

OHDSI Year In Review 2024



When poll is active respond at **PollEv.com/patrickryan800**



What was your favorite OHDSI highlight in 2024?

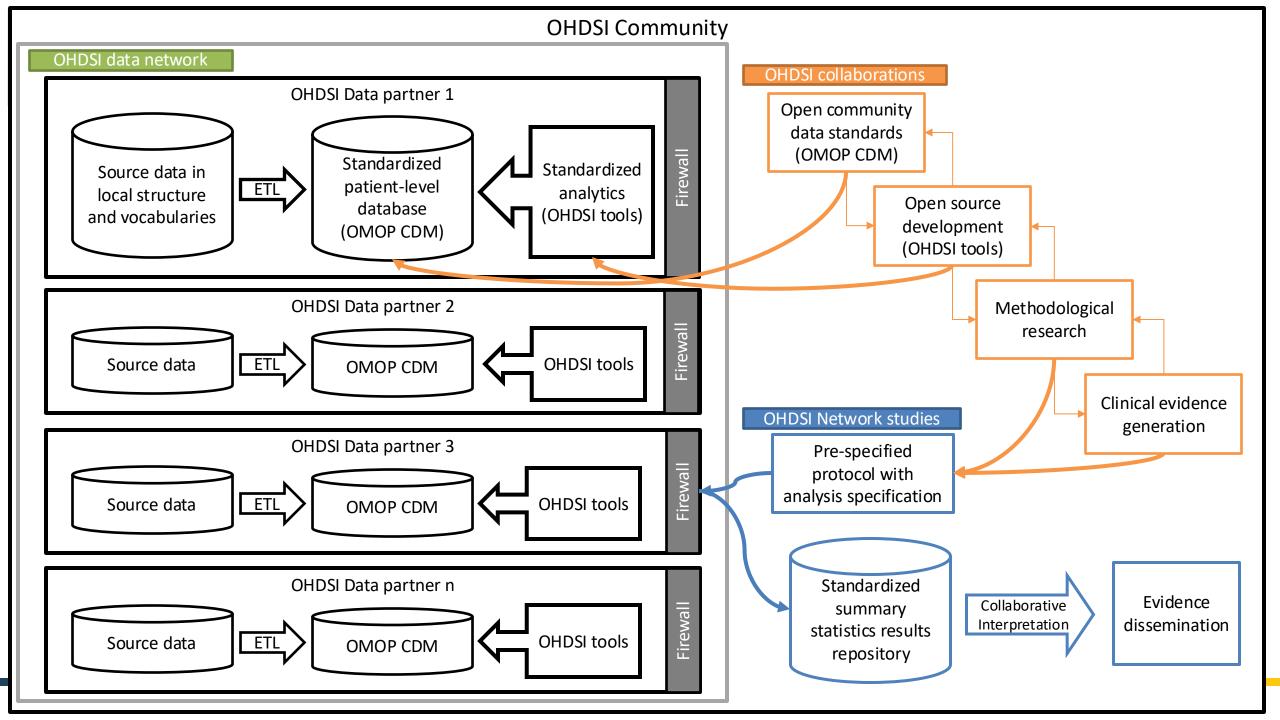
Nobody has responded yet.

Hang tight! Responses are coming in.



OHDSI's mission

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



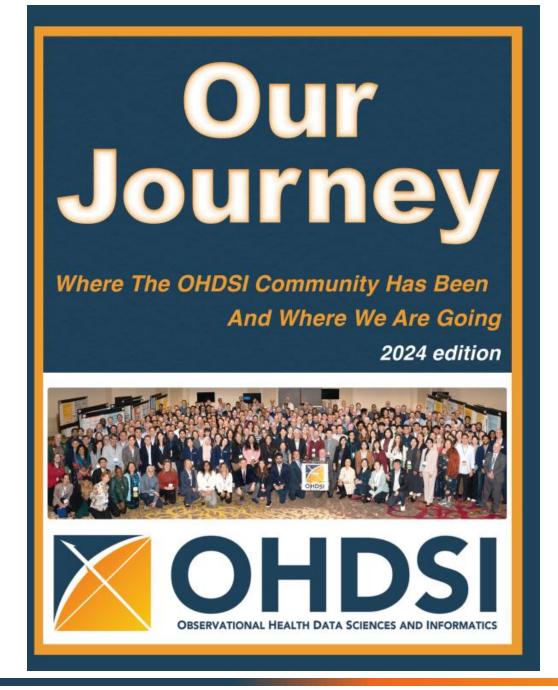


OHDSI collaborators



Join the Journey at https://ohdsi.org/





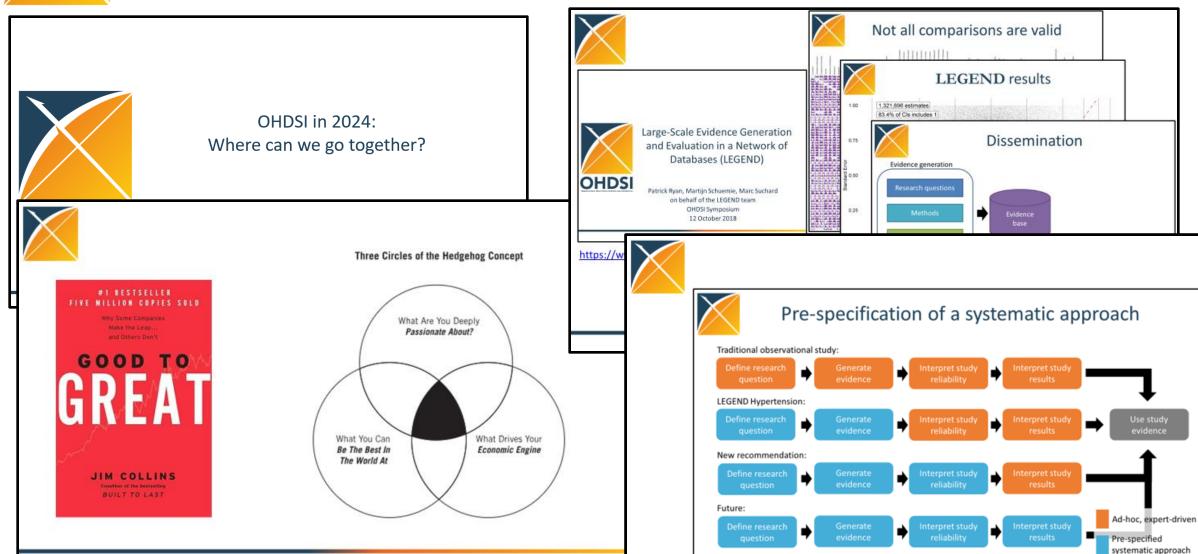




Kickoff of 2024...

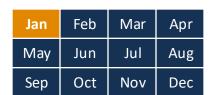
Jan	Feb	Mar	Apr
May	Jun	Jul	Aug
Sep	Oct	Nov	Dec

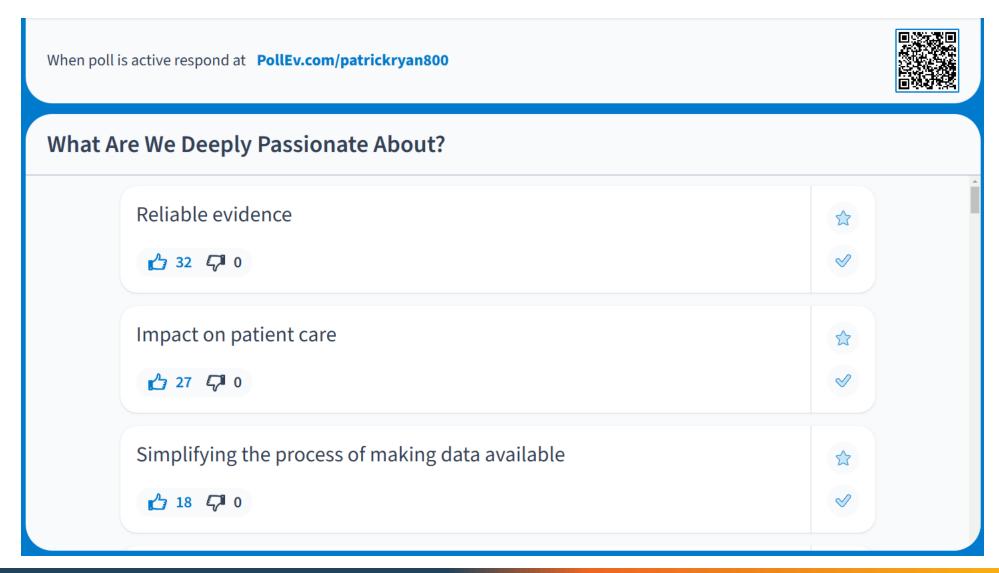
OHDSI Symposium 2022





What we said at the start of 2024...







