



Workgroup OKRs + Phenotype Phebruary, Session 2

OHDSI Community Call
Feb. 11, 2025 • 11 am ET



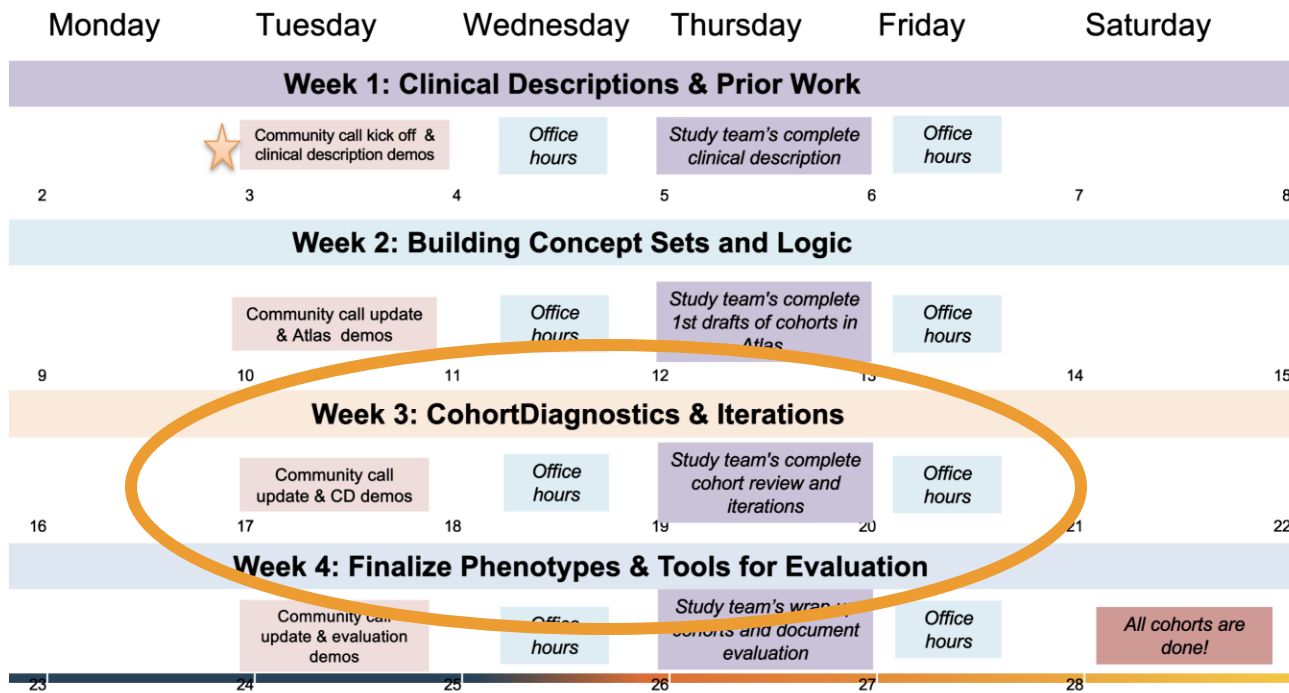
Upcoming Community Calls

Date	Topic
Feb. 11	Second Week of 2025 Workgroup OKRs/Phenotype Phebruary
Feb. 18	Third Week of 2025 Workgroup OKRs/Phenotype Phebruary
Feb. 25	Fourth Week of 2025 Workgroup OKRs/Phenotype Phebruary
Mar. 4	Vocabulary Release Update, Winter 2025



Feb. 18 Community Call

Phenotype February 2025 Calendar



Workgroup OKRs:

Common Data Model

Evidence Network

Patient-Level Prediction (PLP)

Early-Stage Researchers

Women of OHDSI

ATLAS

Methods Research



Three Stages of The Journey

Where Have We Been?

Where Are We Now?

Where Are We Going?





Workgroup OKRs

Each year, workgroup representatives join a February community call to present the mission, objectives and key results for their respective groups. These 2-4 minute presentations are recorded and posted on the Workgroups homepage on OHDSI.org.

Please choose a date to sign up for a February date – Feb. 25 is now closed.



Already Signed Up:

Africa Chapter
CDM Survey Subgroup
Clinical Trials
Common Data Model
Data Bricks
Evidence Network
Eye Care and Vision Research
GIS - Geographic Information System
Health Equity
Health Systems Interest Group
Latin America
Medical Devices
Natural Language Processing
Oncology
Pregnancy and Reproductive Health
Psychiatry
Rare Disease
Rehabilitation
Steering
Surgery and Perioperative Medicine
Themis
Transplant
Vocabulary
Women of OHDSI



Global Symposium: Oct. 7-9

The 2025 OHDSI Global Symposium will return to the Hyatt Regency Hotel in New Brunswick, N.J., on Oct. 7-9, 2025.

More details will be shared when available.





#OHDSISocialShowcase This Week

Monday

Evaluating the impact of different vocabulary versions on cohort definitions and CDM

(Dmitry Dymshyts, Frank DeFalco, Anna Ostroplets, Gowtham Rao, Azza Shoaibi, Clair Blacketer)

Title: Evaluating the impact of different vocabulary versions on cohort definitions and CDM

PRESENTER: Dmitry Dymshyts

INTRO:

- OHDSI phenotype library cohort definitions should reflect the same clinical idea regardless of the vocabulary version used.
- OHDSI vocabulary is constantly updated. From Dec-2017 to Aug-2024 37,726 (39%) ICD10CM concepts changed mapping and 21,497 (22%) changed target domain.
- Here we describe a process of evaluating how vocabulary changes affect concept sets included in phenotype definitions.

