

Current Practices in Estimation and Prediction

OHDSI Community Call April 22, 2025 • 11 am ET

in ohdsi



Upcoming Community Calls

Date	Topic	
Apr. 22	Current Practices in Estimation and Prediction	
Apr. 29	DevCon 2025 Review	
May 6	Evidence Synthesis	
May 13	Maternal Health Fellowship Review	
May 20	Guideline-Driven Evidence Study Review	
May 27	Collaborator Showcase Brainstorm (Deadline is July 1)	







Three Stages of The Journey

Where Have We Been?
Where Are We Now?
Where Are We Going?







OHDSI Shoutouts!



Congratulations to the team of Daniel Kapitan, Femke Heddema, André Dekker, Melle Sieswerda, Bart-Jan Verhoeff, and Matt Berg on the publication of **Data Interoperability** in Context: The Importance of Open-**Source Implementations When Choosing Open Standards** in the Journal of Medical Internet Research.

JOURNAL OF MEDICAL INTERNET RESEARCH

Kapitan et al

Viewpoint

Data Interoperability in Context: The Importance of Open-Source Implementations When Choosing Open Standards

Daniel Kapitan^{1,2,3}, DPhil; Femke Heddema², MSc; André Dekker⁴, Prof Dr; Melle Sieswerda⁵, MD, MSc; Bart-Jan Verhoeff⁶, MD; Matt Berg⁷, BA, MBA

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Abstract

Following the proposal by Tsafnat et al (2024) to converge on three open health data standards, this viewpoint offers a critical reflection on their proposed alignment of openEHR, Fast Health Interoperability Resources (FHIR), and Observational Medical Outcomes Partnership (OMOP) as default data standards for clinical care and administration, data exchange, and longitudinal analysis, respectively. We argue that open standards are a necessary but not sufficient condition to achieve health data interoperability. The ecosystem of open-source software needs to be considered when choosing an appropriate standard for a given context. We discuss two specific contexts, namely standardization of (1) health data for federated learning, and (2) health data sharing in low- and middle-income countries. Specific design principles, practical considerations, and implementation choices for these two contexts are described, based on ongoing work in both areas. In the case of federated learning, we observe convergence toward OMOP and FHIR, where the two standards can effectively be used side-by-side given the availability of mediators between the two. In the case of health information exchanges in low and middle-income countries, we see a strong convergence toward FHIR as the primary standard. We propose practical guidelines for context-specific adaptation of open health data standards.



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OHDSI Shoutouts!



Congratulations to the team of Young Hwa Lee, Young June Choe, Yoon Sun Yoon, Ji Young Park, Yun-Kyung Kim, Hyung Joon Joo, Sujin Choi, Hyun Jung Kim and Lorenzo Bertizzolo on the publication of **Predicting ICU Admission Risk in Children with Respiratory Syncytial Virus** in Infectious Diseases and Therapy.

Infect Dis Ther https://doi.org/10.1007/s40121-025-01155-w

121-025-01155-w



ORIGINAL RESEARCH

Predicting ICU Admission Risk in Children with Respiratory Syncytial Virus

Young Hwa Lee · Young June Choe · Yoon Sun Yoon · Ji Young Park · Yun-Kyung Kim · Hyung Joon Joo · Sujin Choi · Hyun Jung Kim · Lorenzo Bertizzolo

Received: February 26, 2025 / Accepted: April 2, 2025 © The Author(s) 2025

ABSTRACT

Introduction: Respiratory syncytial virus (RSV) is a common infection in young children and a frequent cause of hospitalization. In some cases, RSV can lead to severe lower respiratory tract illness requiring admission to the intensive care unit (ICU). Here, we explore risk factors for RSV-related ICU admission in children.

Methods: We conducted a retrospective study using Electronic Medical Record (EMR) data

Prior Presentation: Part of this study was presented at the RSVVW'24 Conference, 13th-16th February 2024, in Mumbai, India.

transformed into the Observational Medical Outcomes Partnership (OMOP) Common Data Model (CDM) from three tertiary care centers in Korea between 2008 and 2022. We identified 1529 children hospitalized with RSV according to the CDM and examined risk factors for ICU admission in this population.

