



ATLAS Deepdive: Data Sources and Vocabularies

OHDSI Community Call
June 10, 2025 • 11 am ET





Upcoming Community Calls

Date	Topic
June 10	ATLAS Deepdive: Data Sources and Vocabularies
June 17	ATLAS Deepdive: Cohorts and Conceptsets
June 24	ATLAS Deepdive: Characterization, Cohort Pathways, Incidence
July 1	ATLAS Deepdive: Technical and Administrative Capabilities
July 8	No Meeting – Europe Symposium
July 15	Europe Symposium Review
July 22	OMOP/OHDSI Research Spotlight



Three Stages of The Journey

Where Have We Been?

Where Are We Now?

Where Are We Going?





OHDSI Shoutouts!



Congratulations to the team of
**Justin Bohn, James Gilbert,
Christopher Knoll, David Kern, and
Patrick Ryan** on the publication of
**Large-scale Empirical
Identification of Candidate
Comparators for
Pharmacoepidemiological Studies
in *Drug Safety*.**

Drug Safety
<https://doi.org/10.1007/s40264-025-01569-y>

ORIGINAL RESEARCH ARTICLE



Large-scale Empirical Identification of Candidate Comparators for Pharmacoepidemiological Studies

Justin Bohn¹ · James P. Gilbert¹ · Christopher Knoll¹ · David M. Kern¹ · Patrick B. Ryan¹

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Abstract

Background and Objective The new user cohort design has emerged as a best practice for the estimation of drug effects from observational data. However, despite its advantages, this design requires the selection and evaluation of comparators for appropriateness, a process that can be challenging. The objective of this work was to introduce an empirical approach to rank candidate comparators in terms of their similarity to a target drug in high-dimensional covariate space.

Methods We generated new user cohorts for each RxNorm ingredient and Anatomic Therapeutic Chemical level 4 class in five administrative claims databases then extracted aggregated pre-treatment covariate data for each cohort across five clinically oriented domains. We formed all pairs of cohorts with ≥ 1000 patients and computed a scalar similarity score, defined as the average of cosine similarities computed within each domain, for each pair. We then generated ranked lists of candidate comparators for each cohort.

Results Across up to 1350 cohorts forming 922,761 comparisons, drugs that were more similar in the Anatomic Therapeutic Chemical hierarchy had higher cohort similarity scores. The most similar candidate comparators for each of six example drugs corresponded to alternative treatments used in the target drug's indication(s), and choosing the top-ranked comparator for randomly selected drugs tended to produce balance on most covariates. This approach also ranked highly those comparators chosen in high-quality published new user cohort design studies.

Conclusion Empirical comparator recommendations may serve as a useful aid to investigators and could ultimately enable the automated generation of new user cohort design-derived evidence, a process that has previously been limited to self-controlled designs.



OHDSI Shoutouts!



Thank you **Lee Evans** for coming to the rescue of OHDSI services over the last week.





Three Stages of The Journey

Where Have We Been?

Where Are We Now?

Where Are We Going?





Upcoming Workgroup Calls



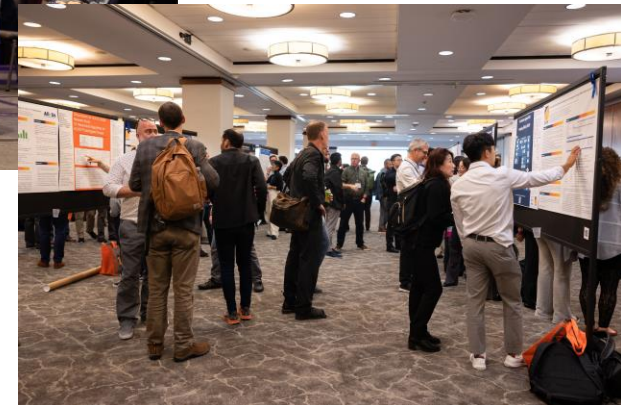
Date	Time (ET)	Meeting
Tuesday	12 pm	Generative AI and Analytics
Tuesday	3 pm	Oncology Outreach/Research Subgroup
Wednesday	7 am	Medical Imaging
Wednesday	9 am	Patient-Level Prediction
Wednesday	11 am	Common Data Model
Wednesday	7 pm	Eyecare and Vision Research
Thursday	9:30 am	Network Data Quality
Thursday	10 am	Rare Diseases
Thursday	10 am	Rehabilitation
Thursday	10:30 am	Evidence Network
Thursday	12 pm	Medical Devices
Friday	9 am	Phenotype Development and Evaluation
Friday	10 am	Transplant
Friday	10 am	GIS-Geographic Information System
Friday	11 am	Clinical Trials
Friday	11 pm	China Chapter
Monday	10 am	Healthcare Systems Interest Group
Monday	11 am	Data Bricks Interest Group
Monday	2 pm	Electronic Animal Health Records



THREE Weeks Remaining

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

More information about the collaborator showcase, including links to the submission form and poster templates, can be found on the #OHDSI2025 homepage.



