2026 Global Symposium Software Demos

OHDSI Community Call
Nov. 24, 2026 • 11 am ET

OHDSI
OBSERVATIONAL HEALTH DATA SCIENCES AND INFORMATICS

Upcoming Community Calls

Date	Topic
Nov. 24	Software Demos
Dec. 1	OHDSI/OMOP Research Spotlight
Dec. 8	How Did OHDSI Do This Year?
Dec. 15	Holiday-Themed Farewell to 2026
Dec. 22	NO CALL – Holiday Break

Three Stages of The Journey

Where Have We Been?

Where Are We Now?

Where Are We Going?

OHDSI Shoutouts!

Congratulations to the team of **Gianluca Fabiano, Njoki Njuki, Antonella Delmestri, and Rafael Pinedo-Villanueva** on the recent publication of **Validation of Primary and Hospital Care Resource Use and Cost Estimates in OMOP-mapped vs Source Healthcare Administrative Datasets** in *Value in Health*.



ELSEVIER

Value in Health

Available online 17 November 2026

In Press, Journal Pre-proof What's this?

Validation of Primary and Hospital Care Resource Use and Cost Estimates in OMOP-mapped vs Source Healthcare Administrative Datasets

Gianluca Fabiano PhD [1], Njoki Njuki BSc [1], Antonella Delmestri PhD [1], Rafael Pinedo-Villanueva PhD [1]

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Highlights

- Analysis of healthcare data mapped to the Observational Medical Outcomes Partnership (OMOP) Common Data Model (CDM) is widely used in pharmacoepidemiology, but its application in health economics is limited, with uncertainty regarding the concordance of resource use and cost estimates against source data.
- We show that resource use and cost estimates derived from OMOP-mapped data are broadly concordant with the source CPRD Aurum–HES data; we identify where discrepancies lie, their root causes and strategies to minimise them.

OHDSI Shoutouts!

Congratulations to the team of **Najat Lechhab and Najib Al Idrissi** on the recent publication of **Fast Healthcare Interoperability Resources and Observational Medical Outcomes Partnership Integration for Health Data Interoperability in Belgium: Mixed Methods Study** in the *Online Journal of Public Health Informatics*.



Original Paper

Fast Healthcare Interoperability Resources and Observational Medical Outcomes Partnership Integration for Health Data Interoperability in Belgium: Mixed Methods Study

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Abstract

Background: Managing health information is one of the greatest challenges in modern health care. In Belgium, decentralization and fragmentation further complicate interoperability. Primary data, collected through electronic health records, and secondary data, used for research and policy, require distinct approaches. Fast Healthcare Interoperability Resources (FHIR) enables real-time clinical data exchange, while the Observational Medical Outcomes Partnership (OMOP) model standardizes heterogeneous datasets for large-scale analysis.

Objective: The goal of this study was to assess the strengths, weaknesses, and feasibility of using FHIR and OMOP together in the context of Belgian health care to identify barriers and opportunities for their combined use.

Methods: To answer the research questions, a mixed methods approach was used (using both qualitative and quantitative methods). This included an analysis of FHIR and OMOP technical documentation and technical literature as well as semistructured interviews with 8 research experts drawn from 3 professional backgrounds, including health data governance, clinical practice, and biomedical research.

OHDSI Shoutouts!

Congratulations to the team of **Brendon Wang, Irene Wang, Andrew Chen, and Mark Lambrechts** on the recent publication of **Association of objectively measured physical activity with incident spinal stenosis in a Fitbit-linked cohort from the All of Us Research Program** in the *Journal of Clinical Neuroscience*.