What we said at the start of 2024...

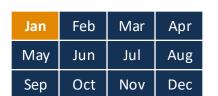
JanFebMarAprMayJunJulAugSepOctNovDec

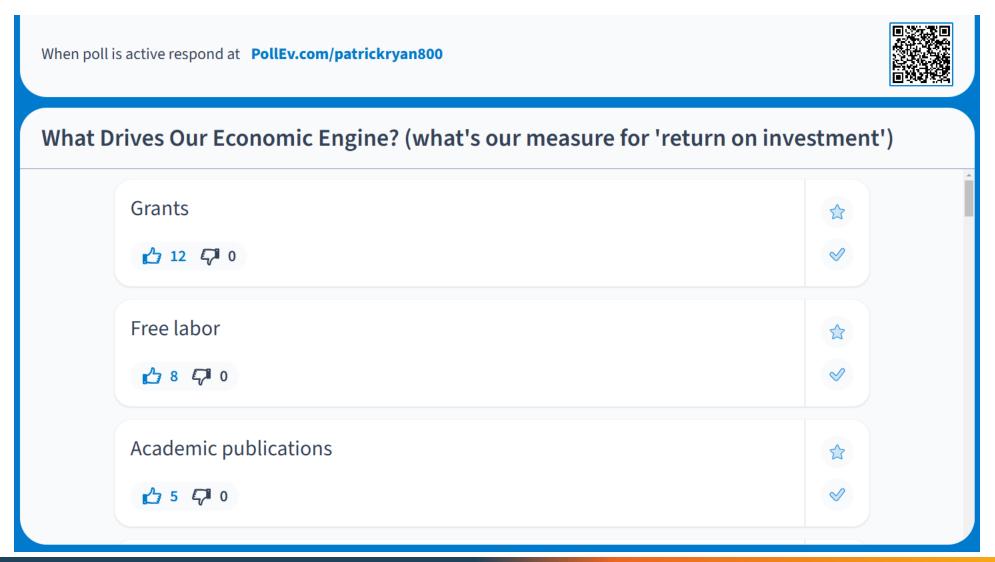
When poll is active respond at **PollEv.com/patrickryan800** What Can We Be the Best at the World At? Large scale evidence ☆ 30 🖓 0 Global network studies **△** 21 **√** 0 Generating reliable evidence at scale \$ 8 🖓 0 developing and validating methods in the use of Real World Data to generate evidence

6 50



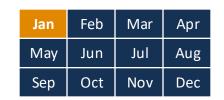
What we said at the start of 2024...







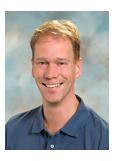
January accomplishments: Open-source tool releases





V1.9

OhdsiShinyModules v2.1.0 PhenotypeLibrary v3.32 PheValuator v2.2.11 Strategus v0.2.0













January publications

Jan	Feb	Mar	Apr
May	Jun	Jul	Aug
Sep	Oct	Nov	Dec

Journal of the American Medical Informatics Association, 2024, 31(3), 583–590 https://doi.org/10.1093/jamia/ocad247 Advance access publication 4 January 2024 Research and Applications





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Data Clinical Concept Encoding Processes. Stud Health Technol Inform. 2024;310:68-73. doi: 10.3233/shti230929. PubMed PMID: 38269767.

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Research and Applications

OHDSI Standardized Vocabularies—a large-scale centralized reference ontology for international data harmonization

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Abstract

Importance: The Observational Health Data Sciences and Informatics (OHDSI) is the largest distributed data network in the world encompassing more than 331 data sources with 2.1 billion patient records across 34 countries. It enables large-scale observational research through standardizing the data into a common data model (CDM) (Observational Medical Outcomes Partnership [OMOP] CDM) and requires a comprehensive, efficient, and reliable ontology system to support data harmonization.

Materials and methods: We created the OHDSI Standardized Vocabularies—a common reference ontology mandatory to all data sites in the network. It comprises imported and *de novo*-generated ontologies containing concepts and relationships between them, and the praxis of converting the source data to the OMOP CDM based on these. It enables harmonization through assigned domains according to clinical categories, comprehensive coverage of entities within each domain, support for commonly used international coding schemes, and standardization of semantically equivalent concepts.

Results: The OHDSI Standardized Vocabularies comprise over 10 million concepts from 136 vocabularies. They are used by hundreds of groups and several large data networks. More than 8600 users have performed 50 000 downloads of the system. This open-source resource has proven to address an impediment of large-scale observational research—the dependence on the context of source data representation. With that, it has enabled efficient phenotyping, covariate construction, patient-level prediction, population-level estimation, and standard reporting.

Discussion and conclusion: OHDSI has made available a comprehensive, open vocabulary system that is unmatched in its ability to support global observational research. We encourage researchers to exploit it and contribute their use cases to this dynamic resource.

Key words: OHDSI; controlled vocabulary; common data model; observational data.



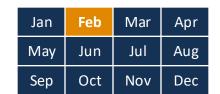
February activities: Workgroup OKRs

JanFebMarAprMayJunJulAugSepOctNovDec





February activities: Phenotype Phebruary



Phenotype Phebruary

- 4 condition phenotypes discussed
- 93 clinical studies identified and reviewed
- 1 Atlas and CohortDiagnostics demo
- 30 Cohort definitions built and publicly shared
- 3 shiny apps with full cohort diagnostics on results.ohdsi.org
- 8784 Incidence rate estimates
- 40 collaborators interacted in the posts, conducted literature review, built cohorts, or attended calls
- 1 AMIA submission accepted for oral presentation

By The Numbers

2024 Phenotype Phebruary team





February accomplishment: OHDSI Standardized Vocabularies release sep

May Aug Jun

Mar

Jan

Feb

Oct Dec

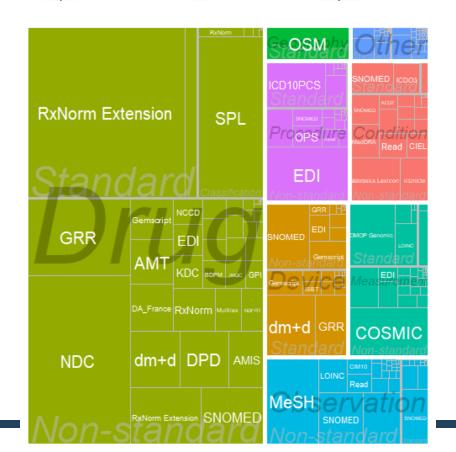






Ostropolets







The team behind us





















Why you should download this vocabulary release

· More concepts:

- Refresh of SNOMED, MedDRA, ICD10PCS, ICD10CM, CVX, RxNorm and more

· Better hierarchies:

- Improved LOINC SNOMED hierarchy
- de-novo constructed MedDRA SNOMED hierarchy

· More good mappings:

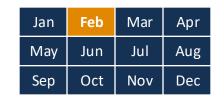
- ICD family refresh
- community contributions
- bug fixing

· What you specifically asked for:

- We closed 41 GitHub issues and addressed many forum posts



February accomplishments: Open-source tool releases





V1.11

OhdsiShinyModules v2.1.2 FeatureExtraction v3.4 DataQualityDashboard v2.6.0











February publications

Jan	Feb	Mar	Apr
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Sep	Oct	Nov	Dec

650. Park WY, Jeon K, Schmidt TS, Kondylakis H, Alkasab T, Dewey BE, You SC, Nagy P. Development of Medical Imaging Data Standardization for Imaging-Based Obsevational Research: OMOP Common Data Model Extension. J Imaging Inform Med. 2024;37(2):899-908. Epub 20240205. doi: 10.1007/s10278-024-00982-6. PubMed PMII 38315345; PubMed Central PMCID: PMC11031512.

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658. Naderalvojoud B, Curtin CM, Yanover C, El-Hay T, Choi B, Park RW, Tabuenca JG, Reeve MP, Falconer T, Humphreys K, Asch SM, Hernandez-Boussard T. To-wards global model generalizability: independent cross-site feature evaluation for patient-level risk prediction models using the OHDSI network. J Am Med Inform Assoc. 2024;31(5):1051-61. doi: 10.1093/jamia/ocae028. PubMed PMID: 38412331; PubMed Central PMCID: PMC11031239.