Announcements

NCI's Office of Data Sharing (ODS) Childhood Cancer Data Jamboree

Day 1: Sept. 29, Building 10, NIH Bethesda Campus.

Day 2: Sept. 30, NCI Shady Grove Campus

Both [Registration](#) and [Project Submissions](#) are required

Virtual options will be provided.

NCI's Office of Data Sharing (ODS) 3rd Annual Symposium

Day 1 & Day 2: Sept. 30 – Oct. 1, NCI Shady Grove Campus or Virtual

[Register now](#)

[Poster Abstract Submission](#)



The NCI Office of Data Sharing presents the ODS Webinar Series: **Reviewing the 2024 NIH Public Access Policy**

June 18, 2025. 2-3 PM EST



- ❖ Explain what is changing from the 2008 Public Access Policy
- ❖ Cover special guide notices relating to publishing rights and costs
- ❖ Question-and-Answer session
- ❖ We aim to prepare stakeholders for the new policy when it goes into effect on July 1, 2025





OHDSI on Bluesky

OHDSI is now on Bluesky!

You can now get updates on all community activities and see all global research through the #OHDSISocialShowcase on Bluesky.



bsky.app/profile/ohdsi.bsky.social



Europe Symposium Agenda

Symposium Agenda – July 7, 2025

Time	Topic
8:00 – 9:00	Registration & Coffee
9:00 – 9:10	Welcome to the European OHDSI Journey (<i>Speakers: Liesbet M. Peeters & Peter Rijnbeek</i>)
9:10 – 9:30	Journey of OHDSI: Where have we been and where can we go together? (<i>Speaker: Patrick Ryan</i>)
9:30 – 11:00	Impact of Leveraging OMOP CDM for Scalable and Reliable Evidence Generation Showcased by the National Nodes (<i>Moderators: Renske Los & Annelies Verbiest</i>)
11:00 – 11:30	Coffee Break
11:30 – 12:45	Collaborator Showcase: Rapid Fire Presentations (<i>Moderator: TBC</i>)
12:45 – 13:45	Lunch
13:45 – 16:00	OHDSI Collaborator Showcase Early Investigator Mentor Meeting (14:00 – 15:00)
16:00 – 17:10	Bridging Policy and Practice: OHDSI's Role in Implementing the European Health Data Space (<i>Panel debate</i>) (<i>Confirmed speakers/moderators: Enrique Bernal-Delgado, Nick Marly, Talita Duarte-Salles, Patrick Ryan, Dipak Kalra</i>)
17:10 – 17:30	Closing remarks (<i>Speakers: Liesbet M. Peeters & Peter Rijnbeek</i>)

Agenda Saturday July 5, 2025

Time	Activity	Track 1A – Newcomers	Track 1B – Newcomers	Track 2 – Advanced	Track 3 – NN/WG
09:30 – 10:00		Registration + coffee			
10:00 – 12:30	Morning Session	Introduction to OHDSI – Tutorial Lead: Renske Los, Aniek Markus & Laura Verbeij (Erasmus MC) Overview of OHDSI, key concepts, and an introduction to the OMOP Common Data Model			HADES hack-a-thon Lead: Martijn Schuermie (J&J), Adam Black (Erasmus MC), Anthony Sena (Janssen R&D) Hands-on coding and tool development in HADES
12:30 – 13:30		Lunch break			
13:30 – 15:00	Afternoon Session I	OMOP CDM & ETL Conventions Lead: Maxim Mainat (Erasmus MC), Sofia Bazakou & Anne van Winzum (The Hyve)	OHDSI Standardized Vocabularies for Research – Part 1.1 Lead: Anna Ostropelets (Janssen R&D), Polina Talapova (Sciforce), Vlad Korsik & Oleg Zhuk (Odysseus) Concept sets & patient identification techniques.		
15:00 – 15:30		Coffee Break			
15:30 – 17:00	Afternoon Session II		OHDSI Standardized Vocabularies for Research – Part 1.2 Lead: Anna Ostropelets (Janssen R&D), Polina Talapova (Sciforce), Vlad Korsik & Oleg Zhuk (Odysseus) Concept sets & patient identification techniques.		
17:15 – 18:45*		*Optional – guided city tour Hasselt (with local specialties)			

Agenda Sunday July 6, 2025

Time	Activity	Track 1A – Newcomers	Track 1B – Newcomers	Track 2 – Advanced	Track 3 – NN/WG
09:30 – 10:00		Registration + coffee			
10:00 – 12:30	Morning Session		OHDSI Standardized Vocabularies for Research – Part 2 Lead: Anna Ostropelets (Janssen R&D), Polina Talapova (Sciforce), Vlad Korsik & Oleg Zhuk (Odysseus) Final discussion & application of concept sets.	NN All Actors Meet Parallel NN meetings	
12:30 – 13:30		Data Partners Lunch Break			
13:30 – 15:00	Afternoon Session I	Whirlwind introduction to Open-Source Analytic Tools – Part 1 Lead: Martijn Schuermie (J&J), Adam Black (Erasmus MC), Anthony Sena (Janssen R&D) Overview of HADES and other key OHDSI tools for analysis.		Running characterisation studies from beginning to end: a tutorial using DARWIN EU standardised analytics – Part 1 Lead: Daniel Prieto-Alhambra (Oxford University)	NN All Actors Meet Parallel NN meetings
15:00 – 15:30		Coffee Break			
15:30 – 17:00	Afternoon Session II	Whirlwind introduction to Open-Source Analytic Tools – Part 2 Lead: Martijn Schuermie (J&J), Adam Black (Erasmus MC), Anthony Sena (Janssen R&D) Overview of HADES and other key OHDSI tools for analysis.		Running characterisation studies from beginning to end: a tutorial using DARWIN EU standardised analytics – Part 2 Lead: Daniel Prieto-Alhambra (Oxford University)	OHDSI Europe NN leads meet Lead: Renske Los (only NN leads/managers)
17:00 – 18:00*		*Optional - networking drink			