Journal of Clinical Neuroscience 156 (2027) 112397

Contents lists available at ScienceDirect

Journal of Clinical Neuroscience

journal homepage: www.journals.elsevier.com/journal-of-clinical-neuroscience

Association of objectively measured physical activity with incident spinal stenosis in a Fitbit-linked cohort from the All of Us Research Program

Brendon Wang [a,*], Irene Wang [b], Andrew Chen [c], Mark Lambrechts [d]

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ARTICLE INFO

Keywords:
Spinal stenosis
Cervical spinal stenosis
Lumbar spinal stenosis
Physical activity
Step count
Fitbit

ABSTRACT

Background: Physical activity is associated with numerous health benefits, but its relationship with the development of spinal stenosis remains unclear. We evaluated whether objectively measured physical activity using consumer wearable devices is associated with incident spinal stenosis.
Methods: We conducted a retrospective cohort study using prospectively collected wearable and electronic health record data from the NIH All of Us Research Program. Adults with at least 6 months of qualifying Fitbit data linked to electronic health records were followed from the end of their sixth qualifying month. Physical activity was quantified using monthly mean daily step counts and minutes of fairly and very active activity. Incident spinal stenosis, cervical stenosis, and lumbar stenosis were identified using standardized SNOMED concepts mapped to the OMOP Common Data Model. Time-varying Cox proportional hazards models with physical activity lagged by 12 months estimated hazard ratios (HRs) for the 75th versus 25th percentile of exposure, adjusted for age, sex, body mass index, education, race, smoking, diabetes, osteoarthritis, hypertension, prior spine pain, comorbidity burden, and health care use, with multiple imputation for missing covariates.
Results: Among 48,709 participants free of spinal stenosis at baseline, 1,494 developed spinal stenosis during 161,900 person-years of follow-up (median 3.42 years), including 640 cervical and 982 lumbar cases. Participants at the 75th percentile of daily steps had a lower hazard of spinal stenosis than those at the 25th percentile (HR 0.84, 95% CI 0.77–0.92). Estimates were similar for cervical stenosis (HR 0.81, 95% CI 0.71–0.92) and lumbar stenosis (HR 0.85, 95% CI 0.77–0.95), and formal tests found no difference between the two. Very active minutes were associated with a lower hazard of any and cervical stenosis (HR 0.89, 95% CI 0.83–0.96, and HR 0.84, 95% CI 0.74–0.94) but not, after adjustment for multiple testing, lumbar stenosis (HR 0.91, 95% CI 0.84–1.00). Fairly active minutes were not associated with stenosis, and we found no evidence of nonlinear dose–response relationships. The association of steps with lumbar stenosis weakened to the null with a 36-month lag, and the association with cervical stenosis was not confirmed under a stricter case definition.
Conclusions: Higher daily step counts were associated with a lower hazard of coded spinal stenosis, with similar associations for cervical and lumbar disease. The associations were modest, and reverse causation, outcome misclassification, and unmeasured confounding could explain part or all of them.
LOE: III.

OHDSI Shoutouts!

Congratulations to the team of **Yiju Park, Jinwoo Yoon, Aleh Zhuk, Anna Ostropolets, and Seng Chan You** on the recent publication of **Integrating Local Vocabulary into the Observational Medical Outcomes Partnership Common Data Model: A Step-by-Step Tutorial** in *Healthcare Informatics Research*.

Tutorial

Healthc Inform Res. 2026 October;32(4):398-403.
https://doi.org/10.4258/hir.2026.32.4.398
pISSN 2093-3681 • eISSN 2093-369X

HIR
Healthcare Informatics Research

Integrating Local Vocabulary into the Observational Medical Outcomes Partnership Common Data Model: A Step-by-Step Tutorial

Yiju Park[1,2], Jinwoo Yoon[3], Aleh Zhuk[4], Anna Ostropolets[5,6], Seng Chan You[1,2,7]