Results: Of 33,674 children aged 0–9 years who tested for RSV, 1529 (4.5%) were positive. The highest proportion of RSV-positive children were less than 10 months old. The ICU admission rate among RSV-positive children was 1.8% (29/1529), and the highest ICU admission rate occurred in children aged 0–5 months (4.4%). In a multivariable logistic regression model, we found that the





OHDSI Shoutouts!



Congratulations to the team of Jenna Reps, Peter Rijnbeek and Patrick Ryan on the publication of Can we develop real-world prognostic models using observational healthcare data? Large-scale experiment to investigate model sensitivity to database and phenotypes in Diagnostic and Prognostic Research.

Reps et al. *Diagnostic and Prognostic Research* (2025) 9:10

https://doi.org/10.1186/s41512-025-00191-x

Diagnostic and Prognostic Research

Open Access

RESEARCH

Can we develop real-world prognostic models using observational healthcare data? Large-scale experiment to investigate model sensitivity to database and phenotypes

Jenna M. Reps^{1,2*}, Peter R. Rijnbeek² and Patrick B. Ryan¹

Abstract

Background Large observational healthcare databases are frequently used to develop models to be implemented in real-world clinical practice populations. For example, these databases were used to develop COVID severity models that guided interventions such as who to prioritize vaccinating during the pandemic. However, the clinical setting and observational databases often differ in the types of patients (case mix), and it is a nontrivial process to identify patients with medical conditions (phenotyping) in these databases. In this study, we investigate how sensitive a model's performance is to the choice of development database, population, and outcome phenotype.

Methods We developed > 450 different logistic regression models for nine prediction tasks across seven databases with a range of suitable population and outcome phenotypes. Performance stability within tasks was calculated by applying each model to data created by permuting the database, population, or outcome phenotype. We investigate performance (AUROC, scaled Brier, and calibration-in-the-large) stability and individual risk estimate stability.

Results In general, changing the outcome definitions or population phenotype made little impact on the model validation discrimination. However, validation discrimination was unstable when the database changed. Calibration and Brier performance were unstable when the population, outcome definition, or database changed. This may be problematic if a model developed using observational data is implemented in a real-world setting.

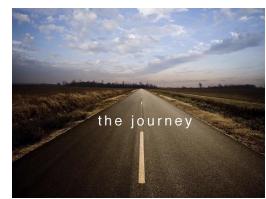
Conclusions These results highlight the importance of validating a model developed using observational data in the clinical setting prior to using it for decision-making. Calibration and Brier score should be evaluated to prevent miscalibrated risk estimates being used to aid clinical decisions.





Three Stages of The Journey

Where Have We Been? Where Are We Now? Where Are We Going?







Upcoming Workgroup Calls



Date	Time (ET)	Meeting	
Tuesday	12 pm	ATLAS	
Wednesday	9 am	Oncology Outreach/Research Subgroup	
Wednesday	12 pm	Latin America	
Thursday	9:30 am	Network Data Quality	
Thursday	7 pm	Dentistry	
Friday	9 am	Phenotype Development and Evaluation	
Monday	9 am	Vaccine Vocabulary	
Monday	10 am	Africa Chapter	
Monday	10 am	The Getting Started Subgroup	
Monday	11 am	Book of OHDSI	
Tuesday	9:30 am	CDM Survey Subgroup	





DevCon 2025: April 25

Agenda

9:00 - 9:15am ET · Welcome & Introduction

· Paul Nagy, Johns Hopkins University

9:15 - 11:30am ET · OHDSI Projects Lightning Talks

- Stabilizing Gaia Core Robert Miller, Miller Data Solutions
- CustomVocabularyBuilder Jared Houghtaling, Tufts University
- CohortConstructor Núria Mercadé-Besora, University of Oxford
- Updates on Strategus Anthony Sena, Johnson & Johnson
- Experiences with SQLMesh/CICD integration with Databricks Vishnu Chandrabalan, Lancashire Teaching Hospitals NHS Foundation Trust
- Updates from the Technical Advisory Board Frank Defalco, Johnson & Johnson