#OHDSISocialShowcase This Week

Monday

Characterizing Asian and Pacific Islander Veterans and Veterans Living Outside the United States

(**Scott L DuVall**, Patrick R Alba, Qiwei Gan, Elizabeth E Hanchrow, Mengke Hu, Gregorio Coronado, Kalani Raphael, Andy Subica, Curtis Lowery, Scott Hofer, Vicki Shambaugh, Benjamin Viernes)



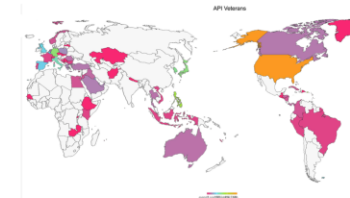
Characterizing Asian and Pacific Islander Veterans and Veterans Living Outside the United States

Scott L DuVall^{1,2}, Patrick R Alba^{1,2}, Qiwei Gan^{1,2}, Elizabeth E Hanchrow¹, Mengke Hu^{1,2}, Gregorio Coronado^{1,3}, Andy Subica¹, Curtis Lowery¹, Scott Hofer^{1,4}, Vicki Shambaugh^{1,4}, Kalani Raphael^{1,3}, Benjamin Viernes^{1,3}

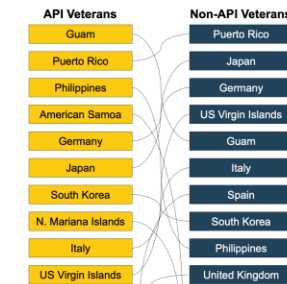
1 – VA Salt Lake City Health Care System, Salt Lake City, UT, USA
2 – Department of Internal Medicine, University of Utah Medical School, Salt Lake City, UT, USA
3 – Center for Pacific Islander Veterans Health, VA Pacific Islands Healthcare System, Honolulu, HI, USA
4 – Pacific Health Research and Education Institute, Honolulu, HI, USA

Background

- The United States (U.S.) Department of Veterans Affairs (VA) is the largest integrated provider of health care and mental health services in the U.S.
- VA provides services to military Veterans, so it reflects the demographics of those who served in the U.S. armed forces.
- This population includes increasing representation from groups historically underrepresented in the U.S., such as Asian and Pacific Islanders (API).
- Qualifying Veterans living outside the U.S. can also receive care, but there are unique and sometimes substantial challenges accessing VA benefits.¹
- A recent U.S. law permits VA to expand telehealth, work with community health centers, ship medications, and reimburse travel for care.^{2,3}
- This study seeks to compare API vs non-API Veterans and describe where these Veterans live at home and abroad.

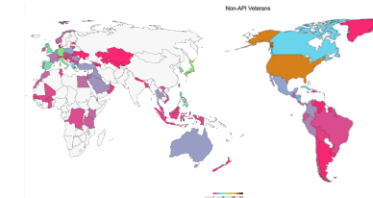


Most common locations for Veterans abroad



Methods

- Veterans were excluded if a race determination could not be made and if they had at least one visit recorded in a VA facility.
- Determination of API was made using a combination of structured records and clinical text using natural language processing.⁴ This additional demographic data was combined with other VA data transformed into the OMOP Common Data Model v5.3.
- When country of residence could not be determined, the country of the assigned care location was used.
- A common practice for Veterans living abroad is to use military post offices, which use local postage to deliver to an assigned PO box within the U.S. that is forwarded on to a military base or other facility abroad. These addresses were mapped to the most granular country.



Results

- 18,277,162 Veterans had at least one visit at a VA facility.
- 5,061,651 (29.1%) had an unknown race and were excluded.
- 53,654 (4.7%) were classified by the algorithm to be API.
- API Veterans on average are younger, have more female Veterans (which also tracks with a younger population), and have similar observation time than their non-API counterparts.
- API Veterans in general have lower average utilization than on-API Veterans, ranging from 6.3% fewer visits to 27.4% fewer medication instances.
- Almost twice the proportion of API Veterans live outside the U.S. (2.0% vs 1.1%) and almost ten-fold the proportion living abroad live in the APAC region (70.8% vs 7.3%) compared to non-API Veterans.