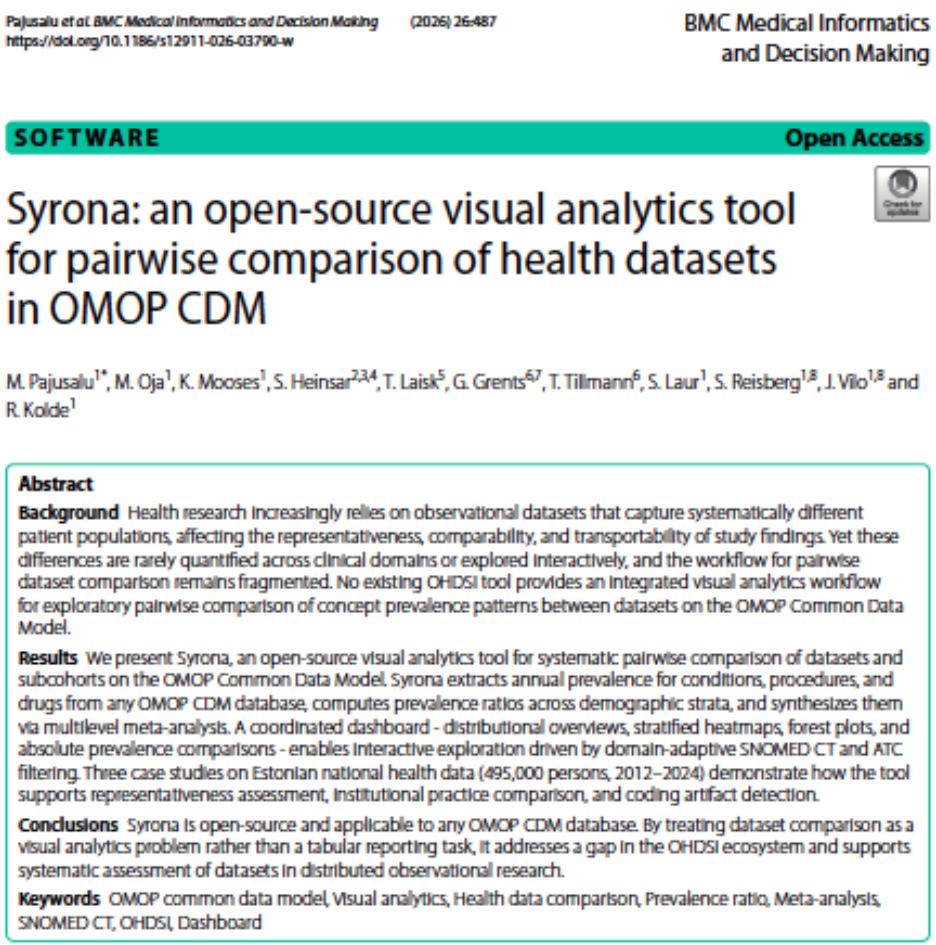
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Objectives: This tutorial offers healthcare informatics researchers a practical guide to integrating local vocabularies into the Observational Health Data Sciences and Informatics (OHDSI) Standardized Vocabularies, using Korean Electronic Data Interchange (EDI) codes as an example. **Methods:** We present a four-stage guide to local vocabulary integration: establishing a comprehensive, continuous system to collect longitudinal EDI codes from November 2000 to May 2024; mapping the codes to the OHDSI Standardized Vocabularies; validating and integrating them through the OHDSI Community Contribution Pipeline; and publishing them on Athena, the official OHDSI vocabulary website. **Results:** Researchers can use this tutorial to integrate local vocabularies into the OHDSI Vocabularies. Of 620,646 EDI codes collected, we integrated 437,807 (70.5%) into the OHDSI Vocabularies and mapped 376,111 (85.9%) of the integrated codes to standard concepts. The integrated vocabulary met all Community Contribution Pipeline requirements and was published on the official OHDSI vocabulary website in September 2024. **Conclusions:** This tutorial provides practical guidance on vocabulary standardization to help healthcare informatics researchers integrate local healthcare data into the Observational Medical Outcomes Partnership Common Data Model. The publicly available codebase ensures reproducible, transparent implementation for researchers working with diverse local vocabularies, promoting international healthcare data interoperability.

Keywords: Medical Informatics, Vocabulary, Controlled, Health Information Interoperability, Clinical Coding, Biological Ontologies

OHDSI Shoutouts!

Congratulations to the team of **M. Pajusalu, M. Oja, K. Mooses, S. Heinsar, T. Laisk, G. Grents, T. Tillmann, S. Laur, S. Reisberg, J. Vilo, and R. Kolde** on the recent publication of **Syrona: an open-source visual analytics tool for pairwise comparison of health datasets in OMOP CDM** in *BMC Medical Informatics and Decision Making*.