11:30 - 12:30pm ET · Developer dialogue: Dev ops, DBT and, of course, LLMs

Moderator: Katy Sadowski, Boehringer Ingelheim

- Eduard Korchmar, EPAM Systems
- · Egill Fridgeirsson, Erasmus MC
- · Martin Lavallee, Boehringer Ingelheim
- Lawrence Adams, Artificial Intelligence Centre for Value Based Healthcare

12:30 - 1:00pm ET · Break

1:00 - 2:00pm ET · Sustainable Open-Source Ecosystems Panel

Moderator: Paul Nagy, Sean O'Reilly

- · Data4Life Peter Hoffmann
- · The Hyve Jan Blom/Wouter Franke
- Cognome James Green

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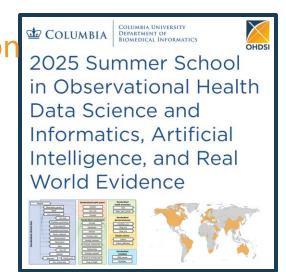
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Columbia Summer School on OHDSI

Registration is open for the first ever Columbia Summer School or OHDSI, held July 14-18, 2025, at the Columbia University Department of Biomedical Informatics in New York City.

The Columbia Summer School in Observational Health Data Science and Informatics, Artificial Intelligence, and Real World Evidence (RWE) offers health professionals, researchers and industry practitioners the opportunity to gain familiarity and hands-on experience with real world data and generating real world evidence. Participants will learn about the different types of healthcare data captured during routine clinical care, including electronic health records and administrative records, and how these data can be standardized to the OMOP Common Data Model to enable distributed data network research.



Meet Our Faculty



Vivian Beaumont Allen Professor of Biomedical Informatics



Patrick Rvan. PhD **Adjuct Assistant Professor of Biomedical Informatics**



Anna Ostropolets, MD PhD **Adjuct Assistant** Professor of Biomedical Informatics



Biomedical Informatics

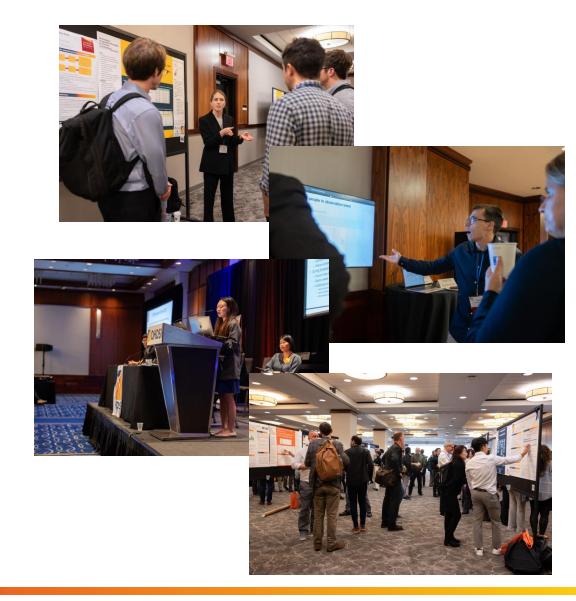




Save The Date!

The submission deadline for the 2025 Global Symposium Collaborator Showcase is July 1.

The showcase will be accepting both posters and software demos, as well as interest in hosting lightning talks. More information on the symposium, including abstract submission and registration links, will be available soon.