Demographics	API Veterans	Non-API Veterans
N	85,654	12,361,857
Age: mean (SD)	52.7 (16.7) years	67.1 (18.3) years
Female: n (%)	107,007 (12.5%)	1,235,481 (10.0%)
Observation Time: mean (SD)	12.3 (7.8) years	12.4 (8.0) years
VA Utilization		
Number of Visits: mean (SD)	136.2 (263.0)	149.7 (263.7)
Number of Dispensing Instances: mean (SD)	284.5 (415.4)	247.4 (415.4)
Number of Measurement Instances: mean (SD)	1097.0 (1793.4)	1484.4 (1988.0)
Number of Procedure Instances: mean (SD)	144.1 (268.6)	153.4 (271.8)
Number of Medication Instances: mean (SD)	341.3 (1456.3)	468.9 (1613.9)

Location	API Veterans	Non-API Veterans
Non-U.S.: n (%)	17,003 (2.0%)	138,907 (1.1%)
API: n (%)	12,030 (15.0% of non-U.S.)	9,717 (7.0% of non-U.S.)
Guam: n (%)	5,899 (49.8% of API)	1,856 (19.6% of API)
Philippines: n (%)	2,401 (20.7% of API)	703 (7.4% of API)
American Samoa: n (%)	1,388 (11.5% of API)	110 (1.1% of API)
Japan: n (%)	771 (6.4% of API)	5,064 (53.9% of API)
AE: n (%)	1,453 (12.1% of non-U.S.)	6,388 (4.6% of non-U.S.)
Germany: n (%)	909 (7.6% of API)	3,353 (37.2% of API)
Italy: n (%)	292 (2.4% of API)	1,835 (20.5% of API)
Spain: n (%)	75 (0.6% of API)	255 (2.8% of API)
United Kingdom: n (%)	49 (0.4% of API)	691 (7.4% of API)
AE: n (%)	3,509 (28.4% of non-U.S.)	115,782 (86.4% of non-U.S.)
Puerto Rico: n (%)	3,382 (20.4% of API)	112,235 (86.9% of API)
US Virgin Islands: n (%)	86 (0.7% of API)	3,110 (2.3% of API)
Colombia: n (%)	10 (0.1% of API)	170 (0.1% of API)
Other non-U.S.: n (%)	<10 (<0.1% of non-U.S.)	50 (<0.4% of non-U.S.)
U.S.: n (%)	827,809 (97.0%)	12,217,854 (98.9%)
California: n (%)	109,080 (13.2% of U.S.)	870,583 (7.1% of U.S.)
Texas: n (%)	87,458 (10.6% of U.S.)	1,005,170 (8.2% of U.S.)
Florida: n (%)	58,706 (7.1% of U.S.)	1,105,581 (9.1% of U.S.)
Unlabeled: n (%)	6,722 (0.8%)	16,096 (0.1%)

Contact: Scott.DuVall@va.gov



#OHDSISocialShowcase This Week

Tuesday

Challenges in Conducting Federated Analysis in CyberOncology Project in Japan

(**Shigemi Matsumoto**, Kosuke Tanaka, Liying Pei, Masafumi Okada, Manabu Muto)



Challenges in Conducting Federated Analysis in CyberOncology Project in Japan

Shigemi Matsumoto¹, Kosuke Tanaka¹, Pei Liying², Masafumi Okada³, Manabu Muto²

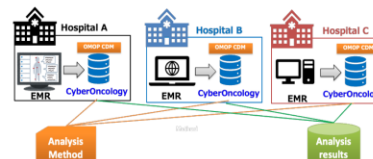
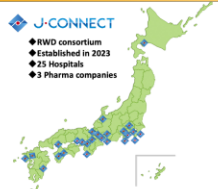
1. Department of Real World Data R & D, Graduate School of Medicine, Kyoto University
2. Department of Medical Oncology, Graduate School of Medicine, Kyoto University
3. Prime Research Institute for Medical RWD, Inc.



Background

There is a growing demand for the development of frameworks to generate Real World Evidence (RWE) using Real World Data (RWD)¹. In recent years, in the field of precision medicine, particularly in oncology, data on patient backgrounds and treatments, and genomic information, including patient-specific biomarkers, have become critical. Additionally, outcomes related to efficacy, safety, and prognosis are indispensable. However, in real-world database research in oncology, there is a strong need to enhance the quality and transparency of RWD sources².

In Japan, there are multiple electronic medical record (EMR) vendors, and customization is common in hospitals. This has posed significant challenges for collecting outcome data, particularly concerning efficacy and safety, which are crucial in oncology. Furthermore, the efficient collection and analysis of RWD from multi-institutional EMRs face various regulatory and ethical challenges, including compliance with the Personal Information Protection Act and ethical guidelines.



To address these challenges, we developed **CyberOncology**, a structured input support tool for EMRs. Through templated input system, this tool allows for standardized data collection across institutions, independent of the EMR vendor, enabling the creation of unified databases and the extraction of statistical insights. Additionally, since April 2023, we have established the **J-CONNECT Consortium**, comprising of 25 institutions nationwide that have adopted CyberOncology. To streamline database creation within CyberOncology, we have integrated cancer registry data from each institution and applied advanced algorithms to ensure comprehensive RWD collection.