Pajusalu et al. BMC Medical Informatics and Decision Making (2026) 26:487
https://doi.org/10.1186/s12911-026-03790-w

BMC Medical Informatics and Decision Making

SOFTWARE Open Access

Syrona: an open-source visual analytics tool for pairwise comparison of health datasets in OMOP CDM

M. Pajusalu[1*], M. Oja[1], K. Mooses[1], S. Heinsar[2,3,4], T. Laisk[5], G. Grents[6,7], T. Tillmann[6], S. Laur[1], S. Reisberg[1,8], J. Vilo[1,8] and R. Kolde[1]

Abstract

Background Health research increasingly relies on observational datasets that capture systematically different patient populations, affecting the representativeness, comparability, and transportability of study findings. Yet these differences are rarely quantified across clinical domains or explored interactively, and the workflow for pairwise dataset comparison remains fragmented. No existing OHDSI tool provides an integrated visual analytics workflow for exploratory pairwise comparison of concept prevalence patterns between datasets on the OMOP Common Data Model.

Results We present Syrona, an open-source visual analytics tool for systematic pairwise comparison of datasets and subcohorts on the OMOP Common Data Model. Syrona extracts annual prevalence for conditions, procedures, and drugs from any OMOP CDM database, computes prevalence ratios across demographic strata, and synthesizes them via multilevel meta-analysis. A coordinated dashboard - distributional overviews, stratified heatmaps, forest plots, and absolute prevalence comparisons - enables interactive exploration driven by domain-adaptive SNOMED CT and ATC filtering. Three case studies on Estonian national health data (495,000 persons, 2012–2024) demonstrate how the tool supports representativeness assessment, institutional practice comparison, and coding artifact detection.

Conclusions Syrona is open-source and applicable to any OMOP CDM database. By treating dataset comparison as a visual analytics problem rather than a tabular reporting task, it addresses a gap in the OHDSI ecosystem and supports systematic assessment of datasets in distributed observational research.

Keywords OMOP common data model, Visual analytics, Health data comparison, Prevalence ratio, Meta-analysis, SNOMED CT, OHDSI, Dashboard

Three Stages of The Journey

Where Have We Been?

Where Are We Now?

Where Are We Going?

Upcoming Workgroup Calls



Date	Time (ET)	Meeting
Wednesday	10 am	Women of OHDSI
Wednesday	10 am	Common Data Model
Wednesday	11:30 am	Surgery and Perioperative Medicine
Thursday	7:30 am	India Community Call
Thursday	8 am	Medical Devices
Thursday	9 am	Phenotype Development & Evaluation
Thursday	11 am	Perinatal and Reproductive Health
Thursday	7 pm	Dentistry
Friday	10 am	Transplant
Friday	10 am	Waveform
Friday	11 am	Clinical Trials
Tuesday	9 am	Data2Evidence

OHDSI/Medical AI Survey

Jiwon Um developed a brief survey focusing on OHDSI in the Era of Medical AI, and she presented preliminary results highlighting a diverse range of perspectives during the recent APAC Symposium.

A key recommendation emerging from the preliminary results is the need to establish a clear community roadmap for how and where AI can be responsibly applied across the journey from data to evidence, with particular emphasis on developing best practices for LLM-assisted data standardization.

If you have not yet participated, please take approximately 10 minutes to complete the survey in the next two weeks before the end of November.

OHDSI in the Era of Medical AI

A Global Community Inquiry into Standardization and Infrastructure Roles

Medical AI is reshaping how observational research evidence is generated and used. The OHDSI community has spent more than a decade building infrastructure — OMOP CDM, standardized vocabularies, federated networks, open-source methodology — that may have a distinctive role in this transition. This survey asks how you, as a member of the community, see that role and the tensions surrounding it.

This **~8 minute** survey covers:

- Your context within OHDSI and your current AI/ML work
- Your position on the role of data standardization in the AI era
- How OHDSI infrastructure relates to four medical-AI failure modes recently identified in the literature
- What future role you hope OHDSI will play, and what should be prioritized