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Journal of Imaging Informatics in Medicine (2024) 37:899–908 https://doi.org/10.1007/s10278-024-00982-6



Development of Medical Imaging Data Standardization for Imaging-Based Observational Research: OMOP Common Data Model Extension

Woo Yeon Park¹ · Kyulee Jeon^{2,3} · Teri Sippel Schmidt¹ · Haridimos Kondylakis⁴ · Tarik Alkasab⁵ · Blake E. Dewey⁶ · Seng Chan You^{2,3} · Paul Nagy¹

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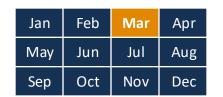
Abstract

The rapid growth of artificial intelligence (AI) and deep learning techniques require access to large inter-institutional cohorts of data to enable the development of robust models, e.g., targeting the identification of disease biomarkers and quantifying disease progression and treatment efficacy. The Observational Medical Outcomes Partnership Common Data Model (OMOP CDM) has been designed to accommodate a harmonized representation of observational healthcare data. This study proposes the Medical Imaging CDM (MI-CDM) extension, adding two new tables and two vocabularies to the OMOP CDM to address the structural and semantic requirements to support imaging research. The tables provide the capabilities of linking DICOM data sources as well as tracking the provenance of imaging features derived from those images. The implementation of the extension enables phenotype definitions using imaging features and expanding standardized computable imaging biomarkers. This proposal offers a comprehensive and unified approach for conducting imaging research and outcome studies utilizing imaging features.

Keywords Data collection [MeSH] · Data standardization · Observational research · Data integration · Multimodal data analysis



March accomplishments: Open-source tool releases





Characterization v0.1.4 SqlRender v1.17







March publications

Jan	Feb	Mar	Apr
May	Jun	Jul	Aug
Sep	Oct	Nov	Dec

682. Marcou Q, Berti-Equille L, Novelli N. Creating a computer assisted ICD coding system: Performance metric choice and use of the ICD hierarchy. J Biomed Inform. 2024;152:104617. Epub 2024;0301. doi: 10.1016/j.ibi.2024.104617. PubMed PMID: 38432534.

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Similar Risk of Kidney Failure among Patients with Blinding Diseases Who Receive Ranibizumab, Aflibercept, and Bevacizumab

An Observational Health Data Sciences and Informatics Network Study

Cindy X. Cai, MD, MS, ¹ Akihiko Nishimura, PhD, ² Mary G. Bowring, MPH, ³ Erik Westlund, PhD, ² Diep Tran, MSc, ¹ Jia H. Ng, MD, MSCE, ⁴ Paul Nagy, PhD, ⁵ Michael Cook, BS, ⁶ Jody-Ann McLeggon, MPH, ⁷ Scott L. DuVall, PhD, ^{8,9} Michael E. Matheny, MD, MPH, ^{10,11} Asieh Golozar, PhD, ^{12,13} Anna Ostropolets, MD, PhD, ¹² Evan Minty, MD, MSc, ¹⁴ Priya Desai, MS, ¹⁵ Fan Bu, PhD, ¹⁶ Brian Toy, MD, ¹⁷ Michelle Hribar, PhD, ^{18,19} Thomas Falconer, MS, ⁷ Linying Zhang, PhD, ⁷ Laurence Laurence-Archer, MSc, ^{12,13} Michael V. Boland, MD, PhD, ²⁰ Kerry Goetz, MS, ¹⁸ Nathan Hall, MS, ²¹ Azza Shoaibi, PhD, ²¹ Jenna Reps, PhD, ²¹ Anthony G. Sena, BA, ^{21,22} Clair Blacketer, MPH, ²¹ Joel Swerdel, PhD, MPH, ²¹ Kenar D. Jhaveri, MD, ²³ Edward Lee, BS, ¹⁷ Zachary Gilbert, BS, ¹⁷ Scott L. Zeger, PhD, ² Deidra C. Crews, MD, ScM, ²⁴ Marc A. Suchard, MD, PhD, ^{8,16} George Hripcsak, MD, MS, ⁷ Patrick B. Ryan, PhD²¹

Purpose: To characterize the incidence of kidney failure associated with intravitreal anti-VEGF exposure; and compare the risk of kidney failure in patients treated with ranibizumab, aflibercept, or bevacizumab.

Design: Retrospective cohort study across 12 databases in the Observational Health Data Sciences and Informatics (OHDSI) network.

Subjects: Subjects aged ≥ 18 years with ≥ 3 monthly intravitreal anti-VEGF medications for a blinding disease (diabetic retinopathy, diabetic macular edema, exudative age-related macular degeneration, or retinal vein occlusion).

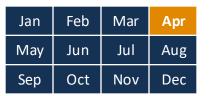
Methods: The standardized incidence proportions and rates of kidney failure while on treatment with anti-VEGF were calculated. For each comparison (e.g., aflibercept versus ranibizumab), patients from each group were matched 1:1 using propensity scores. Cox proportional hazards models were used to estimate the risk of kidney failure while on treatment. A random effects meta-analysis was performed to combine each database's hazard ratio (HR) estimate into a single network-wide estimate.

Main Outcome Measures: Incidence of kidney failure while on anti-VEGF treatment, and time from cohort entry to kidney failure.

Results: Of the 6.1 million patients with blinding diseases, 37 189 who received ranibizumab, 39 447 aflibercept, and 163 611 bevacizumab were included; the total treatment exposure time was 161 724 person-years. The average



April activities: **April Olympians**





Focused on identifying and collecting ratified CDM conventions



Writers

Tasked with documenting these conventions for the resource library



Responsible for constructing the actual library

Thank You, Organizers, Leads & Contributors!





Melanie Philofsky



Erica Voss



Evanette Burrows



Jiawei Qian

Meghan Pettine

Loyd Shipman

Adam Bouras

Dave Jarvis



Katy Sadowski



Solmaz Eradat **Brooke Lawler** Ben Martin Andrew Kanter

Maxim Moinat

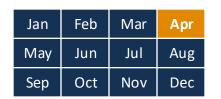
Alvaro Alvarez Agnes Wojciechowski Masha Khitrun

THEMIS Conventions

General Conventions
Person Exclusion
Gender Identity
One-to-Many Mappings
Providers with Multiple Addresses
Records with values
Patient reported data
Events outside of the Observation Period
Observation Periods for EHR data
CDM Tables ▼
Tag Browser ▼



April accomplishments: Open-source tool releases





V1.12

Characterization v0.2

CirceR v1.3.3

In CRAN!

Eunomia v2.0

In CRAN!

FeatureExtraction v3.5

OhdsiShinyModules 2.1.3

PatientLevelPrediction v6.3.7















April publications

Jan	Feb	Mar	Apr
May	Jun	Jul	Aug
Sep	Oct	Nov	Dec

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THE LANCET Respiratory Medicine

Effectiveness of COVID-19 vaccines to prevent long COVID: data from Norway

Nhung TH Trinh ^a Annika M Jödicke ^b · Martí Català ^b · Núria Mercadé-Besora ^b · Saeed Hayati ^a · Angela Lupattelli ^a Daniel Prieto-Alhambra ^{b,c,d} · Hedvig ME Nordeng ^{a,e} Show less

Affiliations & Notes ∧ Article Info ∨ Linked Articles (1) ∨

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- Pharmaco- and Device Epidemiology Group, Health Data Sciences, Botnar Research Centre, NDORMS, University of Oxford, Oxford, UK
- c Oxford NIHR Biomedical Research Centre, University of Oxford, Oxford, UK
- Department of Medical Informatics, Erasmus Medical Center, Rotterdam, Netherlands
- e Department of Child Health and Development, Norwegian Institute of Public Health, Oslo, Norway

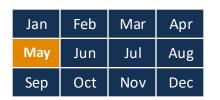


Show Outline 💸

Our recent study using data from more than 20 million participants has shown that COVID-19 vaccines consistently prevent long COVID symptoms in adults, with meta-analytic calibrated subdistribution hazard ratio (sHRs) of 0·54 (95% CI 0·44–0·67) in CPRD GOLD, 0·48 (0·34–0·68) in CPRD AURUM, 0·71 (0·55–0·91) in SIDIAP, and 0·59 (0·40–0·87) in CORIVA. In addition, when considering post-COVID thromboembolic and cardiovascular complications as outcomes of interest, recently published data have shown that vaccination with any COVID-19 first vaccine dose (ChAdOx1, BNT162b2, and mRNA-1273) is associated with reduced risk of post-acute heart failure (0·45 [0·38–0·53] 0–30 days after SARS-CoV-2 infection; 0·61 [0·51–0·73] 91–180 days after SARS-CoV-2 infection), venous thromboembolism (sHR 0·22 [95% CI 0·17–0·29] 0–30 days after SARS-CoV-2 infection; 0·53 [0·40–0·70] 91–180 days after SARS-CoV-2 infection), and arterial thrombosis (0·53 [0·44–0·63] 0–30 days after SARS-CoV-2 infection; 0·72 [0·58–0·88] 91–180 days after SARS-CoV-2 infection). With the use of the Observational Medical Outcomes Partnership (OMOP) common data model (CDM), all our analyses were conducted across three European countries (Estonia, Spain, and the UK) without transferring patient data, using federated analyses similar to those used by the European Medicines Agency-funded Data Analysis and Real World Interrogation Network.