Method

Mapping strategy

Description	CyberOncology Table	Vocabulary used in CO	OMOP CDM v5.4	CDM vocabulary
Patient demographics	episode	person	person	person
Adverse events (begin - end dates)	reaction	observation_period	observation_period	observation_period
Last visit date	episode	visit_occurrence	visit_occurrence	visit_occurrence
Cancer diagnosis	cancer	ICD-O-3	condition_occurrence	ICD-O-3
Prescriptions / Injection	prescription, injection	YJ Code	drug_exposure	ATC
Laboratory data	laboratory	CTCAE	measurement	LOINC
Adverse events	reaction	CTCAE	observation	MedDRA
Biomarker	biomarker	(Text)	measurement	LOINC
Outcome	outcome		death	

CyberOncology is a structured oncology database integrated with electronic medical records (EMRs), with the definitions of each table outlined in the Mapping Strategy. Additionally, the data structure is designed to be both compatible with the similar to the OMOP Common Data Model (OMOP CDM). The CDM vocabulary is defined as specified in the corresponding documentation.

The following is an example of a CTCAE transformation recorded in CyberOncology. The variables and vocabulary associated with a case of Grade 3 anemia (Hb 7.0 g/dL) diagnosed on February 15, 2021, and resolved on February 28, 2021, are shown in the table on the right.

CDM table	Variable	Value	Concept name	Vocabulary
observation	observation_concept_id	35122651	Anemia	MedDRA
observation	observation_date	2021-02-15		
observation	qualifier_concept_id	4309261	Grade 3 on a scale of 0 to 5	SNOMED
observation_preid	observation_period_start_date	2021-02-15		
observation_preid	observation_period_end_date	2021-02-28		
observation_preid	period_type_concept_id	32817	EHR	Type Concept
measurement	measurement_concept_id	3000963	Hemoglobin [Mass/volume] in Blood	LOINC
measurement	measurement_date	2021-02-15		
measurement	measurement_type_concept_id	32856	Lab	Type Concept
measurement	value_as_number	7		
measurement	unit_concept_id	8713	gram per deciliter	UCUM

Summary

We initiated a project to develop a federated analysis platform for the 25 member institutions of the J-CONNECT consortium by transforming CyberOncology, a structured tool integrated with electronic medical records (EMRs), into the OMOP Common Data Model (OMOP CDM). The platform is expected to become fully operational for analysis by April 2025.

References

1. Concato J, Corrigan-Curay J. Real-World Evidence -Where Are We Now? New Engl J Med 2022;386:1680-1682.
2. Ramsey SD, Onar-Thomas A, Wheeler SB. Real-World Database Studies in Oncology: A Call for Standards. J Clin Oncol 2024;42(9).



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#OHDSISocialShowcase This Week

Wednesday

From dbt to SQLMesh: Enhancing OMOP CDM Data Conversion Efficiency

(Nongnaphat Wongpiyachai, Chinapat Onprasert, Sornchai Manosorn, Natthawut Adulyanukosol)



From dbt to SQLMesh: Enhancing OMOP CDM Data Conversion Efficiency

Presenter: Nongnaphat Wongpiyachai
Chinapat Onprasert, Sornchai Manosorn, Natthawut Adulyanukosol

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Siriraj Informatics and
Data Innovation Center



1. Background

- Converting to the OMOP Common Data Model (CDM) requires a robust ETL pipeline to standardize diverse data sources.
- While widely used for OMOP CDM conversions, also showcased by Siriraj Hospital at the OHDSI Global Symposium 2022 [1], *dbt faces challenges* with data consistency and collaboration in large-scale transformations.
- “SQLMesh”, an open-source tool developed by Tobiko Data, Inc., offers a more efficient and reliable solution for managing the OMOP CDM conversion pipeline, addressing key limitations of dbt.

3. Results

1. **SQL Translation:** SQLMesh uses SQLGlot [6] to parse SQL queries, detect syntax errors at compile time, and optimize performance. It enables query reuse across multiple database dialects.
2. **Column-Level Lineage:** Tracks data flow and transformations at the column level, enhancing traceability.
3. **Environment Management:** Generates isolated schemas for data transformations, ensuring consistency before deployment. Supports multiple testing and development environments.
4. **Incremental Loading:** Loads only new or updated data, reducing processing time and cost for large datasets.
5. **Data Validation:** Offers tools for audits and unit tests to ensure accuracy and block flawed data from production.
6. **Versioning:** Tracks data changes, supports rollbacks, and ensures traceability alongside source code version control.