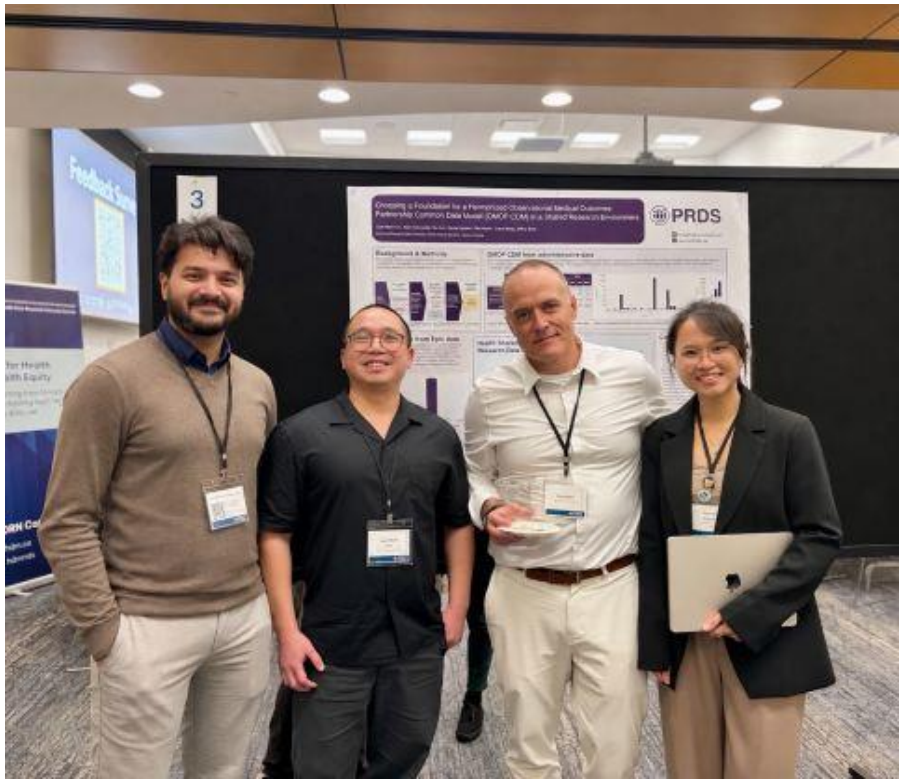
There are no right or wrong answers. We are interested in how the community is actually thinking — including where it is divided. Your responses are anonymous; no personal identifiers are collected. The findings from this survey are intended solely for academic research purposes.

*Working definition. In this survey, "**medical AI**" refers broadly to any application of machine learning, deep learning, generative AI (including LLMs), or AI-driven automation to observational health research and real-world evidence — for prediction, phenotyping, causal inference, study design, evidence summarization, or other purposes. Both fully integrated and exploratory work are in scope.*

Pre-registered Protocol on Github: https://github.com/dr-you-group/ohdsi-ai-survey

Canada Symposium: Nov. 17-18







Sweden Symposium: Today

OMOP4SWEDEN!

← All events

OHDSI SWEDEN SYMPOSIUM 2026

Turning health data into impact!

How to make health data more available and reusable in a reliable way

The symposium brings together researchers, healthcare organizations, authorities, industry, patient organizations and the OHDSI community to explore how the international data model OMOP and complementary standards can support reliable reuse of Swedish health data. Presentations, panels, interactive demonstrations and a poster fair connect practical experience with national priorities and opportunities for collaboration.

OHDSI BOSTON

YOU'RE INVITED

Boston OHDSI In-Person Meetup

Join the first in-person gathering of the Boston OHDSI node.

DEC 09

Wednesday, December 9, 2026
5:30–7:30 PM

Johnson & Johnson
320 Bent Street · Cambridge, MA

ALL ARE WELCOME

RSVP Bill O'Brien · wobrien8@its.jnj.com



Real-world health evidence, generated in the open.

India Symposium: Dec. 11

The **OHDSI India Symposium** will be held in Dec. 11 in Chennai. This 1-day, hands-on symposium will focus on:

- Standardizing health data with the **OMOP CDM**
- Leveraging **real-world data** for research and better patient outcomes
- Interactive discussions led by **experts and practitioners**
- **Networking** with clinicians, researchers, data scientists, and healthcare innovators

Capacity is limited to 60 seats only. Register your interest today and be part of India's growing health data ecosystem.