Monday

PHederation - the federated network of **Pulmonary Hypertension** registries

(Eva-Maria Didden, Valerie van Baalen, Michel van Speybroeck, **Monika Brand)**



The Federated Network of **Pulmonary Hypertension** Registries

A PRESENTER: Michael Briganti

CO-AUTHORS: Eva-Maria Didden, Valerie van Baalen, Michel van Speybroeck, Monika Brand

- · Pulmonary Arterial Hypertension (PAH) is a rare subgroup of Pulmonary Hypertension (PH).
- · Real-world evidence (RWE) generation in rare diseases is often restricted due to small patient numbers, geographic distribution, and limited data access.
- Federated Data Networks (FDNs) can bring togethe multiple fit-for-purpose data sources.
- PHederation is a public-private partnership connecting disease-specific clinical data sources for enhanced, transparent, and reproducible research in PH (Ref.1)

- · Each database custodian is in control of patient-level data and responsible for privacy, ethics and legal compliance.
- . The IT infrastructure consists of a central hub and local software instances, for controlled exchange of queries and



All data were originally mapped to OMOP CDM v.5.3.1 (Ref. 2-3) and undergo refreshes to OMOP CDM v.5.4.1

- 1. Select databases from Data Catalogue (Table 1) and perform fit for purpose evaluations
- 2. Create study team to develop protocol and analysis plan
- 3. Translate analysis plan into executable queries.
- 4. Distribute queries, execute analysis, share aggregate results, and potentially conduct meta-analysis.
- 5. Interpret results, write study report, publish

PHederation

sets a blueprint

for future disease-specific

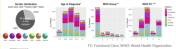
federated data networks.

Visit us at PHederation.org!



Title of the database	Description	Observation period	Number of PH and PAH patients	Regions	Source d format/ collectio
Canadian PH Registry (CPHR)	Prospective PH patient registry	2017 - ongoing	PH - 1'995 PAH - 1'076	Canada	PAHToo
EXPOSURE (EUPAS19085)	Registry of PAH patients newly treated with either Uptravi or another PAH- specific therapy	2017 - ongoing	PAH - 2'354	Europe, Canada	CDISC SDTM
OPUS (NCT02126943)	Opsumit drug registry	2014 - 2018	PH - 2'674 PAH - 2'208	USA	CDISC SDTM
ORPHEUS (NCT03197688)	Opsumit user medical chart review to supplement OPUS	2013 - 2017	PH - 3'031 PAH - 2'410	USA	CDISC SDTM

Porto center of Portuguese PH network	Northern Region Portuguese PH registry	2001 - ongoing	PAH - 216	Northern Region	PAHTool	
SPHERE (NCT03278002)	Selexipag drug registry	2016 - 2020	PH - 829 PAH - 759	USA	Registry- specific	
Stanford clinical PH database	PH Registry	2004 - ongoing	PH - 1'189 PAH - 987	USA - Western Region	Registry- specific	





characteristics at enrolment, and geographic coverage

CONCLUSION & OUTLOOK

- PHederation established a network of databases
- of diverse purpose and origin
- with the goal of advancing scientific knowledge in PH through distributed data sources and analytics. harmonization, and automation

First PHederation network study (ongoing):

- Objective: Drug utilization assessment of ERAs and PDE
- 5 inhibitors in newly-diagnosed PAH patients.
- Goal: To complement DARWIN-EU's EUPAS106052
- (Ref.4) with evidence from a disease-specific FDN

- . Transparency and reproducibility through disease-specific FDNs:
- . Standardizing PH registry data to the OMOP Common Data Model
- Handbook for PH registries to OMOP CDM conversion
- https://github.com/OHDSI/ETL--PulmonaryHypertensionRegistries EUPA\$106052; https://catalogues.ema.europa.eu/node/3797/adm







Tuesday

Gap Analysis of Static Automated Perimetry Concept Representation in OMOP CDM

(Shahin Hallaj, William Halfpenny, Niloofar Radgoudarzi, Michael V. Boland, Swarup S. Swaminathan, Sophia Y. Wang5, Benjamin Y. Xu, Dilru C. Amarasekera, Brian Stagg, Michelle Hribar, Kaveri A. Thakoor, Kerry E. Goetz, Jonathan S. Myers, Aaron Y. Lee, Mark A. Christopher, Linda M. Zangwill, Robert N. Weinreb, Sally L. Baxter)