Feature	Custom scripts SQL/Python	dbt	SQLMesh
Language	SQL, Python	SQL, Jinja	SQL, Python, Jinja
Platform Support	Any	Multiple databases	Multiple databases with SQL translation
Data Lineage	Manual tracking	Table-level	Column-level
Change Management	Manual	Schema contracts	Automatic schema and data contracts
Testing Framework	Custom	Built-in (including unit tests)	Built-in (including unit tests)
Scalability	Depends on implementation	Can be costly for large datasets	Efficient for large datasets
Cost	No licensing costs	Open-source (paid options available)	Open-source (paid options available)
Community & Ecosystem	N/A	Large, active community	Smaller, growing community

Table 1: Side-by-side comparison of data transformation tools

SQLMesh: Streamlining OMOP CDM Conversion
SQLMesh has optimized data transformation at Siriraj Hospital, boosting efficiency and reliability. This transition standardizes data for research while offering developers enhanced tools.

References

- [1] Nongnaphat Wongpiyachai et al. dbt: A Data Build Tool. In: OHDSI Global Symposium 2022. 2022.
- [2] Nongnaphat Wongpiyachai et al. dbt: A Data Build Tool. In: OHDSI Global Symposium 2022. 2022.
- [3] Nongnaphat Wongpiyachai et al. dbt: A Data Build Tool. In: OHDSI Global Symposium 2022. 2022.
- [4] Nongnaphat Wongpiyachai et al. dbt: A Data Build Tool. In: OHDSI Global Symposium 2022. 2022.
- [5] Nongnaphat Wongpiyachai et al. dbt: A Data Build Tool. In: OHDSI Global Symposium 2022. 2022.
- [6] Nongnaphat Wongpiyachai et al. dbt: A Data Build Tool. In: OHDSI Global Symposium 2022. 2022.

2. Methods

Siriraj Hospital has transitioned to SQLMesh, enhancing the efficiency and reliability of its data transformation processes (see Figure 1).

1. **Pipeline Overview:** Relevant data is pulled from hospital's diverse databases, incorporating OHDSI standardized vocabularies and DDLs necessary for transformation.
2. **Mapping and Transformation:** SQLMesh simplifies this process by allowing the separation of plans within the pipeline to target specific tasks.
3. **Quality Assurance and Validation:** Rigorous checks ensure accuracy and consistency, version control and tracking enhance reproducibility and traceability.
4. **Deployment:** Once data passes quality checks, it is integrated into the production environment for research and analysis. SQLMesh orchestrates the entire process efficiently.

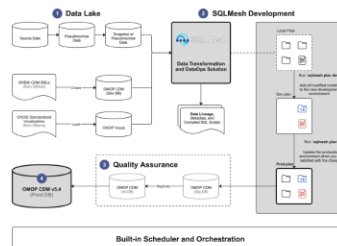


Figure 1: Overview of the OMOP CDM Conversion Pipeline at Siriraj Hospital



Figure 2: Visualization of data lineage automatically generated by SQLMesh

```
MODEL:
  name: omop_atc_persons, -- Base of the model
  kind: VIEW,
  schema: omop,
  refresh: 1,
  columns: (
    PERSON_ID,
    PERSON_NAME,
    PERSON_ADDRESS,
    PERSON_CITY,
    PERSON_STATE,
    PERSON_COUNTRY,
    PERSON_ZIP,
    PERSON_PHONE,
    PERSON_EMAIL,
    PERSON_GENDER,
    PERSON_RACE,
    PERSON_ETHNICITY,
    PERSON_RELIGION,
    PERSON_OCCUPATION,
    PERSON_EDUCATION,
    PERSON_MARITAL_STATUS,
    PERSON_LAST_UPDATED
  ),
  sql:
    SELECT * FROM omop_atc_persons
```

Figure 3: Illustration of SQLMesh Model Configuration





#OHDSISocialShowcase This Week

Thursday

Applying the OMOP Common Data Model to Facilitate Benefit-Risk Assessments of Medicinal Products Using Real-World Data from Singapore and South Korea

(**Hui Xing Tan**, Desmond Chun Hwee Teo, Dongyun Lee, Chungsoo Kim, Jing Wei Neo, Cynthia Sung, Haroun Chahed, Pei San Ang, Doreen Su Yin Ta⁵, Rae Woong Park, Sreemanee Raaj Dorajoo)

Applying the OMOP Common Data Model to Facilitate Benefit-Risk Assessments of Medicinal Products Using Real-World Data from Singapore and South Korea

HX Tan^{1*}, DCH Teo^{2*}, D Lee³, C Kim⁴, JW Neo¹, C Sung^{1,4}, H Chahed¹, PS Ang¹, DSY Tan⁵, RW Park^{2,3}, SR Dorajoo¹



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² Department of Biomedical Informatics, Ajou University School of Medicine, Suwon, South Korea
³ Department of Biomedical Sciences, Graduate School of Medicine, Ajou University, Suwon, South Korea
⁴ Health Services and Systems Research, Duke-NUS Medical School, Singapore
⁵ Department of Pharmacy, Khoo Teck Puat Hospital, Singapore



INTRODUCTION

The changing regulatory landscape of health products has led to an increasing interest in incorporating real-world evidence (RWE) for regulatory decision-making. Using a common data model (CDM) may address the challenges encountered in using multiple databases for evidence generation, such as those arising from the use of disparate data coding standards, database architectures, and vocabularies.