METHODS

The OHDSI Phenotype library cohort definitions were assessed based on the following metrics:

- Presence of non-standard concepts in concept set expression
- Changes in Included Source Codes.
 - The following source vocabularies were evaluated: ICD10, ICD10CM, CPT4, HCPCS, NDC, ICD9CM, ICD9Proc, ICD10PCS, ICDO3, JMDC, LOINC.
- Concepts included in concept sets that changed domains
- Similar principles were applied to the J&J Phenotype library

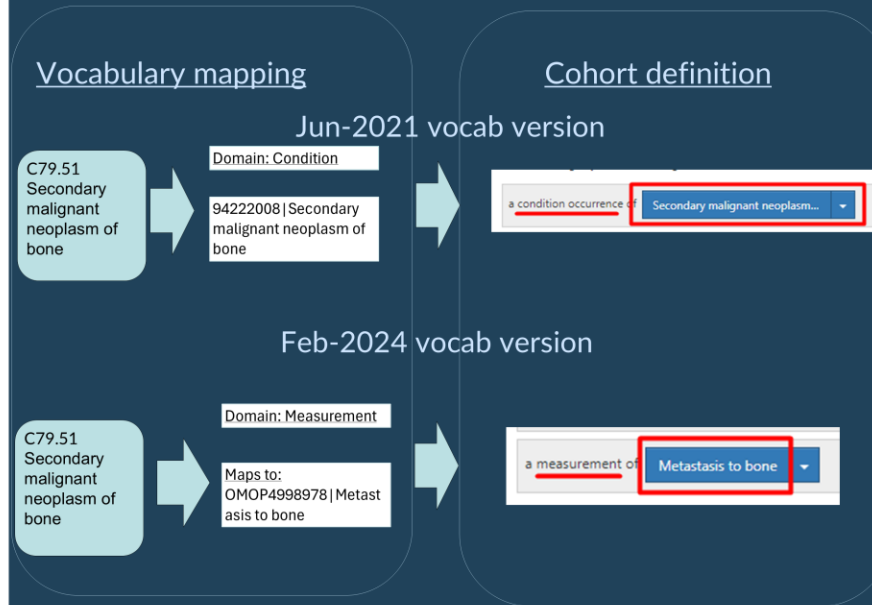
The 2024-Feb vocabulary version was compared with the vocabulary version of a cohort (different cohorts have different vocabulary versions).

RESULTS

- 343 out of 599 cohorts from the OHDSI Phenotype library have at least one change described above.
- Among these cohorts 630 different non-standard concepts are used
- 2665 unique related source concepts were added
- 854 unique source concepts were removed from concept sets.
- 114 included concepts changed their domain

About half (343 / 599) of the OHDSI Phenotype library cohorts changed due to the OHDSI vocabulary updates

Example of vocabulary change, and cohort adaption needed to capture the same medical event:



Scan to access the github page



Scan to access the electronic version of the poster and abstract



Example Output

Mapping difference	
COHORT_ID	14092
COHORT_NAME	Metastatic castration-resistant prostate cancer
CONCEPTSET_NAME	Any cancer
CONCEPTSET_ID	2
SOURCE_CONCEPT_ID	45552285
RECORD_COUNT	46362527
ACTION	Removed
SOURCE_CONCEPT_NAME	Secondary malignant neoplasm of bone
SOURCE_VOCABULARY_ID	ICD10CM
SOURCE_CONCEPT_CODE	C79.51
OLD_MAPPED_CONCEPT_ID	78097
OLD_MAPPED_CONCEPT_NAME	Secondary malignant neoplasm of bone
OLD_MAPPED_VOCABULARY_ID	SNOMED
NEW_MAPPED_CONCEPT_ID	36769301
NEW_MAPPED_CONCEPT_NAME	Metastasis to bone
NEW_MAPPED_VOCABULARY_ID	Cancer Modifier

This shows which medical event with the given source code wasn't picked up by the concept set, and which concepts should be used to include this event in the cohort

Practical implementation:

- 32 cohorts were modified in order to keep the same meaning after the vocabulary update in J&J Phenotype Library
- 48 cohorts were NOT modified, since the changes due to vocabulary update are either insignificant, good, or due to vocabulary mapping inaccuracies, which are fixed in the most recent vocabulary release
- This way we can suggest that 40% of cohorts will require changes in OHDSI PL as well.

Dmitry Dymshyts, Frank DeFalco, Anna Ostroplets, Gowtham Rao, Azza Shoaibi, Clair Blacketer





#OHDSISocialShowcase This Week

Tuesday

The state of federated health data networks globally in 2024

(Michael Briganti, Valerie van Baalen, Eva-Maria Didden, Monika Brand)



The State of Federated Health Data Networks Globally in 2024

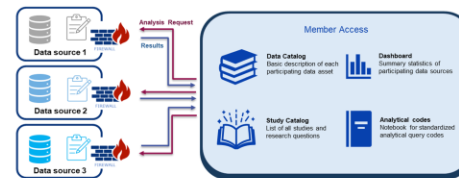
Michael Briganti, PhD, MPH; Valerie van Baalen, MSc; Eva-Maria Didden, PhD; Monika Brand, BSc
Johnson & Johnson Innovative Medicine, Research & Development

Background

What is a Federated Data Network (FDN)?