May accomplishments: Open-source tool releases





V1.13

CapR v2.0.8

CohortGenerator v0.09

CohortMethod v5.3

ResultsModelManager v0.5.7

SelfControlledCaseSeries 5.2.0

SqlRender v1.18











May publications

Jan	Feb	Mar	Apr
May	Jun	Jul	Aug
Sep	Oct	Nov	Dec

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Open access Original research

BMJ Health & Care Informatics

Taipei Medical University Clinical Research Database: a collaborative hospital EHR database aligned with international common data standards

Phung-Anh Nguyen ¹ ,^{1,2,3} Min-Huei Hsu,^{4,5} Tzu-Hao Chang,^{3,6,7} Hsuan-Chia Yang ³ ,^{3,6,7,8} Chih-Wei Huang,^{6,7} Chia-Te Liao,^{9,10,11} Christine Y. Lu,^{12,13,14} Jason C. Hsu^{1,2,3,15}

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Additional supplemental material is published online only. To view, please visit the journal online (https://doi.org/10.1136/ bmjhci-2023-100890).

Received 05 September 2023 Accepted 29 April 2024

ABSTRACT

comprehensive overview of the development and features of the Taipei Medical University Clinical Research Database (TMUCRD), a repository of real-world data (RWD) derived from electronic health records (EHRs) and other sources.

Methods TMUCRD was developed by integrating EHRs from three affiliated hospitals, including Taipei Medical University Hospital, Wan-Fang Hospital and Shuang-Ho Hospital. The data cover over 15 years and include diverse patient care information. The database was converted to the Observational Medical Outcomes Partnership Common Data Model (OMOP CDM) for standardisation.

Objective The objective of this paper is to provide a

Results TMUCRD comprises 89 tables (eg, 29 tables for each hospital and 2 linked tables), including demographics, diagnoses, medications, procedures and measurements, among others. It encompasses data from more than 4.15 million patients with various medical records, spanning from the year 2004 to 2021. The dataset offers insights into disease prevalence, medication usage, laboratory tests and patient characteristics.

Discussion TMUCRD stands out due to its unique advantages, including diverse data types, comprehensive patient information, linked mortality and cancer registry.

WHAT IS ALREADY KNOWN ON THIS TOPIC

Existing knowledge encompasses the increasing use of digital solutions in healthcare, the importance of real-world data (RWD) for generating real-world evidence, and the limitations of traditional clinical trials with limited participant diversity.

WHAT THIS STUDY ADDS

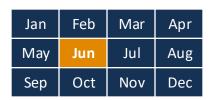
This study presents the development and features of the Taipei Medical University Clinical Research Database (TMUCRD), highlighting its extensive collection of RWD spanning multiple hospitals over a decade. TMUCRD provides valuable insights into patient medical records, underscoring its role as a robust platform for collaborative research and evidence-driven healthcare improvements.

HOW THIS STUDY MIGHT AFFECT RESEARCH, PRACTICE OR POLICY

This study's establishment of the TMUCRD will significantly impact research by providing a rich source of RWD for diverse healthcare investigations. It has the potential to enhance evidence-based medical



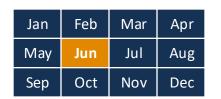
June activities: OHDSI Europe Symposium







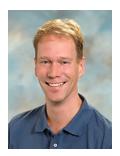
June accomplishments: Open-source tool releases





V1.14

KEEPER 0.2.0 ResultsModelManager v0.5.8 Strategus 0.3.0











June publications

Jan	Feb	Mar	Apr
May	Jun	Jul	Aug
Sep	Oct	Nov	Dec

693. Barclay NL, Burkard T, Burn E, Delmestri A, Miquel Dominguez A, Golozar A, Guarner-Argente C, Avilés-Jurado FX, Man WY, Roselló Serrano À, Rose Tietzova I, Prieto Alhambra D, Newby D. The Impact of the COVID-19 Pandemic on Incidence and Short-Term Survival for Common Solid Tumours in the Ur Cohort Analysis. Clin Epidemiol. 2024;16:417-29. Epub 20240611. doi: 10.2147/clep.S463160. PubMed PMID: 38882578; PubMed Central PMCID: PMC111 694. Sibert NT, Solf J, La Ferla S, Quaranta M, Kremer A, Kowalski C. Transforming a Large-Scale Prostate Cancer Outcomes Dataset to the OMOP Comm Model-Experiences from a Scientific Data Holder's Perspective. Cancers (Basel). 2024;16(11). Epub 20240530. doi: 10.3390/cancers16112069. PubMed PM PubMed Central PMCID: PMC11171220.

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Journal of the American Medical Informatics Association, 2024, 31(7), 1514–1521 https://doi.org/10.1093/jamia/ocae109 Advance access publication 20 May 2024

Research and Applications





Research and Applications

Comparing penalization methods for linear models on large observational health data

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Abstract

Objective: This study evaluates regularization variants in logistic regression (L1, L2, ElasticNet, Adaptive L1, Adaptive ElasticNet, Broken adaptive ridge [BAR], and Iterative hard thresholding [IHT]) for discrimination and calibration performance, focusing on both internal and external validation.

Materials and Methods: We use data from 5 US claims and electronic health record databases and develop models for various outcomes in a major depressive disorder patient population. We externally validate all models in the other databases. We use a train-test split of 75%/25% and evaluate performance with discrimination and calibration. Statistical analysis for difference in performance uses Friedman's test and critical difference diagrams.

Results: Of the 840 models we develop, L1 and ElasticNet emerge as superior in both internal and external discrimination, with a notable AUC difference. BAR and IHT show the best internal calibration, without a clear external calibration leader. ElasticNet typically has larger model sizes than L1. Methods like IHT and BAR, while slightly less discriminative, significantly reduce model complexity.

Conclusion: L1 and ElasticNet offer the best discriminative performance in logistic regression for healthcare predictions, maintaining robustness across validations. For simpler, more interpretable models, L0-based methods (IHT and BAR) are advantageous, providing greater parsimony and calibration with fewer features. This study aids in selecting suitable regularization techniques for healthcare prediction models, balancing performance, complexity, and interpretability.

Key words: logistic regression; electronic health records; regularization; discrimination; calibration.

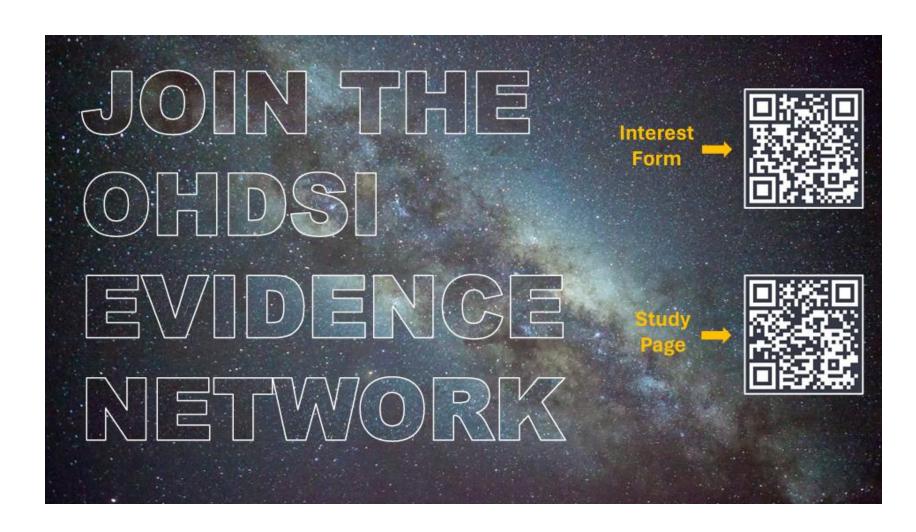


July activities: OHDSI Evidence Network

Jan	Feb	Mar	Apr
May	Jun	Jul	Aug
Sep	Oct	Nov	Dec

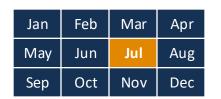
OHDSI Evidence Network progress to date:

- 37 data sources across 18 data partner organizations
- >50 data partners in the onboarding process





July activities: OHDSI Evidence Network in Action



Research

JAMA Ophthalmology | Original Investigation

Risk of Nonarteritic Anterior Ischemic Optic Neuropathy in Patients Prescribed Semaglutide

Jimena Tatiana Hathaway, MD, MPH; Madhura P. Shah, BS; David B. Hathaway, MD; Seyedeh Maryam Zekavat, MD, PhD; Drenushe Krasniqi, BA; John W. Gittinger Jr, MD; Dean Cestari, MD; Robert Mallery, MD; Bardia Abbasi, MD; Marc Bouffard, MD; Bart K. Chwalisz, MD; Tais Estrela, MD; Joseph F. Rizzo III, MD

conclusions and Relevance This study's findings suggest an association between semaglutide and NAION. As this was an observational study, future study is required to assess causality.

