอนาคต และในสถานการณ์ใด
9	which body may review research proposals for future use of the data	หน่วยงานใดสามารถตรวจสอบข้อเสนอการวิจัยสำหรับการใช้ข้อมูลในอนาคต
10	appropriate mechanisms for keeping donors informed of research outcomes	กลไกที่เหมาะสมสำหรับการแจ้งให้ผู้ให้ข้อมูลทราบผลการวิจัย

[https://cioms.ch/wp-content/uploads/2017/01/WEB-CIOMS-EthicalGuidelines.pdf]

THE COUNCIL FOR INTERNATIONAL ORGANIZATIONS OF MEDICAL SCIENCES (CIOMS) International Ethical Guidelines for Health-related Research Involving Humans (2016), GUIDELINE 12: COLLECTION, STORAGE AND USE OF DATA IN HEALTH-RELATED RESEARCH (cont'd)

	สิ่งที่ต้องกำหนดตาม Commentary Guideline 12	สรุปใจความสำคัญ
11	how participatory engagement with patient groups or the wider community is organized	วิธีการจัดการมีส่วนร่วมกับกลุ่มผู้ป่วยหรือสังคม
12	to which other sources of personal information the results of analyses with data may be linked	แหล่งข้อมูลส่วนบุคคลอื่นที่ผลการวิเคราะห์ด้วยข้อมูลอาจถูกเชื่อมโยง
13	in broad terms, which types of research will be pursued	ประเภทของการวิจัยที่จะมีการดำเนินการโดยคร่าว
14	which types of research will be excluded or included only after recontacting the donor for consent	ประเภทของการวิจัยที่จะต้องดำเนินการได้หลังจากติดต่อผู้ให้ข้อมูลเพื่อขอความยินยอมแล้วเท่านั้น
15	to whom any benefits from the research are expected to accrue	ใครที่คาดหวังว่าจะได้รับประโยชน์จากการวิจัย
16	appropriate mechanisms for keeping participants informed of research outcomes	กลไกที่เหมาะสมสำหรับการแจ้งให้ผู้เข้าร่วมทราบผลการวิจัย
17	how the rights and welfare of individuals from whom the data were collected are not adversely affected	วิธีการที่สิทธิและสวัสดิภาพของบุคคลที่ข้อมูลถูกเก็บรวบรวมจะไม่ได้รับผลกระทบในทางลบ

[https://cioms.ch/wp-content/uploads/2017/01/WEB-CIOMS-EthicalGuidelines.pdf]

World Medical Association (WMA) DECLARATION OF TAIPEI ON ETHICAL CONSIDERATIONS REGARDING HEALTH DATABASES AND BIOBANKS (2016)

Mahidol University
Faculty of Medicine
Siriraj Hospital

	Declaration of Taipei ข้อ 21	สรุปใจความสำคัญ
1	The purpose of the Health Database or Biobank	วัตถุประสงค์ของฐานข้อมูลสุขภาพหรือ Biobank
2	The nature of health data and biological material that will be contained in the Health Database or Biobank	ลักษณะของข้อมูลสุขภาพและวัตถุชีวภาพที่จะถูกจัดเก็บในฐานข้อมูลสุขภาพหรือ Biobank
3	Arrangements for the length of time for which the data or material will be stored	กำหนดระยะเวลาการจัดการเก็บข้อมูลหรือวัตถุ
4	Arrangements for regulations of the disposal and destruction of data or material	กำหนดระเบียบการทำลายข้อมูลหรือวัตถุ
5	Arrangement for how the data and material will be documented and traceable in accordance with the consent of the concerned persons	กำหนดการจัดการวิธีการบันทึกและติดตามข้อมูลและวัตถุตามความยินยอมของบุคคลที่เกี่ยวข้อง
6	Arrangement for how the data and material will be dealt with in the event of change of ownership or closure	กำหนดการจัดการวิธีการจัดการข้อมูลและวัตถุในกรณีที่มีการเปลี่ยนเจ้าของหรือปิดโครงการ
7	Arrangement for obtaining appropriate consent or other legal basis for data or material collection	กำหนดการจัดการในการขอความยินยอมที่เหมาะสมหรือฐานกฎหมายอื่นสำหรับการเก็บข้อมูลหรือวัตถุ
8	Arrangements for protecting dignity, autonomy, privacy and preventing discrimination	กำหนดการจัดการในการปกป้องเกียรติยศ อิสรภาพ ความเป็นส่วนตัว และป้องกันการเลือกปฏิบัติ
9	Criteria and procedures concerning the access to and the sharing of the health data or biological material including the systematic use of Material Transfer Agreement (MTA) when necessary	เกณฑ์และขั้นตอนเกี่ยวกับการเข้าถึงและการแบ่งปันข้อมูลสุขภาพหรือวัตถุชีวภาพ รวมถึงระบบการใช้ Material Transfer Agreement (MTA) เมื่อจำเป็น
10	The person or persons who are responsible for the governance	บุคคลหรือผู้ที่รับผิดชอบในการจัดการธรรมาภิบาล
11	The security measures to prevent unauthorized access or inappropriate sharing	มาตรการรักษาความปลอดภัยเพื่อป้องกันการเข้าถึงโดยไม่ได้รับอนุญาตหรือการแบ่งปันที่ไม่เหมาะสม
12	The procedures for re-contacting participants where relevant	ขั้นตอนสำหรับการติดต่อผู้เข้าร่วมเข้าในที่เกี่ยวข้อง
13	The procedures for receiving and addressing enquiries and complaints	ขั้นตอนสำหรับรับและจัดการคำปรึกษาและข้อร้องเรียน