- FDNs facilitate data sharing and analysis through a collaborative network of different organizations
- FDN definitions vary, but share the following core components:
 - Data partners remain in full control of their data
 - Data partners are responsible for patient privacy and consent
 - Patient-level data is de-centralized, only aggregate info is shared via central hub
 - Data is harmonized into a common data model (CDM)

An example FDN network structure:



Project Objectives

- FDNs utilize rapidly developing methodology yet lacks standardized terminology
- Lack of standardization decreases discoverability and transparency
- There are zero publications on the health-related FDN landscape
- The goal of this poster is to provide a high level overview of the existing FDN landscape

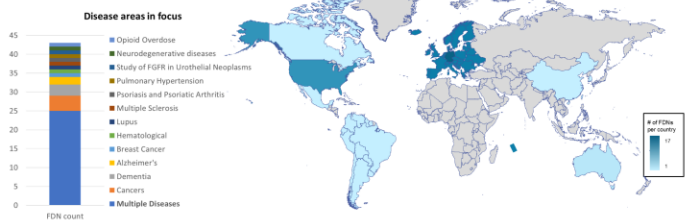
Methods

- Search PubMed for keyword "Federated Data Network" over the past 5 years
Identify publications describing an FDN + health data
Use identified publications and references to identify other relevant publications (i.e. snowball search)
- Supplement initial findings with Natural Language Processing and Large Language Model techniques that finds other publications based on similarity scoring
- Unstructured interviews with FDN subject matter experts to identify gaps or other known FDNs, as not all FDNs have publications

Contact: mbrigant@its.jnj.com

Results

- This landscape identified 43 FDNs, and this number continues to grow
- A majority contain data on multiple diseases, 13 FDNs are disease-specific (most commonly dementia)
- Most common underlying source data is from electronic health records (n = 18)
- United States has largest country-specific presence (n = 13)
- OMOP CDM is the most frequently used CDM among these 43 FDNs



Conclusions

Search Results

- The identified FDNs are diverse, but share core federated data principles
- Our search identified a lack of standardized terminology
 - Many networks here are self-described as "Decentralized Data Network", "Secure Data Network", or "Collaborative Data Network."
 - FDN technology and methods borrowed from other fields, a health-specific FDN definition (FHDN) may help future researchers to narrow their focus to relevant networks

What Can We Learn from FDNs

- FDNs may generate new evidence leading to improved patient care over time
 - In rare diseases, FDNs may be necessary when a single data partner does not have sufficient data
 - FDNs can decrease time needed to obtain required sample size
- FDNs alleviates growing privacy and data security concerns, data never leaves original data owner
- Growth of an FDN leads to more diverse patient sample
 - More generalizable results, stronger evidence generation

Overall Conclusion

- This landscape serves as a first step towards understanding what FHDNs exist, and highlighting the need for standard FHDN terminology to drive the field forward.

#OHDSISocialShowcase This Week

Wednesday

Comparison of Deep Learning and Conventional Strategies for Disease Onset Prediction: An OHDSI Network Study

(Henrik John, Chungsoo Kim, Jan Kors, Junhyuk Chang, Hannah Morgan-Cooper, Priya Desai, Chao Pang, Peter Rijnbeek, Jenna Reps, Egill Fridgeirsson)



Comparison of deep learning and conventional methods for disease onset prediction

Luis H. John¹, Chungsoo Kim², Jan A. Kors¹, Junhyuk Chang³, Hannah Morgan-Cooper⁴, Priya Desai⁵, Chao Pang⁶, Peter R. Rijnbeek¹, Jenna M. Repp^{1,6}, Egill A. Fridgeirsson¹
¹Department of Medical Informatics, Erasmus University Medical Center, Rotterdam, The Netherlands; ²Section of Cardiovascular Medicine, Department of Internal Medicine, Yale School of Medicine, New Haven, CT, United States; ³Department of Biomedical Informatics, Ajou University Graduate School of Medicine, Suwon, Republic of Korea; ⁴Stanford School of Medicine and Stanford Health Care, Palo Alto, CA, United States; ⁵Department of Biomedical Informatics, Columbia University Irving Medical Center, New York, NY, United States; ⁶Janssen Research and Development, Titusville, NJ, United States

Background: Identifying individuals at high risk of disease at an early stage allows for improved care and risk-factor targeted intervention. Conventional approaches such as logistic regression and gradient boosting (XGBoost) have long served as reliable tools for predictive modeling in the clinical domain. However, the continuous advancement of deep learning methods, such as ResNet and Transformer, offers the promise of improved prediction accuracy and the ability to extract intricate patterns from complex clinical data. This study compares these conventional and deep learning methods to predict dementia in persons aged 55 – 84, bipolar disorder in patients newly diagnosed with major depressive disorder, and lung cancer in patients aged 45 – 65. We use observational data from administrative claims and electronic health records mapped to the OMOP CDM and follow the standardized OHDSI patient-level prediction approach for onset prediction in Figure 1.

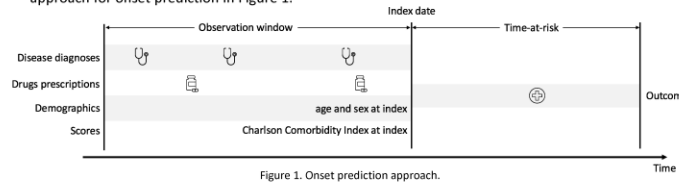


Figure 1. Onset prediction approach.

Methods: A study overview is presented in Figure 2. We evaluate internal and external validation performance using AUROC for discrimination and E_{avg} for calibration. Friedman's test is used to detect ranking differences of the different prediction methods. If the null hypothesis for no difference in ranks between the methods is rejected, we proceed with a post-hoc test to examine all pairwise differences, controlling for multiplicity. The results are plotted in a critical difference (CD) diagram of the Nemenyi test, which shows the mean ranks of each prediction method.