JAMA Ophthalmol. doi:10.1001/jamaophthalmol.2024.2296 Published online July 3, 2024.



Nov. 19: Evidence Network in Action The Semaglutide Study



Cindy Cai
Assistant Professor of Ophthalmology
Wilmer Eye Institute at Johns Hopkins Hospital

Topic: Semaglutide and NAION: An OHDSI Network Study



Paul Nagy
Program Director for G

Program Director for Graduate Training in Biomedical Informatics and Data Science Johns Hopkins University

Topic: Evidence Network



Linying Zhang
Assistant Professor of Biostatistics
Washington University

Topic: Methods



Anthony Sena

Director, Observational Health Data Analytics Johnson & Johnson

Topic: Strategus



Ben Martin
Postdoctoral Fellow
Johns Hopkins University

Topic: Using the Results Schema



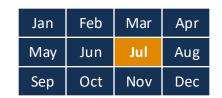
Erik Westlund

Assistant Scientist Johns Hopkins University

Topic: Using the Results Schema



July accomplishments: Open-source tool releases





V1.15

CohortGenerator v0.10

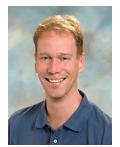
CohortIncidence v4.0.0

DataQualityDashboard v2.6.1

DeepPatientLevelPrediction v2.1.0

FeatureExtraction v3.6

OhdsiShinyModules v2.1.5

















July publications

Jan	Feb	Mar	Apr
May	Jun	Jul	Aug
Sep	Oct	Nov	Dec

701. Shang Y, Tian Y, Lyu K, Zhou T, Zhang P, Chen J, Li J. Electronic Health Record-Oriented Knowledge Graph System for Collaborative Clinical Decision Support Using Multicenter Fragmented Medical Data: Design and Application Study. J Med Internet Res. 2024;26:e54263. Epub 20240705. doi: 10.2196/54263. PubMed PMID: 38968598; PubMed Central PMCID: PMC11259764.

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John et al. BMC Medicine (2024) 22:308 https://doi.org/10.1186/s12916-024-03530-9

BMC Medicine

RESEARCH ARTICLE

Open Access

Development and validation of a patientlevel model to predict dementia across a network of observational databases



Luis H. John^{1*}, Egill A. Fridgeirsson¹, Jan A. Kors¹, Jenna M. Reps², Ross D. Williams¹, Patrick B. Ryan² and Peter R. Rijnbeek¹

Abstract

Background A prediction model can be a useful tool to quantify the risk of a patient developing dementia in the next years and take risk-factor-targeted intervention. Numerous dementia prediction models have been developed, but few have been externally validated, likely limiting their clinical uptake. In our previous work, we had limited success in externally validating some of these existing models due to inadequate reporting. As a result, we are compelled to develop and externally validate novel models to predict dementia in the general population across a network of observational databases. We assess regularization methods to obtain parsimonious models that are of lower complexity and easier to implement.

Methods Logistic regression models were developed across a network of five observational databases with electronic health records (EHRs) and claims data to predict 5-year dementia risk in persons aged 55–84. The regularization methods L1 and Broken Adaptive Ridge (BAR) as well as three candidate predictor sets to optimize prediction performance were assessed. The predictor sets include a baseline set using only age and sex, a full set including all available candidate predictors, and a phenotype set which includes a limited number of clinically relevant predictors.

Results BAR can be used for variable selection, outperforming L1 when a parsimonious model is desired. Adding candidate predictors for disease diagnosis and drug exposure generally improves the performance of baseline models using only age and sex. While a model trained on German EHR data saw an increase in AUROC from 0.74 to 0.83 with additional predictors, a model trained on US EHR data showed only minimal improvement from 0.79 to 0.81 AUROC. Nevertheless, the latter model developed using BAR regularization on the clinically relevant predictor set



August accomplishments: OHDSI Standardized Vocabularies release

• 99,192,928 ancestral relationships

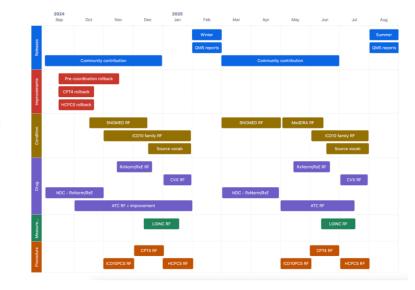
5,009,796 concept synonyms

Mar Feb Jan Apr May Jul Jun Aug Sep Oct Nov Dec

OHDSI Vocabularies By The Numbers

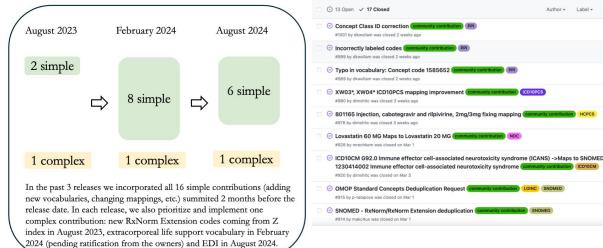
86,668,674 concept relationships

- 11,561,982 concepts
 - · 3,720,296 standard concepts
 - · 883,766 classification concepts
- 143 vocabularies
- 43 domains
- 1 Shared Resource to Enable Data Standards



Community contributions

The formal pipeline we launched last year has enabled the community to incorporate their vocabularies and change the existing vocabulary content more easily, seamlessly as faster.



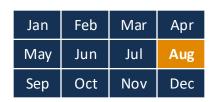
The roadmap for 2024/2025 was built using the insights from the landscape assessment to prioritize needs of the majority of the community and includes refreshes of the commonly used standard vocabularies such as SNOMED, CPT4 and LOINC, improvements in the mappings of the commonly used source terminologies and continuation of the work on a new approach to building drug classification to ATC (https://github.com/OHDSI/Voc

abulary-v5.0/wiki/Vocab.-ATC).

Author + Label + Pr



August accomplishments: Open-source tool releases





Characterization v2.0
OhdsiShinyModules v3.0.0
PatientLevelPrediction v6.3.9
ResultsModelManager v0.5.10
SelfControlledCaseSeries v5.3.0
ShinyAppBuilder v3.0.0











August publications

Jan	Feb	Mar	Apr
May	Jun	Jul	Aug
Sep	Oct	Nov	Dec

708. Amadi D, Kivuwa-Muyingo S, Bhattacharjee T, Taylor A, Kiragga A, Ochola M, Kanjala C, Gregory A, Tomlin K, Todd J, Greenfield J. Making Metadata Machine-Readable as the First Step to Providing Findable, Accessible, Interoperable, and Reusable Population Health Data: Framework Development and Implementation Study. Online J Public Health Inform. 2024;16:e56237. Epub 20240801. doi: 10.2196/56237. PubMed PMID: 39088253; PubMed Central PMCID: PMC11327634.

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718. Popoff B, Delange B, Kallout J, Cuggia M, Clavier T, Bouzille G. How to Accurately Detect Renal Replacement Therapy Weaning in Intensive Care: Data Quality and Standardization Considerations for the OMOP Common Data Model. Stud Health Technol Inform. 2024;316:1584-8. doi: 10.3233/shti240724. PubMed PMID: 39176511.

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727. Santos RL, Cruz-Correia R. Improving Healthcare Quality with a LHS: From Patient-Generated Health Data to Evidence-Based Recommendations. Stud Health Technol Inform. 2024;316:230-4. doi: 10.3233/shti240367. PubMed PMID: 39176716.

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Article

Early Clinical Experience of Finerenone in People with Chronic Kidney Disease and Type 2 Diabetes in Japan—A Multi-Cohort Study from the FOUNTAIN (FinerenOne mUltidatabase NeTwork for Evidence generAtIoN) Platform

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Abstract: Background: In the phase 3 clinical trials FIGARO-DKD and FIDELIO-DKD, finerenone reduced the risk of cardiovascular and kidney events among people with chronic kidney disease (CKD) and type 2 diabetes (T2D). Evidence regarding finerenone use in real-world settings is limited. Methods: A retrospective cohort study (NCT06278207) using two Japanese nationwide hospital-based databases provided by Medical Data Vision (MDV) and Real World Data Co., Ltd. (RWD Co., Kyoto Japan), converted to the OMOP common data model, was conducted. Persons with CKD and T2D initiating finerenone from 1 July 2021, to 30 August 2023, were included. Baseline characteristics were described. The occurrence of hyperkalemia after finerenone initiation was assessed. Results: 1029 new users of finerenone were included (967 from MDV and 62 from RWD Co.). Mean age was 69.5 and 72.4 years with 27.3% and 27.4% being female in the MDV and RWD Co.