[https://www.wma.net/policies-post/wma-declaration-of-taipei-on-ethical-considerations-regarding-health-databases-and-biobanks/]

พระราชบัญญัติสุขภาพแห่งชาติ พ.ศ. 2550

มาตรา 7 ข้อมูลด้านสุขภาพของบุคคล เป็นความลับส่วนบุคคล ผู้ใดจะนำไปเปิดเผยในประการที่น่าจะทำให้บุคคลนั้นเสียหายไม่ได้ เว้นแต่การเปิดเผยนั้นเป็นไปตามความประสงค์ของบุคคลนั้นโดยตรง หรือมีกฎหมายเฉพาะบัญญัติให้ต้องเปิดเผย แต่ไม่ว่าในกรณีใด ๆ ผู้ใดจะอาศัยอำนาจหรือสิทธิตามกฎหมายว่าด้วยข้อมูลข่าวสารของราชการหรือกฎหมายอื่นเพื่อขอเอกสารเกี่ยวกับข้อมูลด้านสุขภาพของบุคคลที่ไม่ใช่ของตนไม่ได้

มาตรา 9 ในกรณีที่ผู้ประกอบวิชาชีพด้านสาธารณสุขประสงค์จะใช้ผู้รับบริการเป็นส่วนหนึ่งของการทดลองในงานวิจัย ผู้ประกอบวิชาชีพด้านสาธารณสุขต้องแจ้งให้ผู้รับบริการทราบล่วงหน้า และต้องได้รับความยินยอมเป็นหนังสือจากผู้รับบริการก่อนจึงจะดำเนินการได้ ความยินยอมดังกล่าว ผู้รับบริการจะเพิกถอนเสียเมื่อใดก็ได้

พระราชบัญญัติคุ้มครองข้อมูลส่วนบุคคล พ.ศ. 2562
PDPA

วัตถุประสงค์และฐานทางกฎหมายการประมวลผลข้อมูลส่วนบุคคล

มาตรา 26 ห้ามมิให้เก็บรวบรวมข้อมูลส่วนบุคคลเกี่ยวกับเชื้อชาติ เผ่าพันธุ์ ความคิดเห็นทางการเมือง ความเชื่อในลัทธิ ศาสนาหรือปรัชญา พฤติกรรมทางเพศ ประวัติอาชญากรรม ข้อมูลสุขภาพ ความพิการ ข้อมูลสหภาพแรงงาน ข้อมูลพันธุกรรม ข้อมูลชีวภาพ หรือข้อมูลอื่นใดซึ่งกระทบต่อเจ้าของข้อมูลส่วนบุคคลในทำนองเดียวกันตามที่คณะกรรมการประกาศกำหนด โดยไม่ได้รับความยินยอมโดยชัดแจ้งจากเจ้าของข้อมูลส่วนบุคคล เว้นแต่