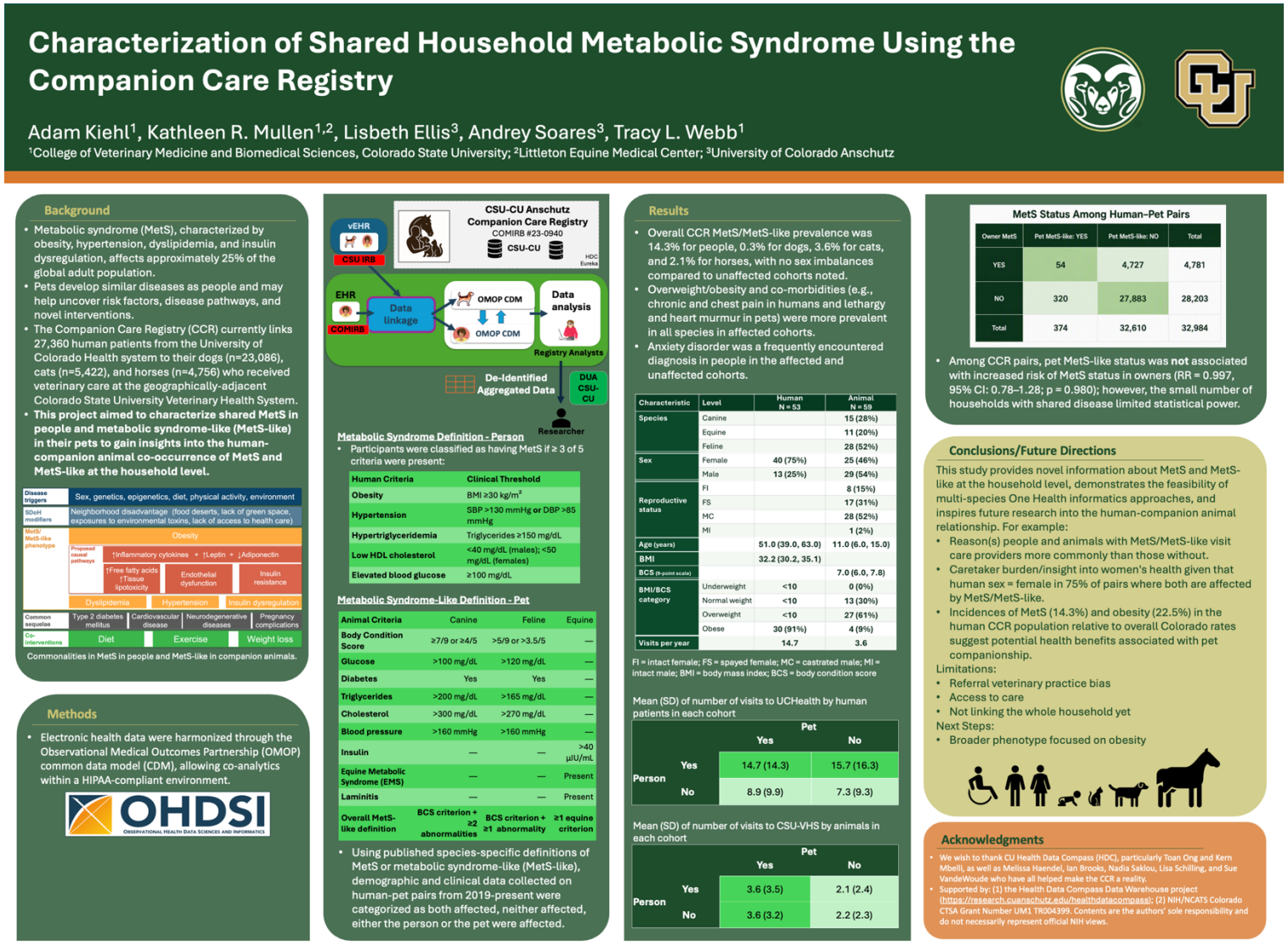


#OHDSISocialShowcase This Week

Monday

Characterization of Shared Household Metabolic Syndrome Using the Companion Care Registry

(Adam Kiehl, Kathleen R. Mullen, Lisbeth Ellis, Andrey Soares, Tracy L. Webb)