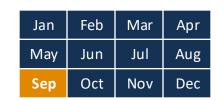
Citation: Sato, A.; Rodriguez-Molina, D.; Yoshikawa-Ryan, K.; Yamashita, S.; Okami, S.; Liu, F.; Farjat, A.; Oberprieler, N.G.; Kovesdy, C.P.; Kanasaki, K.; et al. Early Clinical Experience of Finerenone in People with Chronic Kidney Disease and Type 2 Diabetes in Japan—A Multi-Cohort Study from the FOUNTAIN (FinerenOne mUltidatabase NeTwork for Evidence generAtloN) Platform. J.



September accomplishments: Open-source tool releases

In CRAN!

In CRAN!





CohortGenerator v0.11.2

CohortMethod v5.4

EmpiricalCalibration v3.1.3

FeatureExtraction v3.7

PhenotypeLibrary v3.33

ResultsModelManager v0.5.11

In CRAN!







ShinyAppBuilder v3.1.0



September publications

Jan	Feb	Mar	Apr
May	Jun	Jul	Aug
Sep	Oct	Nov	Dec

732. Khera R, Aminorroaya A, Dhingra LS, Thangaraj PM, Pedroso Camargos A, Bu F, Ding X, Nishimura A, Anand TV, Arshad F, Blacketer C, Chai Y, Chattopadhyay S, Cook M, Dorr DA, Duarte-Salles T, DuVall SL, Falconer T, French TE, Hanchrow EE, Kaur G, Lau WCY, Li J, Li K, Liu Y, Lu Y, Man KKC, Matheny ME, Mathioudakis N, McLeggon JA, McLemore MF, Minty E, Morales DR, Nagy P, Ostropolets A, Pistillo A, Phan TP, Pratt N, Reyes C, Richter L, Ross JS, Ruan E, Seager SL, Simon KR, Viernes B, Yang J, Yin C, You SC, Zhou JJ, Ryan PB, Schuemie MJ, Krumholz HM, Hriposak G, Suchard MA. Comparative Effectiveness of Second-Line Antihyperglycemic Agents for Cardiovascular Outcomes: A Multinational, Federated Analysis of LEGEND-T2DM. J Am Coll Cardiol. 2024;84(10):904-17. doi: 10.1016/j.jacc.2024.05.069. PubMed PMID: 39197980.

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tients with hypertension. Front Neurol. 2024;15:1410389. Epub 20240827. doi: 10.3389/ineur.2024.1410389. PubMed PMID: 39258156; PubMed Central PMCID: PMC1138457
735. Sato A, Rodriguez-Molina D, Yoshikawa-Ryan K, Yamashita S, Okami S, Liu F, Farjat A, Oberprieler NG, Kovesdy CP, Kanasaki K, Vizcaya D. Early Clinical Experience of Finerenone in People with Chronic Kidney Disease and Type 2 Diabetes in Japan-A Multi-Cohort Study from the FOUNTAIN (FinerenOne mUltidatabase NeTwork for

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AND DATA MINING. AI TRAINING. AND SIMILAR TECHNOLOGIES

Comparative Effectiveness of Second-Line Antihyperglycemic Agents for Cardiovascular Outcomes



VOL. 84, NO. 10, 2024

A Multinational, Federated Analysis of LEGEND-T2DM

Rohan Khera, MD, MS, a,b,c Arya Aminorroaya, MD, MPH, a Lovedeep Singh Dhingra, MBBS, a Phyllis M. Thangaraj, MD, PhD, a Aline Pedroso Camargos, PhD, a Fan Bu, PhD, Xiyu Ding, MS, Akihiko Nishimura, PhD, Tara V. Anand, BS, Faaizah Arshad, BS, Clair Blacketer, MPH, Yi Chai, PhD, Shounak Chattopadhyay, PhD, Michael Cook, BSc, David A. Dorr, MD, MS, Talita Duarte-Salles, PhD, Acounak Chattopadhyay, PhD, Michael Cook, BSc, David A. Dorr, MD, MS, Talita Duarte-Salles, PhD, Acounak Chattopadhyay, PhD, Michael Cook, BSc, David A. Dorr, MD, MS, Talita Duarte-Salles, PhD, Acounak Chattopadhyay, PhD, Michael E. French, RN, CPHQ, App Elizabeth E. Hanchrow, RN, MSN, App Guneet Kaur, MS, Wallis C.Y. Lau, BSc, PhD, Fist, Wallis Li, MS, Kelly Li, BS, Yuntian Liu, MPH, Ab, Yuan Lu, ScD, Kenneth K.C. Man, BSc, MPH, PhD, Fist, Wallis C.Y. Lau, BSc, PhD, MS, Wallis C.Y. Lau, BSc, PhD, Fist, Wallis C.Y. Lau, BSc, PhD, MS, Fist, Wallis C.Y. Lau, BSc, PhD, Fist, Wall, Wallis C.Y. Lau, BSc, PhD, Fist, Wallis C.Y. Lau, BSc, PhD, Fi



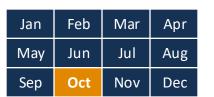
October activities: OHDSI India Symposium

Jan	Feb	Mar	Apr
May	Jun	Jul	Aug
Sep	Oct	Nov	Dec





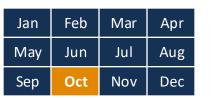
October activities: EHDEN Symposium

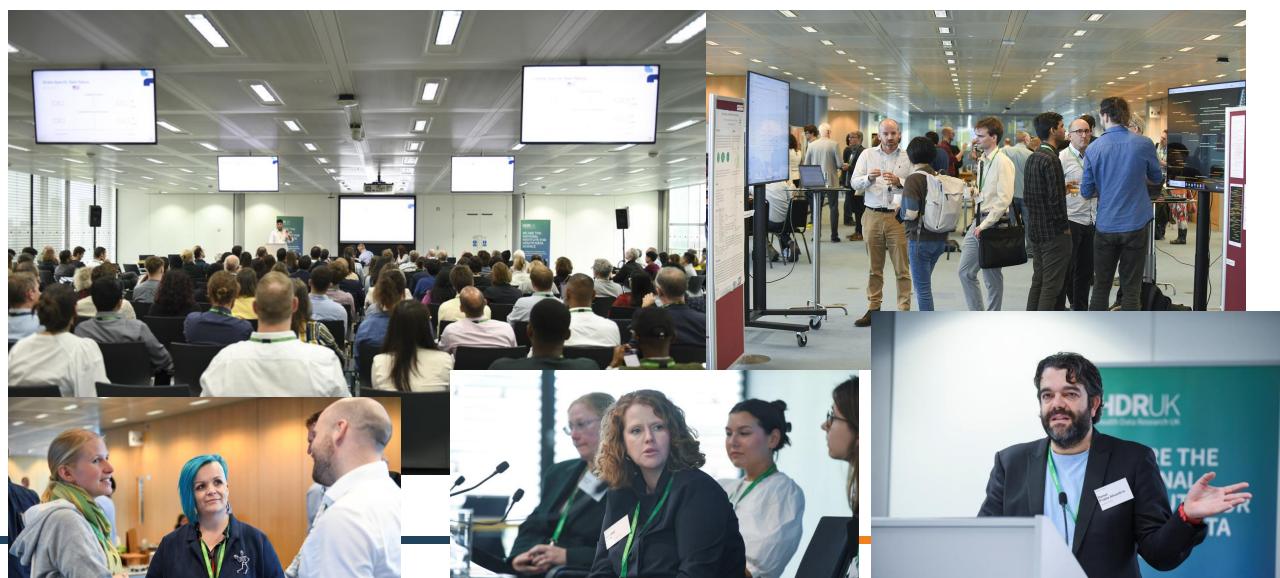






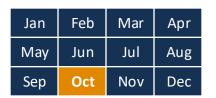
October activities: OHDSI UK Symposium







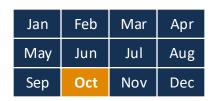
October activities: OHDSI Global Symposium







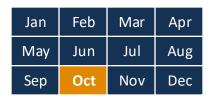
October activities: OHDSI Global Symposium: LEGEND-T2DM







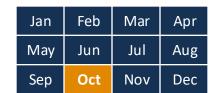
October activities: OHDSI Global Symposium: JACC