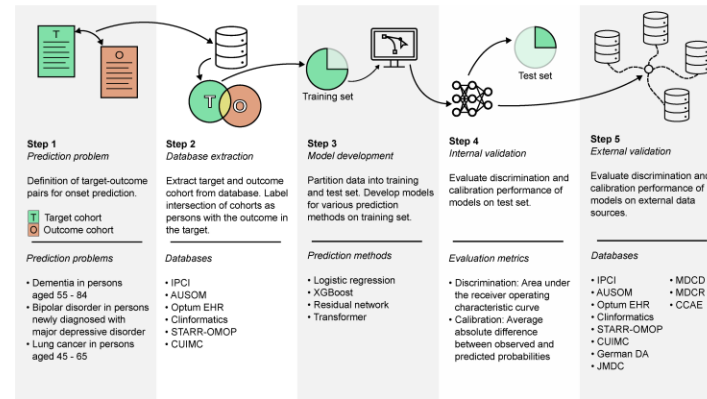


Figure 2. Study overview.

Contact: l.john@erasmusmc.nl

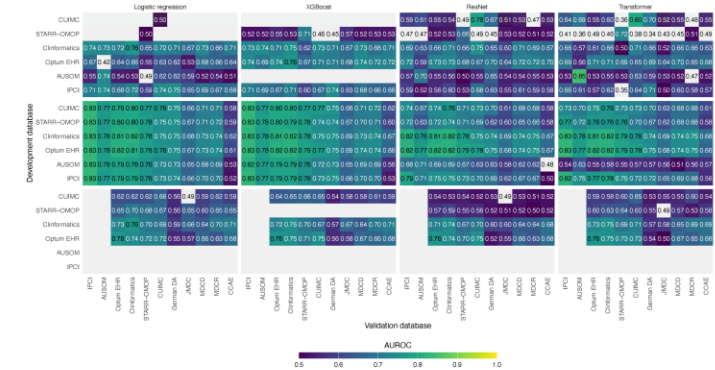


Figure 3. Internal and external discrimination performance (AUROC) across prediction methods and prediction problems.

Discussion: Discrimination performance across databases, prediction methods, and prediction problems is presented in Figure 3. Using these measures, the CD diagram in Figure 4A reveals that conventional methods outperform deep learning methods. However, assessing only internal validation performance, no significant difference between methods is found and no post-hoc test is performed. This is confirmed by learning curve analysis in Figure 5, which shows that performance of conventional and deep learning methods converges if enough data is available. Conventional models transport better (Figure 4B) and rank better on small data (Figure 4C). Small data also causes poor calibration in ResNet.

Our finding highlights the current limitations of deep learning methods when applied to observational healthcare data. These methods are more complex and require more data to train, but do not show better performance than conventional methods. However, the type of data we use, flattened tabular data, likely does not exploit the full capabilities of deep learning methods. Future work should focus on techniques that utilize the temporal nature of observational data to fully take advantage of the complex nature and pattern recognition capabilities of deep learning.

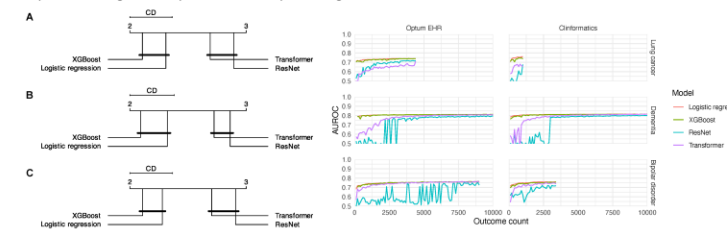


Figure 4. Ranking of prediction method based on AUROC for (A) internal and external validation, (B) external validation, (C) models developed on small data.

Figure 5. AUROC performance on the test set for increasingly larger subsets of the training set



#OHDSISocialShowcase This Week

Thursday

Prediction of Severe Respiratory Infections in Patients with Diabetes

(**Nguyen Thi Kim Hien**, Phan Thanh Phuc, Septi Melisa, Muhammad Solihuddin Muhtar, Nguyen Phung-Anh, Jason Hsu)

Prediction of Severe Respiratory Infections in Patients with Diabetes

PRESENTER: **Nguyen Thi Kim Hien**
Contact: da07113002@tmu.edu.tw

INTRO

- Patients with type 2 diabetes (T2DM) are more vulnerable to infections due to impaired immune function caused by hyperglycemia.
- Patients with T2DM face a much higher risk of serious respiratory infections like pneumonia and tuberculosis.
- This study aim to develop predictive models to assess the risk of severe respiratory infections over three years in individuals aged 45+ with T2DM.

METHODS

1. **Study design:** Retrospective cohort study.
2. **Data sources:** EHR data obtained from three hospitals affiliated with Taipei Medical University and converted to the OHDSI OMOP-CDM for analysis.
3. **Cohort:** Individuals aged 45+ with T2DM. Excluded those with a history of pneumonia within the last 30 days or tuberculosis within the last 365 days.
4. **Outcomes:**
 - Hospitalized pneumonia.
 - Developing tuberculosis.
5. **ML Algorithms:** Logistic Regression (LR), LightGBM (LGBM), Random Forest, XGBoost.
6. **Features:** Patient attributes, coexisting medical conditions, and medication utilization.