(5) เป็นการจำเป็นในการปฏิบัติตามกฎหมายเพื่อให้บรรลุวัตถุประสงค์เกี่ยวกับ

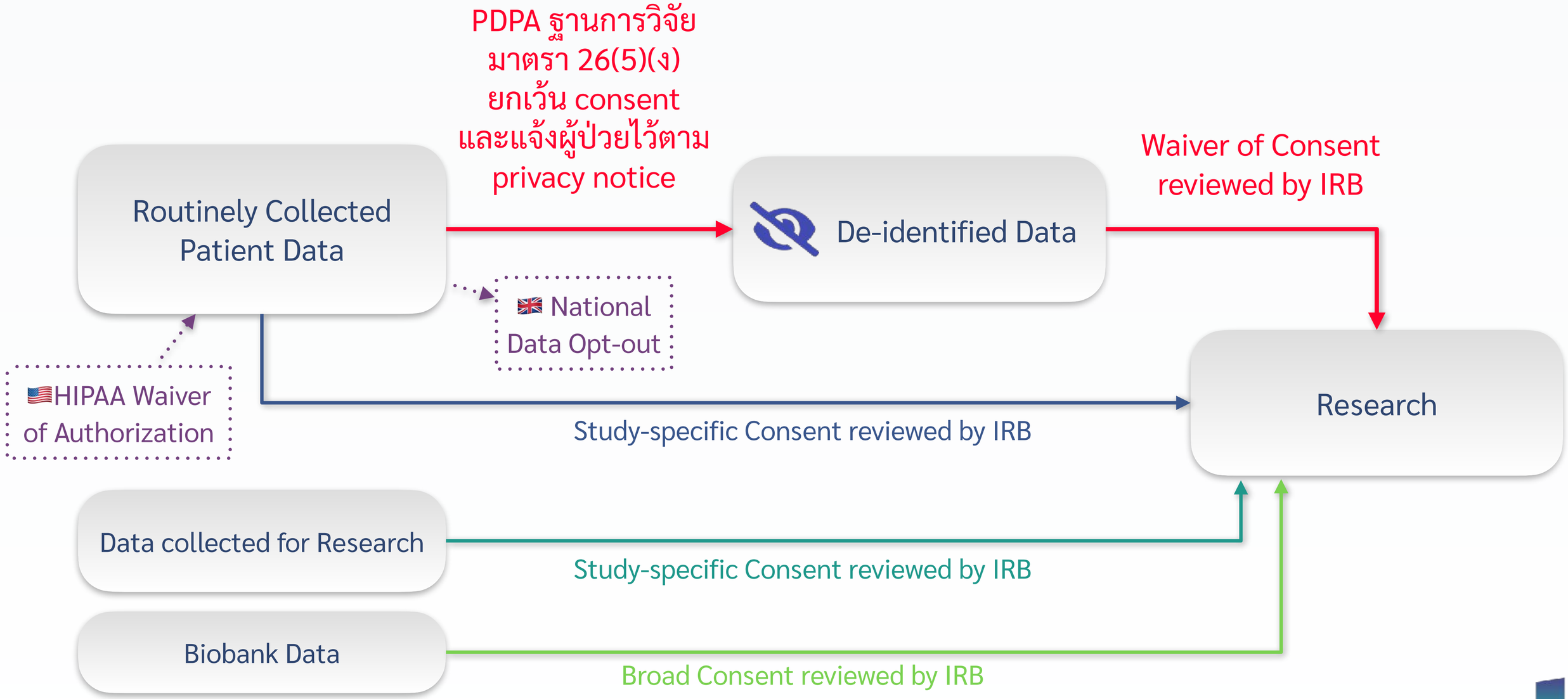
(ง) การศึกษาวิจัยทางวิทยาศาสตร์ ประวัติศาสตร์ หรือสถิติ หรือประโยชน์สาธารณะอื่น ทั้งนี้ ต้องกระทำเพื่อให้บรรลุวัตถุประสงค์ดังกล่าวเพียงเท่าที่จำเป็นเท่านั้น และได้จัดให้มีมาตรการที่เหมาะสมเพื่อคุ้มครองสิทธิขั้นพื้นฐานและประโยชน์ของเจ้าของข้อมูลส่วนบุคคล ตามที่คณะกรรมการประกาศกำหนด

สิทธิของเจ้าของข้อมูลส่วนบุคคล ตามพระราชบัญญัติฯ

มาตรา 32 เจ้าของข้อมูลส่วนบุคคลมีสิทธิคัดค้านการเก็บรวบรวม ใช้ หรือเปิดเผยข้อมูลส่วนบุคคลที่เกี่ยวกับตนเมื่อใดก็ได้ ดังต่อไปนี้