October activities: **OHDSI Global Symposium:** Collaborating on Evidence at Scale



LEGEND-T2DM Evidence Dissemination Summary

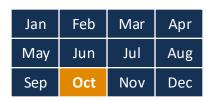
- · Target (class): Semaglutide (GLP-1 Receptor Agonists)

ata source	Persons exposed	Person-time (yr	s) Persons with outcome	IR (/1,000 PY
QVIA DA Germany	-		-	
QVIA LDP France		50.00	- 60	
QVIA Open Claims Merative CCAE	99,708 20,240	52,93 9,38		
Merative CCAE	20,240	9,30	00 14	
Merative MDCR	619	27		
optum Clinformatics	7,607	3,8		
optum EHR	6,717	2,09		
eterans Affairs	1,258	88		0.00
Compa	arator 📗 Target 📒 Be	efore 🗏 After 📗 M	DRR • Negative control	Calibrated estimate
IQVIA LDP France				
IQVIA Open Claims		ASDM = 0.03 MDRF ASDM = 0.06 MDRF	E E	0.66 (0.42 - 1.02) 0.57 (0.20 - 1.61)
Merative MDCD				
Merative MDCR		ASDM = 0.18 MDRF		
Optum Clinformatics	H	ASDM = 0.05 MDRF	12/23	0.82 (0.25 - 2.68)
Optum EHR Equip	ooise = 0.25	ASDM = 0.08 MDRF	R = 2.5 EASE = 0.09	1.73 (0.56 - 5.30)
Veterans Affairs				
o.o Prefer		0.5 1 1 4 ASDM MD	10 0.5 1 2 RR Hazard ratio	0.5 1 2 Hazard ratio
What have we learne	d from the OHDSI	Network? (Meta-ar	nalysis diagnostics and	estimate)
	MDRR	Negative control	◆ Estimate	Calibrated estimate
	RR = 15	EASE = 0.04	I ² = 0	0.67 (0.47 - 0.94)





October accomplishments: 2024 OHDSI Titans





2024 Titan Awards











Data Standards



2024 Titan Awards X







Linying Zhang



Methodological Research #JoinTheJourney





2024 Titan Awards 🔀

Martin Lavallee









Community Leadership

2024 Titan Awards 🔀







Clinical Applications



2024 Titan Awards





Community Support



2024 Titan Awards 🔀





Natthawut 'Max' Adulyanukosol



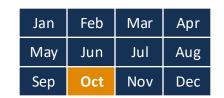


Open-Source Development #JoinTheJournet

Community Collaboration #JoinTheJourne



October accomplishments: Open-source tool releases





CohortDiagnostics v3.3

FeatureExtraction v3.7.2

OhdsiShinyModules v3.1.1

PhenotypeLibrary v3.34

PheValuator v2.2.12

SqlRender v1.19

Strategus v1.0











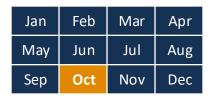








October publications



Incidence of post-acute COVID-19 symptoms across healthcare settings in seven countries: an international retrospective cohort study using routinely-collected data



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Summary

Background The World Health Organisation (WHO) has identified a range of symptomatic manifestations to aid in the clinical diagnosis of post-COVID conditions, herein referred to as post-acute COVID-19 symptoms. We conducted an international network cohort study to estimate the burden of these symptoms in North American, European, and Asian populations.

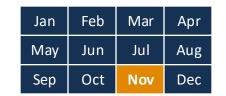
Methods A federated analysis was conducted including 10 databases from the United Kingdom, Netherlands, Norway, Estonia, Spain, France, South Korea, and the United States, between September 1st 2020 and latest data availability (which varied from December 31st 2021 to February 28th 2023), covering primary and secondary care, nationwide registries, and claims data, all mapped to the Observational Medical Outcomes Partnership

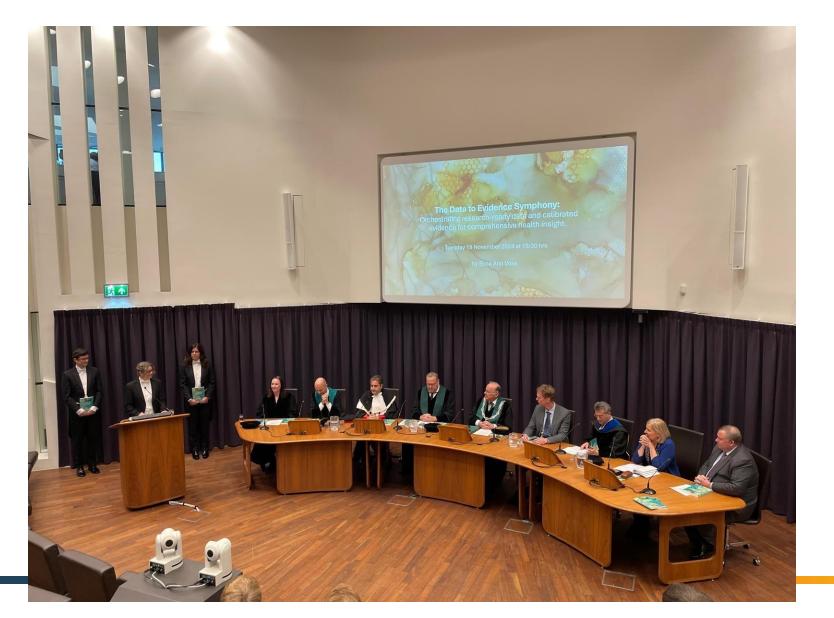
eClinicalMedicine 2024;77: 102903

Published Online 30 October 2014 https://doi.org/10. 1016/j.eclinm.2024 102903



November accomplishments: Dr. Erica Voss

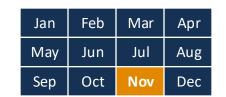








November accomplishments: Open-source tool releases





Cyclops v3.5

SqlRender v1.19.1

In CRAN!







November publications

Jan	Feb	Mar	Apr
May	Jun	Jul	Aug
Sep	Oct	Nov	Dec

Pharmacoepidemiology and Drug Safety

WILEY

ORIGINAL ARTICLE OPENACCESS

Standardised and Reproducible Phenotyping Using Distributed Analytics and Tools in the Data Analysis and Real World Interrogation Network (DARWIN EU)

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Funding: This work is part of the DARWIN EU initiative, funded by the European Medicines Agency. Francesco Dernie, Annika Jodicke, Dantel Prieto-Alhambra and Albert Prats-Uribe receive partial support from the National Institute for Health and Care Research (NIHR) in the form of the Oxford NIHR Blomedical Research Centre.

Keywords: pancreatic cancer | phenotyping | systemic lupus erythematosus

ABSTRACT

Purpose: The generation of representative disease phenotypes is important for ensuring the reliability of the findings of observational studies. The aim of this manuscript is to outline a reproducible framework for reliable and traceable phenotype generation based on real world data for use in the Data Analysis and Real-World Interrogation Network (DARWIN EU). We illustrate the use of this framework by generating phenotypes for two diseases: pancreatic cancer and systemic lupus erythematosus (SLE).

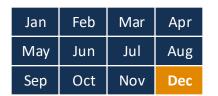
Methods: The phenotyping process involves a 14-steps process based on a standard operating procedure co-created by the DARWIN EU Coordination Centre in collaboration with the European Medicines Agency. A number of bespoke R packages were utilised to generate and review codelists for two phenotypes based on real world data mapped to the OMOP Common Data Model.

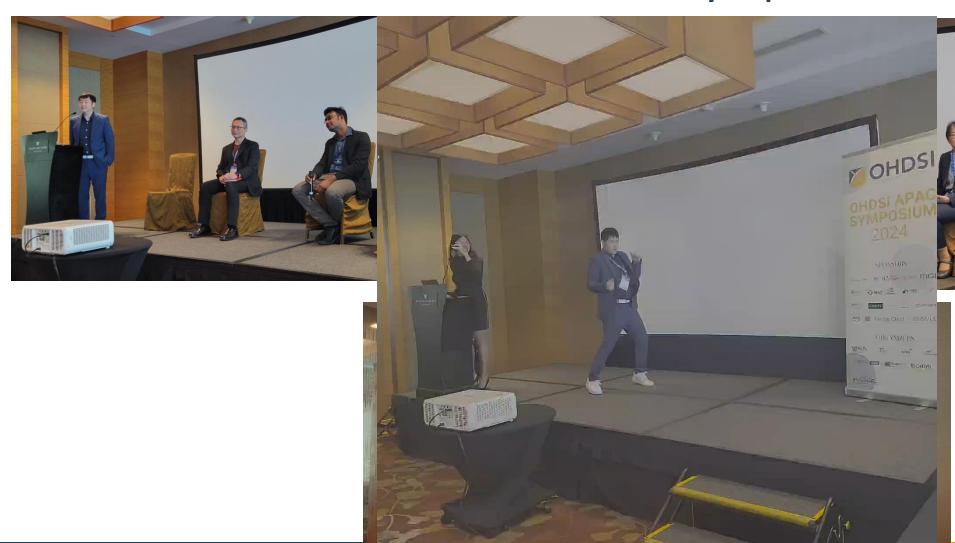
Results: Codelists were generated for both pancreatic cancer and SLE, and cohorts were generated in six OMOP-mapped databases. Diagnostic checks were performed, which showed these cohorts had broadly similar incidence and prevalence figures to previously published literature, despite significant inter-database variability. Co-occurrent symptoms, conditions, and medication use were in keeping with pre-specified clinical descriptions based on previous knowledge.