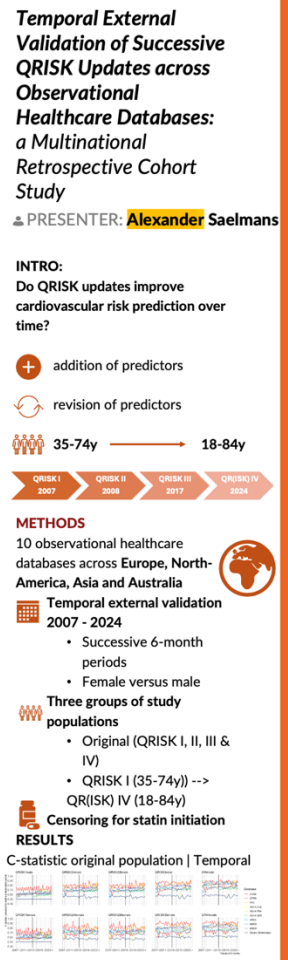


#OHDSISocialShowcase This Week

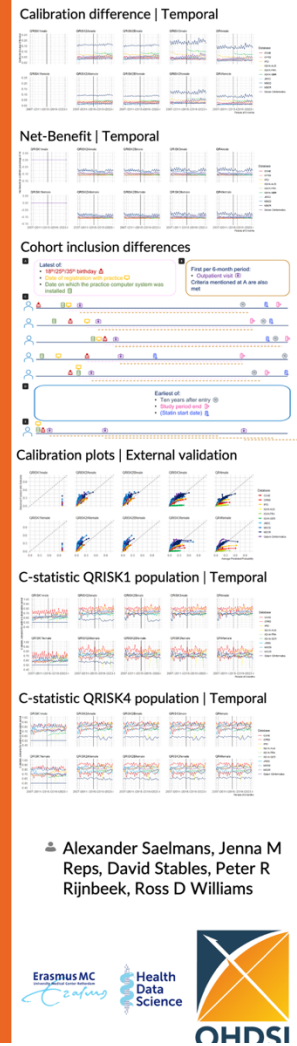
Tuesday

Temporal External Validation and External Validation of an Implemented and Updated Survival Model, QRISK 1-4, on Observational Health Care Databases: a Multinational Retrospective Cohort Study

(Alexander Saelmans, Jenna Reps, Peter Rijnbeek, Ross D. Williams)



Across ten multinational databases, QRISK performance remained broadly stable. Apparent improvements were primarily attributable to broader population coverage, particularly age range expansion, rather than correction of model or data drift



Alexander Saelmans, Jenna M Reps, David Stables, Peter R Rijnbeek, Ross D Williams