Advancing Towards Representation of Static Perimetry Data in the OMOP CDM: A Collaborative Approach to Overcoming

Shahin Hallaj 1,2, Swarup S. Swarinathan 3, Sophia Y. Wang 4, Benjamin Y. Xu 5, Dilru Amarasekera 6, Michael V. Boland 7, Brian Stagg 8,9, Michelle Hribar 10,11,12, Kaveri A. Thakoor 13,14, Kerry E. Goetz15, Jonathan S. Myers6, Aaron Y. Lee 16, Mark A. Christopher1, Linda M. Zangwill1, Robert N. Weinreb1, Sally L. Baxter1,2

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- ✓ The endpoint of clinical glaucoma care is to preserve vision. and minimize visual field loss.
- This data is often unavailable in "big data", e.g., All of Us, institutional EHR data warehouses, and Epic Cosmos.
- Enhancing data harmonization and interoperability will facilitate clinical research and, ultimately, patient





Figure 1. Workflow and reviewed modalities of the study. Contact: shallai@health.ucsd.edu

Limited adoption of ophthalmic visual field (OPV) DICOM standard across institutions and vendors

Table 1. Variations in data export methods and resulting files as one of the main

Data Source	Extraction Method	File Formats
Humphrey Field Analyzer	Advanced export tool or direct extraction	Proprietary DICOM, PDF encapsulated DICOM, Raw DICOM, XML, OPV DICOM



Research export tool or

DICOM export tool requires

- Vendors charge for granting access to data export modules
- Non-comparable Data Elements between Perimeters from Different
 - Because of differences in:

Octopus 900

- Maximum stimulus luminance used (OPS:4.000 asb. HFA: 10.000 asb) . This may differ in different models/versions of the same device
- Device-specific normative databases
- . Mean defect vs. mean deviation: HFA algorithms assign more weight to the central points, whereas OPS weights all the pi
- Limited Concept Coverage Within The OMOP CDM
 - No representation of point-level and clusterlevel data elements
 - No representation of trend analysis
 - Notably, OMOP CDM included codes describing phenotypes (e.g., paracentral scotoma)

results of gap

CSV, ESX, OPV DICOM,

Peri Data



Figure 2. Mapping of the extracted data elements to OMOP concepts.

- Harmonization and representation of the perimetry data elements can enable the addition of these data elements in big data resources, enabling powerful modeling, discovery, and innovation.
- Limited adaptation of OPV DICOM standards by the vendors and institutions hinder application of the existing powerful DICOM-based developed tools in ophthalmology.
- Addressing these challenges is crucial for achieving data harmonization, promoting interoperability, implementing artificial intelligence, and empowering future multicenter clinical research.

Financial support: Research to prevent blindness, National Institutes of Health grants: OT20D032644, DP50D029610,







Adverse events: detection on ICI

Table 1. Patient demographics. The sex, age and performance status are shown for the

Age (median)

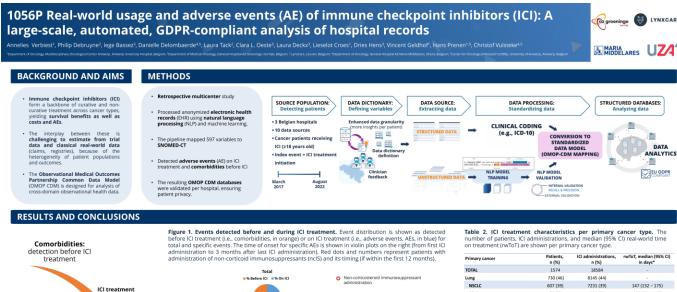
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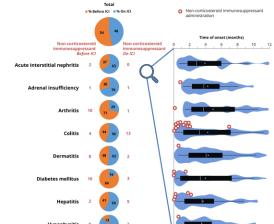
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Wednesday