Conclusions: Our detailed phenotyping process makes use of bespoke tools and allows for comprehensive codelist generation and review, as well as large-scale exploration of the characteristics of the resulting cohorts. Wider use of structured and reproducible phenotyping methods will be important in ensuring the reliability of observational studies for regulatory purposes.



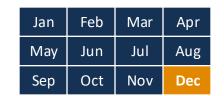
December activities: OHDSI APAC Symposium







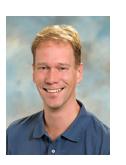
December accomplishments: Open-source tool releases





V1.16

Characterization v2.1 ShinyAppBuilder v3.2.0 Strategus v1.1.2









December publications

Jan	Feb	Mar	Apr
May	Jun	Jul	Aug
Sep	Oct	Nov	Dec

Evolution of a Graph Model for the OMOP Common Data Model

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Appl Clin Inform 2024;15:1056-1065.

Abstract

Objective Graph databases for electronic health record (EHR) data have become a useful tool for clinical research in recent years, but there is a lack of published methods to transform relational databases to a graph database schema. We developed a graph model for the Observational Medical Outcomes Partnership (OMOP) common data model (CDM) that can be reused across research institutions.

Methods We created and evaluated four models, representing two different strategies, for converting the standardized clinical and vocabulary tables of OMOP into a property graph model within the Neo4j graph database. Taking the Successful Clinical Response in Pneumonia Therapy (SCRIPT) and Collaborative Resource for Intensive care Translational science, Informatics, Comprehensive Analytics, and Learning (CRITICAL) cohorts as test datasets with different sizes, we compared two of the resulting graph models with respect to database performance including database building time, query complexity, and runtime for both cohorts.

Results Utilizing a graph schema that was optimized for storing critical information as topology rather than attributes resulted in a significant improvement in both data creation general information and querying. The graph database for our larger cohort, CRITICAL, can be built within 1 hour for 134,145 patients, with a total of 749,011,396 nodes and 1,703,560,910 edges.

Discussion To our knowledge, this is the first generalized solution to convert the OMOP CDM to a graph-optimized schema. Despite being developed for studies at a single institution, the modeling method can be applied to other OMOP CDM v5.x databases. Our evaluation with the SCRIPT and CRITICAL cohorts and comparison between the current and previous versions show advantages in code simplicity, database building, and guery speed.

Conclusion We developed a method for converting OMOP CDM databases into graph databases. Our experiments revealed that the final model outperformed the initial

Keywords databases

model

clinical data

management electronic health

records and systems

systems and technologies in

clinical settings OMOP common data

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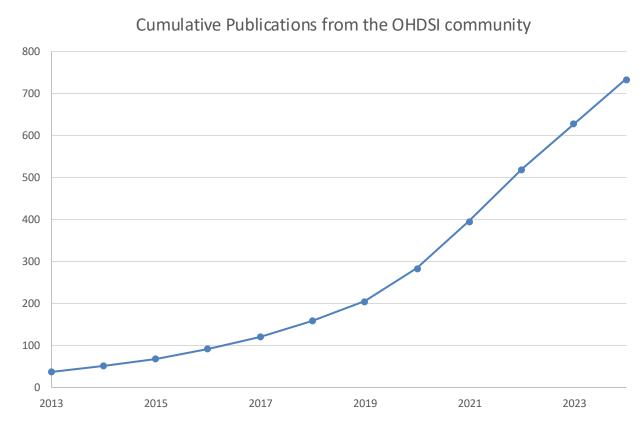
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Academic scholarship and clinical evidence generation

- >750 publications, including in top clinical journals (JAMA, BMJ, Lancet, JAMA Internal Medicine, JACC) and leading methodological journals (JAMIA, JBI, Nature Digital Medicine)
- Clinical evidence generated to inform range of therapeutic areas, including hypertension, diabetes, COVID-19, vision care, depression, oncology





Open-source software development

- HADES is an ecosystem of 37 R packages to support standardized analytics for the OMOP CDM and across OHDSI network
- OHDSI CRAN
 packages have
 been downloaded
 >800,000 times

Package	Version	Maintainer(s)	Availability
Achilles	v1.7.2	Frank DeFalco	CRAN
<u>Andromeda</u>	v0.6.7	Martijn Schuemie	CRAN
<u>BigKnn</u>	v1.0.2	Martijn Schuemie	GitHub
BrokenAdaptiveRidge	v1.0.0	Marc Suchard	CRAN
Capr	v2.0.8	Martin Lavallee	GitHub
Characterization	v2.0.1	Jenna Reps	GitHub
CirceR	v1.3.3	Chris Knoll	CRAN
CohortDiagnostics	v3.3.0	Jamie Gilbert	GitHub
CohortExplorer	v0.1.0	Gowtham Rao	CRAN
CohortGenerator	v0.11.2	Anthony Sena	GitHub
CohortIncidence	v4.0.0	Chris Knoll	GitHub
CohortMethod	v5.4.0	Martijn Schuemie	GitHub
Cyclops	v3.4.1	Marc Suchard	CRAN
<u>DatabaseConnector</u>	v6.3.2	Martijn Schuemie	CRAN
<u>DataQualityDashboard</u>	v2.6.1	Katy Sadowksi	GitHub
<u>DeepPatientLevelPrediction</u>	v2.1.0	Egill Fridgeirsson	GitHub
EmpiricalCalibration	v3.1.3	Martijn Schuemie	CRAN
EnsemblePatientLevelPrediction	v1.0.2	Jenna Reps	GitHub
Eunomia	v2.0.0	Frank DeFalco	CRAN
EvidenceSynthesis	v0.5.0	Martijn Schuemie	CRAN
FeatureExtraction	v3.7.1	Ger Inberg	CRAN
<u>Hydra</u>	v0.4.0	Anthony Sena	GitHub
<u>IterativeHardThresholding</u>	v1.0.2	Marc Suchard	CRAN
Keeper	v0.2.0	Anna Ostropolets	GitHub
MethodEvaluation	v2.3.0	Martijn Schuemie	GitHub
OhdsiSharing	v0.2.2	Lee Evans	GitHub
<u>OhdsiShinyModules</u>	v3.0.2	Jenna Reps	GitHub
<u>ParallelLogger</u>	v3.3.1	Martijn Schuemie	CRAN
<u>PatientLevelPrediction</u>	v6.3.9	Egill Friogeirsson & Jenna Reps	GitHub
PhenotypeLibrary	v3.34.0	Gowtham Rao	GitHub
<u>PheValuator</u>	v2.2.11	Joel Swerdel	GitHub
ResultModelManager	v0.5.11	Jamie Gilbert	GitHub
<u>ROhdsiWebApi</u>	v1.3.3	Gowtham Rao	GitHub
SelfControlledCaseSeries	v5.3.0	Martijn Schuemie	GitHub
SelfControlledCohort	v1.6.0	Jamie Gilbert	GitHub
ShinyAppBuilder	v3.1.0	Jenna Reps	GitHub
SqlRender	v1.18.1	Martijn Schuemie	CRAN

The open-source tools that empower OHDSI research are not only available to the community, but they are DEVELOPED by the community. We thank the many developers

and maintainers who empower our research initiatives around the world!











Lavallee







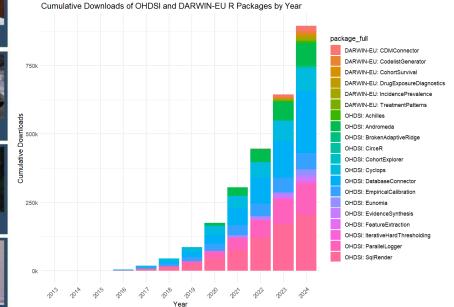














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What was your favorite OHDSI highlight in 2024?

Nobody has responded yet.

Hang tight! Responses are coming in.