Prediction of Severe Respiratory Infections in Patients with Diabetes

Table 1. The cohort count

Target/ Outcome	Target cohort	Outcome cohort	Incidence (%)
T2DM / Hospitalized pneumonia	42863	1876	4.38
T2DM / Pulmonary tuberculosis	43860	107	0.25

Table 2. Performance of prediction models

Outcome	Model type	AUROC (95% CI)	AUPRC
Hospitalized pneumonia	Logistic	0.800 (0.780 - 0.820)	0.175
	XGBoost	0.808 (0.787 - 0.828)	0.195
Pulmonary tuberculosis	Logistic	0.785 (0.721 - 0.849)	0.007
	XGBoost	0.690 (0.599 - 0.781)	0.006

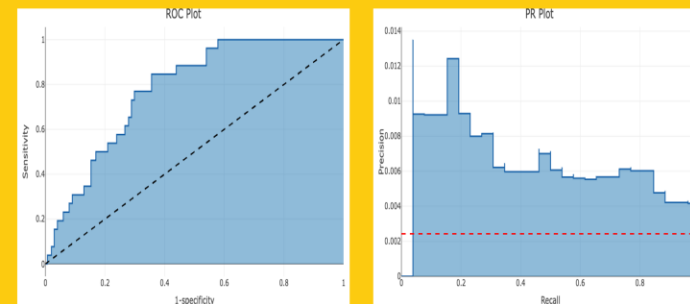


Figure 1. ROC and PR Curves in predicting the risk of Hospitalized Pneumonia by using XGBoost Algorithm

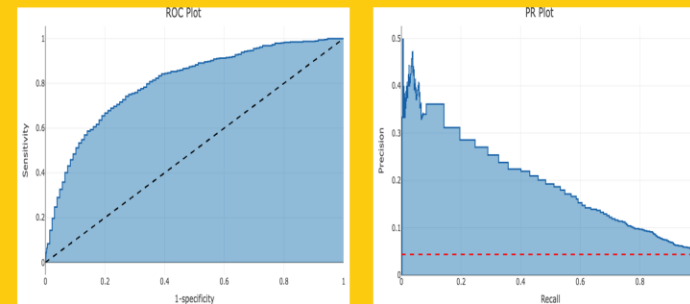


Figure 2. ROC and PR Curves in predicting the risk of Onset Pulmonary tuberculosis by using Logistic Regression Algorithm

RESULTS

- The study analyzed 78,322 T2DM patients, excluding those with insufficient follow-up. Over three years, the incidence of pneumonia was 4.38%, and tuberculosis was 0.25%.
- All the other correlations in the ammo bar. XGBoost performed best in predicting hospitalized pneumonia, with an AUROC of 0.805 and an AUPRC of 0.195. For predicting tuberculosis in T2DM patients, logistic regression showed the highest performance, achieving an AUROC of 0.785 and an AUPRC of 0.007.

CONCLUSION

Diabetes independently raises the risk of severe pneumonia, hospitalization, and death due to pneumonia. It also increases the chances of developing active tuberculosis. This study developed models to predict the risk of hospitalized pneumonia and tuberculosis onset in individuals aged 45+ with T2DM using machine learning algorithms. The models showed acceptable accuracy and discrimination, making them useful for early detection of severe respiratory infections. However, larger studies or prospective cohorts are needed to further validate these findings.

Nguyen Thi Kim Hien, Phan Thanh Phuc, Septi Melisa, Muhammad Solihuddin Muhtar, Jason Hsu





#OHDSISocialShowcase This Week

Friday

Visualising OMOP concept relationships with omopcept

(Andy South)

Andy South



University College London Hospitals
NHS Foundation Trust

Visualising omop concept relationships with omopcept - a new R package

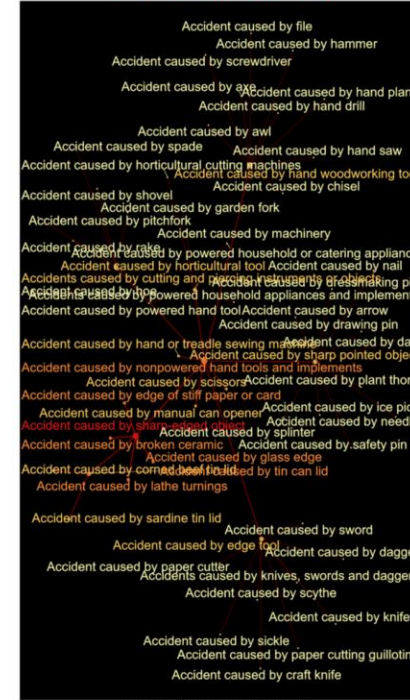
example drug relationships



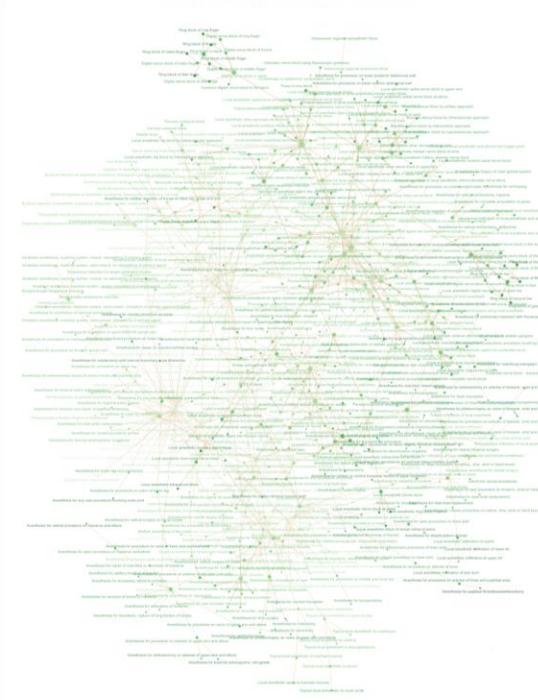
What omopcept does :

1. Query OMOP concepts reproducibly & offline from R
2. Easily join concept names onto concept ids to make data extracts more understandable for researchers & clinicians
3. Visualise OMOP concept hierarchies

example SNOMED hierarchy



example SNOMED procedures



<https://github.com/SAFEHR-data/omopcept>

southandy@gmail.com





Where Are We Going?