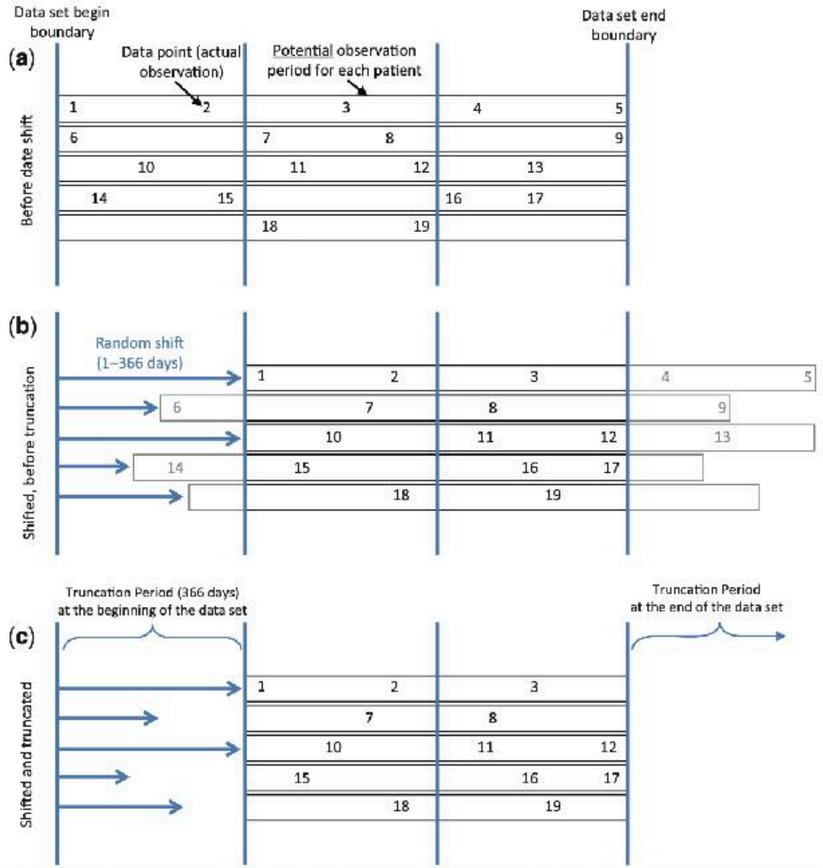
(3) กรณีที่เป็นการเก็บรวบรวม ใช้ หรือเปิดเผยข้อมูลส่วนบุคคลเพื่อวัตถุประสงค์เกี่ยวกับการศึกษาวิจัยทางวิทยาศาสตร์ ประวัติศาสตร์ หรือสถิติ เว้นแต่เป็นการจำเป็นเพื่อการดำเนินภารกิจเพื่อประโยชน์สาธารณะของผู้ควบคุมข้อมูลส่วนบุคคล

รูปแบบการขอ consent การวิจัย จากข้อมูลชนิดต่าง ๆ



Shift and Truncate (SANT) for De-identification

Figure 1: Shift and Truncate. Each row is a unique patient, each number is a unique data point for a patient, and each rectangle represents the time that the patient was *potentially* observed. **(a)** Original data set. Patients are potentially observed for 3 years (each vertical line marks 1 year). Patients need not have data, but simply the potential to have been observed (even if they lived elsewhere or were not born yet, someone had the potential to have been observed). **(b)** Shifted data set. Patient records are shifted forward by 1–366 days. Data points that were previously aligned across patients are no longer aligned, but points within a given patient remain at the same relative distances from each other. **(c)** Shifted and truncated data set. Data points from the first 366 days of the shifted data set and from the last 366 days of the shifted data set are removed from the data set.



Preserving temporal relations in clinical data while maintaining privacy

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George Hripcsak,[1] Parsa Mirhaji,[2] Alexander FH Low,[3] and Bradley A Malin[4,5]

AMIA INFORMATICS PROFESSIONALS: LEADING THE WAY
OXFORD UNIVERSITY PRESS

ABSTRACT

Objective Maintaining patient privacy is a challenge in large-scale observational research. To assist in reducing the risk of identifying study subjects through publicly available data, we introduce a method for obscuring date information for clinical events and patient characteristics.
Methods The method, which we call Shift and Truncate (SANT), obscures date information to any desired granularity. Shift and Truncate first assigns each patient a random shift value, such that all dates in that patient's record are shifted by that amount. Data are then truncated from the beginning and end of the data set.
Results The data set can be proven to not disclose temporal information finer than the chosen granularity. Unlike previous strategies such as a simple shift, it remains robust to frequent – even daily – updates and robust to inferring dates at the beginning and end of date-shifted data sets. Time-of-day may be retained or obscured, depending on the goal and anticipated knowledge of the data recipient.
Conclusions The method can be useful as a scientific approach for reducing re-identification risk under the Privacy Rule of the Health Insurance Portability and Accountability Act and may contribute to qualification for the Safe Harbor implementation.