Enhancing Cardiovascular Adverse Event Detection in ICI-Treated Cancer Patients: Lessons Learned from Natural Language Processing Integration with OMOP CDM

(Clara L. Oeste, Danielle Delombaerde, lege Bassez, Annelies Verbiest, Philip Debruyne, Christof Vulsteke, Dries Hens)





Primary cancer	n (%)	n (%)	in days*
TOTAL	1574	18584	-
Lung	730 (46)	8145 (44)	
NSCLC	607 (39)	7231 (39)	147 (132 - 175)
SCLC	72 (5)	485 (3)	126 (88 - 147)
Unspecified	51 (3)	429 (2)	106 (73 - 181)
Melanoma	229 (15)	3580 (19)	252 (168 - 336)
Head and neck	139 (9)	1481 (8)	84 (70 - 124)
Urothelial	137 (9)	1451 (8)	105 (63 - 147)
Renal cell	133 (9)	2169 (12)	203 (160 - 336)
Mesothelioma	59 (4)	684 (4)	126 (105 - 210)
Hepatocellular	34 (2)	308 (2)	85 (42 - 560)
Breast	32 (2)	326 (2)	168 (114 - not reache
Esophageal	26 (2)	206 (1)	91 (67 - 141)
Endometrial	16 (1)	123 (1)	85.5 (42 - not reached
Colorectal	13 (1)	160 (1)	971 (70 - not reached
Other (cervical, gastric, billary, cutaneous squamous cell carcinoma, basal cell carcinoma, Merkel cell carcinoma, Hodgkin lymphoma)	26 (2)	427 (2)	
*rwTOT is aggregated by cancer type and includes (monotherapy and combination). This grouping is			
CONCLUSIONS:			
We were able to build hospitals on >1500 ICI		al-world data wa	rehouses across

- · Lung carcinoma constituted 46% of ICI-indications
- Among AFs that can be ICI-related diabetes mellitus was the main AF detected before start of ICI (21% patients)
- AFs detected on ICI-treatment varied



Thursday

Electrocardiogram-Based Identification of Acute Heart Failure in Chronic Heart Failure: A MIMIC-IV and **OMOP-CDM Standardized Approach**

(Seung Wook Lee)

Electrocardiogram-Based Identification of Acute Heart Failure in Chronic Heart Failure: A MIMIC-IV and OMOP-CDM Standardized Approach

♣ PRESENTER: Seung Wook Lee

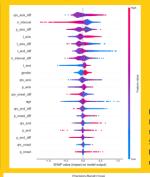
- · Acute heart failure (AHF) is a rapid worsening of heart failure due to fluid overload, leading to symptoms like shortness of breath and swelling. This is especially concerning for chronic heart failure (CHF) patients, who face higher risks of hospitalization and mortality.
- · Diagnosing AHF typically involves imaging and lab tests, but these require medical attention or specialized
- · This study explores using ECG data as a non-invasive tool to identify AHF in CHF patients, leveraging data from the MIMIC-IV database standardized to OMOP-CDM guidelines.

www.ohdsi.org

- 1. Dataset: MIMIC-IV and MIMIC-IV-ECG from PhysioNet, standardized to OMOP-CDM, (Observation period:
- 2. Inclusion Criteria: those with diagnosis of CHF, those with ECG measured within 12 hours of ED admission, those with concurrent diagnosis of AHF during observation period
- 3. Study Population: Final cohort included 6,988 CHF patients with 40,239 ECGs
- 4. Baseline ECG and demographic features were idenitifed. ECG differences were computed for 33,251 studies after excluding 6,988 baseline
- 5. Final Analysis Group: 21,315 non-AHF ECGs. 11.936 AHF ECGs
- Analysis: XGBoost model developed using age, gender, and ECG-derived features. Performance measured using AUROC and AUPRC.

ECG data may assist in identifying acute heart failure in chronic heart **failure** patients, offering a potential tool to support diagnosis.