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



Three Stages of The Journey

Where Have We Been?

Where Are We Now?

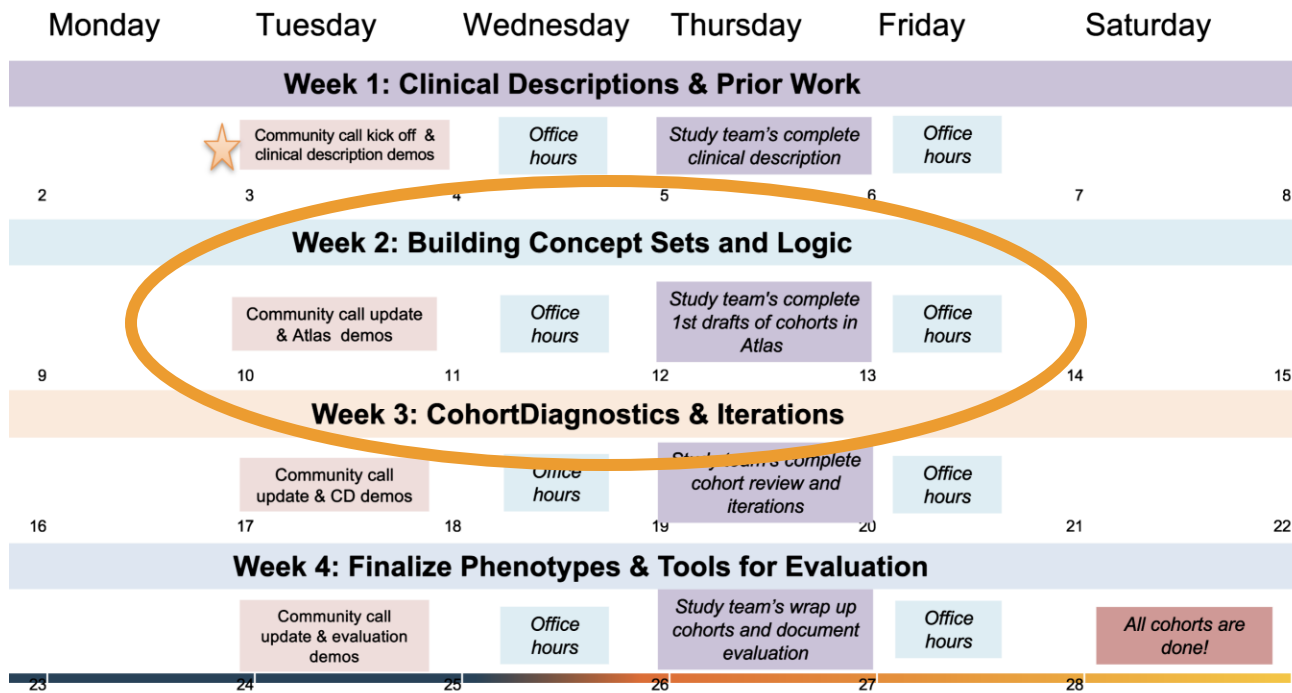
Where Are We Going?





Feb. 11 Community Call

Phenotype Phebruary 2025 Calendar



Workgroup OKRs:

Common Data Model

Evidence Network

Patient-Level Prediction (PLP)

Early-Stage Researchers

Women of OHDSI

ATLAS

Methods Research



Methods Research Workgroup 2025 OKRs



Mission

Empower real-world evidence generation through collaborative innovation in statistical and computational methods

Objectives and key results for 2025

Objective: **Promote awareness and collaboration** in methods research

- Maintain a comprehensive directory of ongoing methods research.
- Have at least 6 presentations of ongoing methods research (i.e. work that hasn't been published yet)
- Have researchers work on at least 3 topics in the never-ending list.

Objective: **Provide resources** for development of new methods

- Inventory options for making data sources available to methods researchers

Objective: **Disseminate best practices** informed by methods research

- 3 drafted manuscripts describing methodological best practices



OHDSI

OBSERVATIONAL HEALTH DATA SCIENCES AND INFORMATICS

Common Data Model Workgroup

2025 OKRs



Purpose

The CDM workgroup exists to maintain and improve the use of the OMOP Common Data Model to make it the premier observational health data model in the world. We ensure the integrity and usability of the OMOP CDM in relation to other working groups by providing guidance on data standardization best practices.



2025 Objectives and Key Results

Objective 1: Lay the groundwork for the next OHDSI Common Data Model (CDM) release by evaluating and refining proposed changes.

- **Determine which proposals** are eligible for inclusion in a new version 5-series release.
- **Obtain feedback from all relevant OHDSI workgroups** on the selected proposals to ensure alignment and minimize disruptions.
- **Establish a timeline and communication strategy** for the 2026 CDM release, ensuring transparency and engagement across the OHDSI community.