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[Hripcsak, G., et al. (2016). https://doi.org/10.1093/jamia/ocw001]

Secure Remote Research Environment

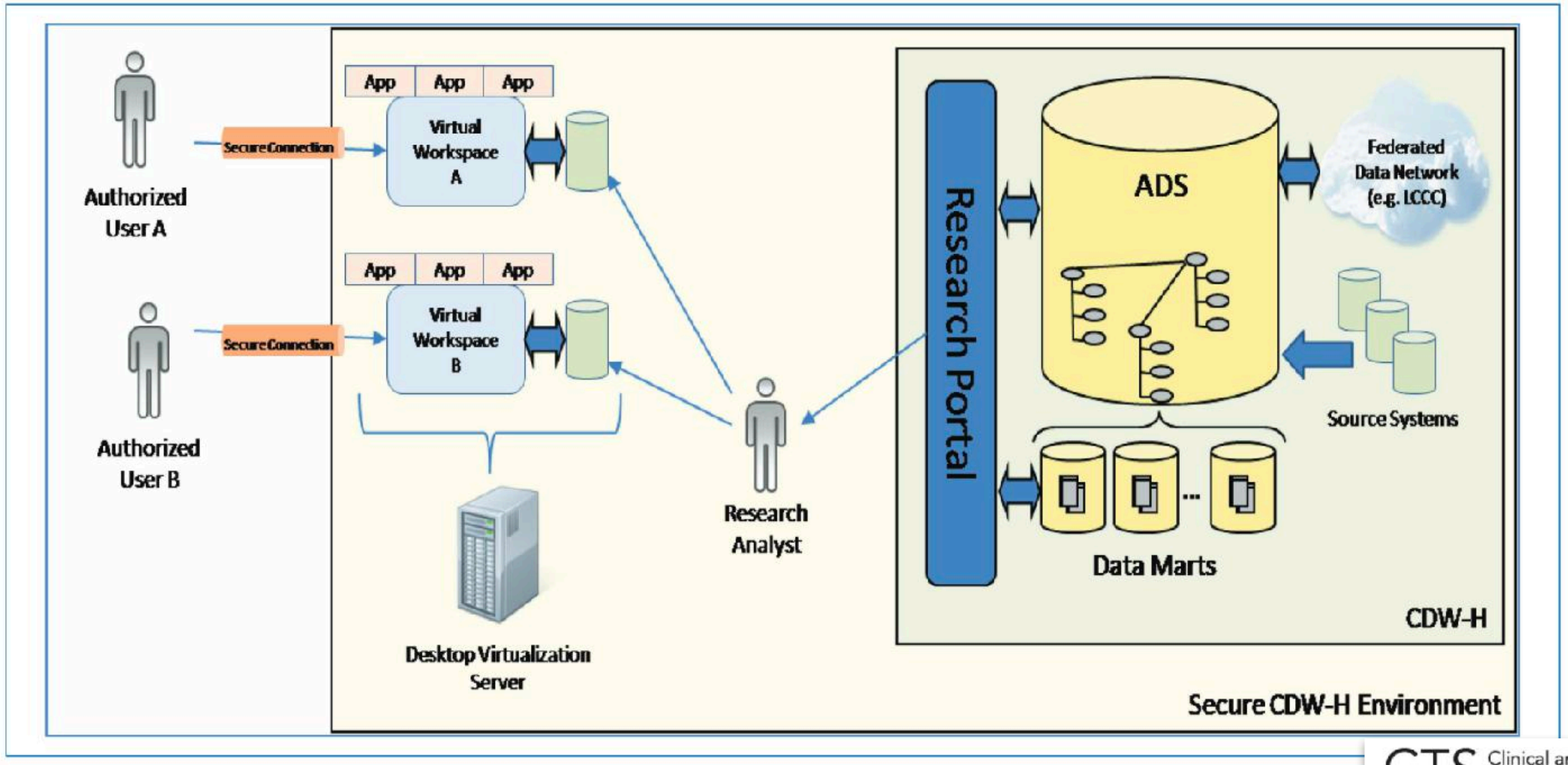

Figure 2. Conceptual view of the SMRW environment.


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The Secure Medical Research Workspace: An IT Infrastructure to Enable Secure Research on Clinical Data

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