OBJECTIVES

- To characterize the benefits of converting Electronic Medical Records (EMRs) to a common data model (CDM).
- To assess the potential of using CDM-converted data to rapidly generate insights for benefit-risk assessments - based on a case study of atrial fibrillation patients newly started on oral anticoagulation from two databases in Singapore and South Korea - to enhance post-market regulatory evaluations and decisions.

METHODOLOGY

Mapping of EMRs to OMOP-CDM schema (Singapore), and use of existing OMOP-converted data (South Korea)

We used EMR data originating from a tertiary acute care hospital in Singapore, comprising information on 260,000 unique patients who visited the hospital between January 2013 and December 2016, and mapped it to the OMOP-CDM version 5.3.0 format.

Existing OMOP-converted data from Ajou Medical Center (AUMC) containing information on about 2,700,000 unique patients who visited the hospital between January 1994 and December 2020 was enlisted for external validation of subsequent analyses of OMOP-converted data

Illustrative analysis following CDM Conversion

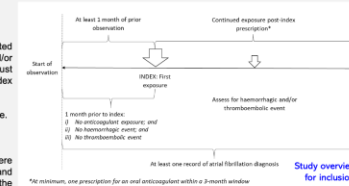
Sample cohort assembly

We identified patients diagnosed with atrial fibrillation (AF) who were newly started with oral anticoagulants (OAC). Patients must not have had any prior bleeding and/or thromboembolic events for at least 1 month before date of initiation of OAC, and must have had at least one OAC dispensing record in the 3 months following index exposure in an inpatient or outpatient setting to be included.

Patients were followed for at least three months after the date of first OAC exposure.

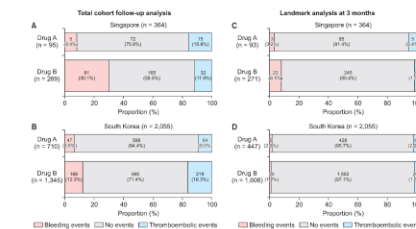
Visualizing comparative safety, effectiveness, and utilization

Existing analytic codes used in a prior OMOP-CDM study by Hripcsak et al [1] were modified to conduct an illustrative analysis of OAC used for AF in Singapore and South Korea, representing the comparative effectiveness, safety and utilization of the drug.



RESULTS & DISCUSSION

Over 90% of records from the original tables in Singapore were mapped over to the CDM, except for dispensing records which included many non-drug items. There were 364 patients from Singapore and 2,055 patients from South Korea who fulfilled the inclusion/exclusion criteria for the illustrative analysis. Most patients were warfarin users (Singapore: n=269 [73.9%], South Korea: n=1,345 [65.4%]).



Illustrative analysis

100%, horizontally stacked, bar charts for the total study period and at 3-month time-point. Bar thickness represents study sample size while the pink and blue regions represent safety and lack of effectiveness, respectively. The grey central region represents the event-free proportion not experiencing any undesirable events.

In both settings, the landmark analysis at 3 months reveals a fairer comparison of the drugs. (A => C, B => D) and show that the unadjusted differences between drugs are far less pronounced.

Baseline characteristics of cohorts

	Warfarin		Rivaroxaban	
	Singapore	South Korea	Singapore	South Korea
Number of patients	269 (73.9)	1,345 (65.4)	95 (26.1)	710 (34.5)
Age (yr)	70 (19)	68 (17)	71 (19)	69 (14)
Sex				
Male	142 (52.7)	854 (63.5)	44 (46.3)	398 (56.1)
Female	127 (47.2)	491 (36.5)	51 (53.7)	312 (43.9)
Race				
Korean	-	1,345 (100)	-	710 (100)
Chinese	163 (60.6)	-	66 (69.6)	-
Malay	66 (24.5)	-	20 (21.1)	-
Indian	20 (7.4)	-	5 (5.3)	-
Others	20 (7.4)	-	4 (4.2)	-

Values are presented as number(%); for age, the median (interquartile range) are used

Discussion

CDM conversion alters only the form, but not the substance of the data. This underscores the need to understand the provenance and processes that generated the data. Conversion can speed up analyses, although some modifications and extensions to previously written code are likely required for specific use cases.

The cohorts from the two countries used were demographically different, which could introduce alternative explanations for the study findings. The proposed bar graphs remain an unadjusted descriptive analysis of the rate of events in different populations exposed to comparator agents. Incorporating methods to adjust for confounders and visualize the adjusted event rates would be important areas of future research.

CONCLUSION

While the structure of the OMOP-CDM and its accessory tools facilitate real-world data analysis, extending them to fulfil regulatory analytic purposes in the post-market setting, such as benefit-risk assessments, may require layering on additional analytic tools and visualisation techniques.

ACKNOWLEDGEMENT

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REFERENCES

- [1] Hripcsak G, Ryan PB, Duke JD, Shah NH, Park RW, Huser V, et al. Characterizing treatment pathways at scale using the OHDSI network. *Proc Natl Acad Sci USA* 2016;113(27):7529-36.