2025 Objectives and Key Results

Objective 2: Prepare the current CDM for a new version

- **Close all bugs** currently identified in the repository.
- **Clean up all documentation** including conventions and user guides related to CDM v5.4

Objective 3: Advance the maturity model for CDM extensions and expansions

- **Identify gaps in the coverage of the CDM** that cannot be addressed with THEMIS conventions
- **Create a list of all extensions and expansions** currently available in the community
- **Define the levels of maturity** of all expansions and extensions currently available in the community



Next Meeting

Tuesday, February 18th, 9:00am EST

To join, go to ohdsi.org ->

workgroups tab ->

select **Common Data Model**



Next Meeting

Tuesday, February 18th, 9:00am EST

To join, go

5. Select the workgroups you want to join (you can refer to the OHDSI workgroups page to learn more about each workgroup's accomplishments and upcoming goals: <https://ohdsi.org/ohdsi-workgroups>) *

ATLAS/WebAPI

Clinical Trials

Common Data Model (includes Vocabularies, CDM Survey Subgroups)

Dentistry

Early-stage Researchers

Education

Electronic Animal Health Records



OHDSI

OBSERVATIONAL HEALTH DATA SCIENCES AND INFORMATICS

OHDSI Evidence Network

2025 OKRs



2025 Objectives and Key Results

Objective 1: Enhance communication and visibility of the OHDSI Evidence Network to engage and support data partners.

- **Build out our website as a landing page**, including:
 - Resources for data partners
 - A decision tree for readiness determination
 - Clear value propositions for participation
- **Write and publish a paper describing the network**, as outlined in the protocol, to establish its scientific and collaborative framework.



2025 Objectives and Key Results

Objective 2: Leverage the OHDSI Evidence Network to enhance the scientific rigor and impact of network studies.

- **Improve the fitness-for-use methodology** to better identify appropriate data sources for each study question.
- **Release v2.0 of data diagnostics** incorporating the improvements to the fitness-for-use methodology.
- **Utilize the OHDSI Evidence Network** to determine potentially appropriate data sources for the OHDSI community's prioritized study questions for 2025.



Next Meeting

Thursday, February 13th, 10:30am EST

To join, go to ohdsi.org ->

workgroups tab ->

select **Evidence Network**



Next Meeting

Thursday, February 13th, 10:30am EST

To join, go to

5. Select the workgroups you want to join (you can refer to the OHDSI workgroups page to learn more about each workgroup's accomplishments and upcoming goals: <https://ohdsi.org/ohdsi-workgroups>)*

- ATLAS/WebAPI
- Clinical Trials
- Common Data Model (includes Vocabularies, CDM Survey Subgroups)
- Dentistry
- Early-stage Researchers
- Education
- Electronic Animal Health Records
- Evidence Network



PLP 2025 OKRs

Jenna Reps



PatientLevelPrediction Workgroup

We meet monthly (2nd Wednesday of the month at 9am ET) to discuss and perform research into best practices for developing prediction models using observational healthcare data.

We also maintain multiple R packages that enable prediction model development for data in the OMOP CDM format.

<https://github.com/OHDSI/PatientLevelPrediction>

<https://github.com/OHDSI/DeepPatientLevelPrediction>



1. Improve workgroup study dissemination

- Create calendar with 2025/2026 conferences of interest to:
 - i) disseminate our research and collaborate with external groups
 - ii) get together face to face more often.

add calendar to PatientLevelPrediction website.

- Improved dissemination on monthly call – use 10 minutes per call to let people discuss/highlight recent studies/publications.
- Improved communication of R package future development using GitHub project tracking.

Next workgroup meeting: 9am ET tomorrow (Feb 12th)



2. Make it easier to use OHDSI prediction R packages

- Perform user and developer survey to find bottlenecks/challenges.
- Increase training on tools – create updated YouTube videos/Ehden academy.
- **Submit PatientLevelPrediction R package to CRAN in 2025.**
- Create new test data for Eunomia that is more suitable for prediction.
- Create docker container for prediction studies.

Congrats to Egill Fridgeirsson for already getting into CRAN: <https://cran.r-project.org/web/packages/PatientLevelPrediction/index.html>



3. Perform Research in PatientLevelPrediction

- Federated learning: i) novel methods and ii) comparison of federated learning vs single database model. Submit journal paper.
- Investigate the benefit of incorporating different data sources: i) impact of data granularity and ii) does adding labs/imaging/NLP improve prediction? Submit journal paper.
- Temporal features: can we develop better models by adding time as a dimension for features? Submit journal paper.
- Transfer learning: i) novel methods and ii) compare transfer learning in small data vs developing model in small data. Submit journal paper.

Last year we had 3+ papers published via collaboration within this workgroup



OHDSI Workgroup Objectives and Key Results (OKR)

Early-Stage Researchers WG

Leads: Harry Reyes Nieva, Benjamin Martin, Shounak Chattopadhyay



Mission Statement

To create an inviting venue for junior OHDSI community members early in their careers to navigate OHDSI's resources, ask questions, present their research, find mentorship through networking, and seek insight on their career trajectories.



Early-Stage Researchers WG 2025 OKR #1

Objective: Align WG activities with needs, priorities, and goals of ESR membership

Key results:

1. Develop and conduct an annual survey to identify and examine OHDSI ESR membership needs, priorities, and goals.
2. Create a strategic plan and roadmap outlining how WG activities will address identified needs and priorities.
3. Report survey results at upcoming ESR monthly meeting and re-evaluate OKRs accordingly.