Seung Wook Lee. Department of Medicine MetroWest Medical Center.





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onsort Diagram for

tudy population and

nclusion/exclusion



Figure 3: Receiver Operating Characteristic Curve (ROC Curve, left), and Precision-Recall Curve (PRC, right) for XGBoost model built based on demographics and ECG-derived features to identify AHF in CHF population

- · Analyzed 6.988 chronic heart failure (CHF) patients, yielding 11,936 ECGs associated with AHF events and 21,315 without AHF.
- Using an XGBoost model, we achieved an AUROC of 0.68 and an AUPRC of 0.54, with a recall of 0.80 and precision of 0.45.
- Key predictors of AHF included ORS axis, RR interval, P wave axis, and T wave axis, reflecting underlying cardiac stress and electrical disturbances commonly seen in AHF

- · ECG data combined with machine learning may assist in identifying acute heart failure (AHF) in chronic heart failure (CHF) patients.
- The model's moderate AUROC and AUPRC suggest it should be used
- alongside other diagnostic tools. High recall indicates its potential for
- identifying patients at risk of AHF. Further validation using external datasets is needed to confirm robustness and generalizability.

- · The model was trained on a single cohort (MIMIC-IV database), limiting generalizability
- External validation in diverse populations is necessary.
- The study used only ECG-derived features and demographic data, excluding other clinical information that may improve accuracy.
- Moderate AUROC (0.68) and low precision indicate this method should supplement, not replace, other diagnostic approaches in clinical





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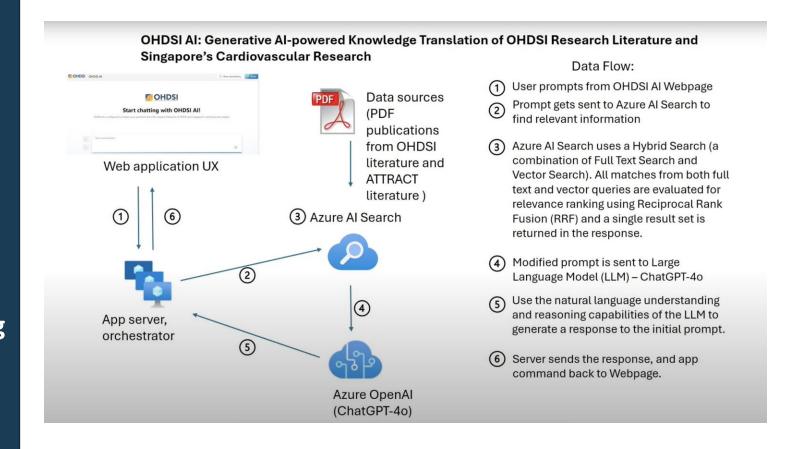




Friday

OHDSI AI: Generative AIpowered Knowledge
Translation of OHDSI Research
Literature and Singapore's
Cardiovascular Research

(Maisie Ng, Cindy Ho, Li Ting Ang, Hang Png, Shuen Lin Tan, Estella Ye, Ismail Mohd, Mengling Feng, Sebastian Maurer-Stroh, Johan G Eriksson, Mukkesh Kumar)



#JoinTheJourney





Where Are We Going?

Any other announcements of upcoming work, events, deadlines, etc?



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April 22: Estimation and Prediction



George Hripcsak

Vivian Beaumont Allen Professor of Biomedical Informatics, Columbia University



Marc Suchard

Professor of Biostatistics, Biomathematics, & Human Genetics, UCLA



Ross Williams

Assistant Professor, Erasmus University Medical Centre



Egill Fridgeirsson

Scientific Researcher/Postdoc, Erasmus University Medical Centre



Jenna Reps

Associate Director, Observational Health Data Analytics, Johnson & Johnson



The weekly OHDSI community call is held every Tuesday at 11 am ET.

Everybody is invited!

Links are sent out weekly and available at: ohdsi.org/community-calls-2025