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Friday

Protective Effects of SGLT2 Inhibitors on Cardiovascular-Kidney-Metabolic (CKM) Syndrome Progression in Type 2 Diabetes with Chronic Kidney Disease: A Multi-Center Data Analysis Using OMOP-CDM

(**Nguyen Phung-Anh**, Christianus Heru Setiawan, Ching-Wen Chiu, Phan Thanh-Phuc, Jason C. Hsu)



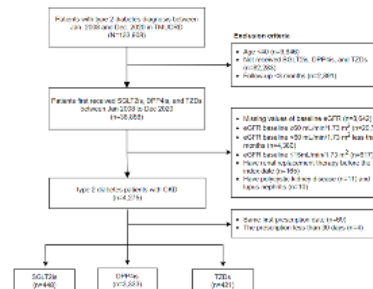
SGLT2 Inhibitors Mitigate Renal Decline and Cardiovascular Events in T2D Patients with CKD, Slowing CKM Syndrome Progression

Protective Effects of SGLT2 Inhibitors on Cardiovascular-Kidney-Metabolic (CKM) Syndrome Progression in Type 2 Diabetes with Chronic Kidney Disease: A Multi-Center Data Analysis Using OMOP-CDM

Background: This study aims to evaluate the protective effects of sodium-glucose co-transporter 2 inhibitors (SGLT2is) on renal and cardiovascular events in type 2 diabetes (T2D) patients with chronic kidney disease (CKD) within the context of Cardiovascular-Kidney-Metabolic (CKM) Syndrome. Specifically, we assess whether SGLT2is can reduce the progression of renal dysfunction and cardiovascular risks, providing real-world insights using multi-center clinical data.

Methods: We conducted a retrospective cohort study using the OMOP-common data model (CDM) with data sourced from the Taipei Medical University Clinical Research Database (TMUCRD) across three hospitals: Taipei Medical University Hospital, Wanfang Hospital, and Shuang Ho Hospital. The study included patients with T2D and CKD who received antidiabetic medications between 2008 and 2020. Propensity score matching was used to balance patient characteristics across SGLT2is, dipeptidyl peptidase-4 inhibitors (DPP4is), and thiazolidinediones (TZDs) groups. A total of 5,005 patients were included, with 524 in the SGLT2is group. Primary outcomes were renal function markers (e.g., sustained $\geq 50\%$ eGFR reduction, eGFR ≤ 15 mL/min/1.73 m², and initiation of kidney replacement therapy [KRT]), and the incidence of 4-point major adverse cardiovascular events (4P-MACE).

Figure 1: Cohort Selection Process



Results : The SGLT2is group exhibited significantly lower rates of renal function decline, with an adjusted hazard ratio (HR) of 0.49 (95% CI: 0.29-0.82) for a $\geq 50\%$ reduction in eGFR, and an HR of 0.41 (95% CI: 0.22-0.77) for eGFR ≤ 15 mL/min/1.73 m², compared to the DPP4is and TZDs groups. Additionally, the incidence of 4P-MACE was significantly reduced in the SGLT2is group (HR: 0.65, 95% CI: 0.47-0.90), including a notable reduction in cardiovascular deaths (HR: 0.37, 95% CI: 0.21-0.65) compared to both DPP4is and TZDs. Subgroup analyses indicated that male patients with pre-existing heart disease particularly benefited from SGLT2is (HR: 0.38, 95% CI: 0.15-0.97).

Conclusion : The use of SGLT2is in T2D patients with CKD significantly mitigates both renal function decline and cardiovascular events, supporting their efficacy in slowing the progression of CKM Syndrome. These findings, based on real-world clinical data from multiple centers, highlight SGLT2is as a valuable therapeutic option for reducing the burden of renal and cardiovascular complications in this high-risk population. This study is expected to be developed into a multinational cooperative research using OHDSI tools and OMOP CDM in the future.

Figure 2: 4P-MACE Outcomes in Patients with SGLT2i or Other Hypoglycemic Agents in Propensity-matched Cohort (1:4)



	Events No.	Participant years of follow up	Incidence rate (Events/100 participant)	Cox model Hazard ratio (95% CI)	P-value	Adjusted model* Hazard ratio (95% CI)	P-value
4P-MACE							
SGLT2i	47	1817	8.0				
vs. non-SGLT2i	274	11435	12.1	0.65 (0.47, 0.90)	0.010	0.68 (0.49, 0.95)	0.024
SGLT2i	42	2842	8.0				
vs. DPP4i	253	11430	12.1	0.65 (0.47, 0.91)	0.012	0.72 (0.52, 1.00)	0.053
SGLT2i	36	1813	11.1				
vs. TZD	40	1136	14.0	0.77 (0.41, 1.45)	0.008	0.76 (0.51, 1.10)	0.017

*Adjusted for age, duration of type 2 DM, Charlson Comorbidity Index (CCI), and eGFR.

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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?





June 10: ATLAS Deepdive

Data Sources and Vocabularies



Christopher Knoll

Director, Observational Health Data Analytics
Janssen Research and Development

Join us
throughout June to help
create the roadmap for
ATLAS!



Week 2 ATLAS Survey



**These weekly surveys
will help us build future
versions of ATLAS!**

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from you!**



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

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