Early-Stage Researchers WG 2025 OKR #2

Objective: Foster mentorship and engagement with more experienced researchers

Key results:

1. Host monthly online talks from experienced researchers, making sure to diversify speaker background
 - All speakers scheduled with date, meeting link, and flyer 2+ weeks prior to each event
 - Greater than 30 participants at each event
2. Organize online and in-person Meet-the-Mentor roundtables
 - Identify a limited set of mentees to be matched with a mentor in advance
3. Develop a Mentor and Membership Directory for matchmaking



Early-Stage Researchers WG 2025 OKR #3

Objective: Facilitate involvement, visibility, and networking opportunities for ESR

Key results:

1. Create onboarding roadmap for trainees in different disciplines and career paths (Informatics, Epidemiology, Medicine, Statistics, etc.)
2. Have at least 5 presentations/posters at OHDSI symposia from ESRs
3. Spotlight ESR members with research in-progress presentations during online monthly meetings



Early-Stage Researchers WG 2025 OKR #4

Objective: **Expand** the group leadership structure and better support **global participation**

Key results:

1. Recruit dedicated members to organize monthly series, mentor/mentee directory, and outreach
2. Identify representatives to liaise with regional chapters
3. Expand ESR WG membership to include active members from at least three regional chapters.



Early-Stage Researchers WG 2025 OKR #5

Objective: Grow OHDSI network and ESR WG membership

Key results:

1. Develop ESR WG promotional materials
2. Advertise OHDSI and ESR WG to institutions and organizations that have not previously participated in OHDSI
3. Distribute OHDSI and ESR promotional materials at non-OHDSI scientific fora, in particular, those that cater to ESRs



ESR Meeting Details

- Monthly Meetings

- 1st Thursday of the month at 2:00-3:00PM Eastern Time

- Next meeting: Thursday, March 6th, 2-3PM EST on MS Teams
- Future meeting times may change to better accommodate time zones that span ESR global membership

- Co-leads:

- Shounak Chattopadhyay (shounak.chattopadhyay@ucla.edu)
 - Benjamin Martin (bmarti86@jh.edu)
 - Harry Reyes Nieva (harry.reyes@columbia.edu)
-



Women of OHDSI (WoO) Workgroup

2025OKRs



WoO Long Term Goals



Research

Dedicated women's health research hub

Milestones

- Evidence review women's health research topics to feed potential OHDSI study ideation
- OHDSI network studies
- Collaborative cross-workgroup activities

Data

Improving gender harmony through RWD collection and standardisation

Milestones

- Collaboration with other OHDSI workgroups on the improvement of gender harmony agenda
- Recommendations for OMOP standardisation of gender health centricity

Empowerment

A 'Safe Space' for all with events, activities and workshops

Milestones

- Planned timetable of speakers, workshops and talks to inspire and develop
- Celebration of key global dates such as International Women's Day, etc



WoO 2025 Commitment



A 'Safe Space' for all with events, activities and workshops to help support everyone's OHDSI collaborative endeavours*

What to expect:

- International Women's Day
- I Am Remarkable workshops
- OHDSI Symposium in-person connect
- Brand of Me activities & workshops
- Career Journeys
- Real stories
- Meet the Mentor (internal and external speakers)
- Ask Me Anything (AMA)
- Networking Opportunities
- Health related webinars

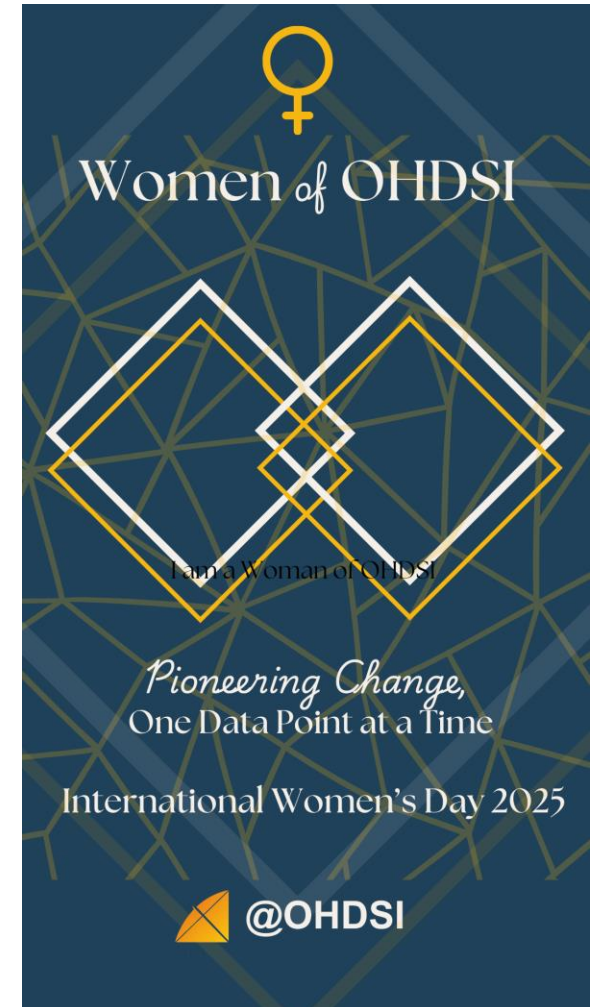
*Disclaimer: this is not an Employee Resource Group (ERG) nor Human Resources nor legal counsel. Simply a safe space for everyone. Bring and share your ideas!

[Sign up](#) for the OHDSI WoO WG!



Celebrate International Women's Day 2025 with WoO!

- Join the celebration wherever you are in the world
- Instagram: Use the template to add your photo and tag @OHDSI + your inspiring women colleagues
- #WomenOfOHDSI #IWD2025





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