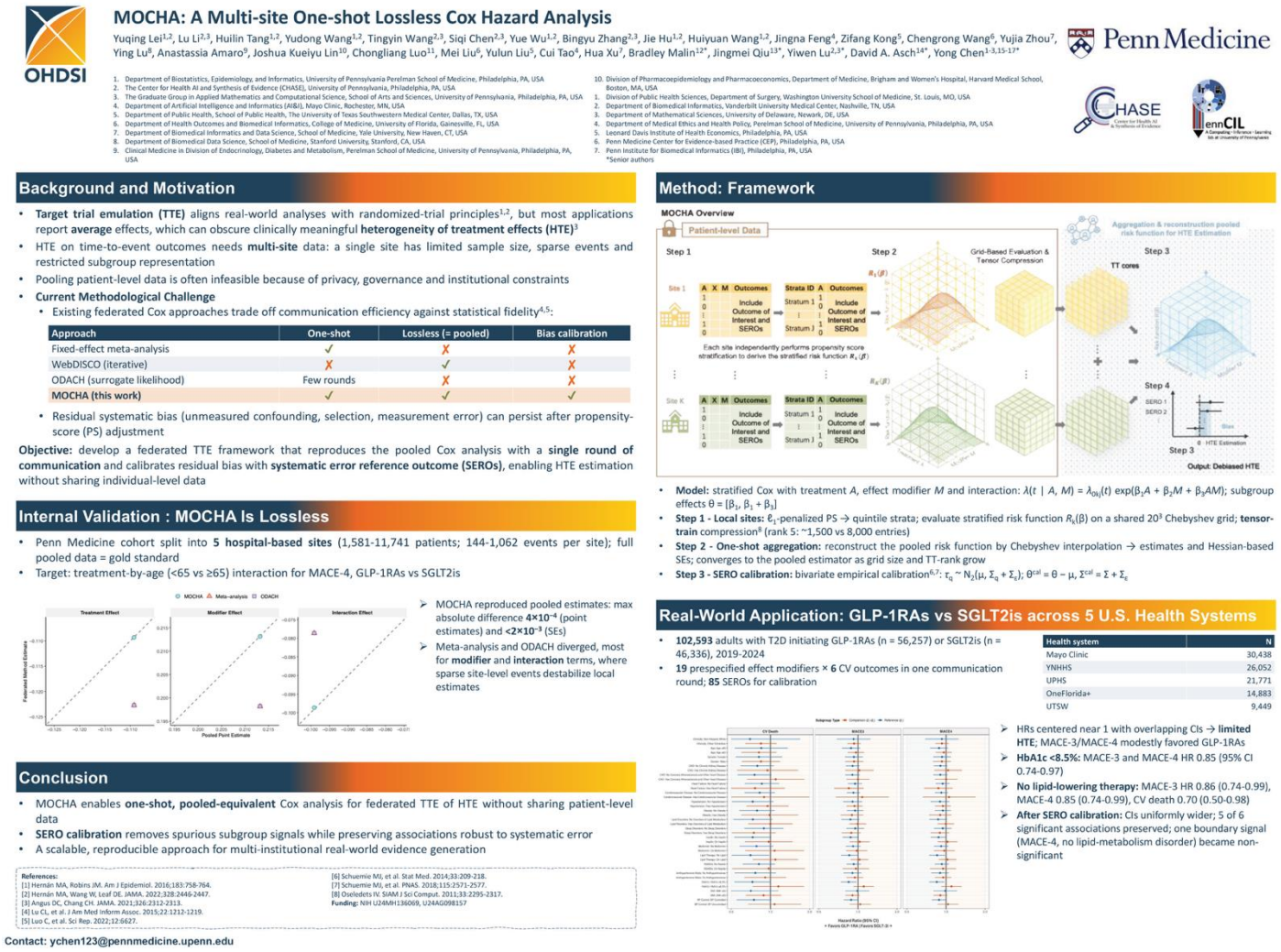
Erasmus MC Health Data Science OHDSI

#OHDSISocialShowcase This Week

Wednesday

MOCHA: A Multi-site One-shot Lossless Cox Hazard Analysis

(Yuqing Lei, Lu Li, Huilin Tang, Yudong Wang, Tingyin Wang, Siqi Chen, Yue Wu, Bingyu Zhang, Jie Hu, Huiyuan Wang, Jingna Feng, Zifang Kong, Chengrong Wang, Yujia Zhou, Ying Lu, Anastassia Amaro, Joshua Kueiyu Lin, Chongliang Luo, Mei Liu, Yulun Liu, Cui Tao, Hua Xu, Bradley Malin, Jingmei Qiu, Yiwen Lu, David A. Asch, Yong Chen)



MOCHA: A Multi-site One-shot Lossless Cox Hazard Analysis

Yuqing Lei[1,2], Lu Li[2,3], Huilin Tang[1,2], Yudong Wang[1,2], Tingyin Wang[2,3], Siqi Chen[2,3], Yue Wu[1,2], Bingyu Zhang[2,3], Jie Hu[1,2], Huiyuan Wang[1,2], Jingna Feng[4], Zifang Kong[5], Chengrong Wang[6], Yujia Zhou[7], Ying Lu[8], Anastassia Amaro[9], Joshua Kueiyu Lin[10], Chongliang Luo[11], Mei Liu[6], Yulun Liu[5], Cui Tao[4], Hua Xu[7], Bradley Malin[12*], Jingmei Qiu[13*], Yiwen Lu[2,3*], David A. Asch[14*], Yong Chen[1-3,15-17*]

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*Senior authors

Background and Motivation

- **Target trial emulation (TTE)** aligns real-world analyses with randomized-trial principles[1,2], but most applications report **average** effects, which can obscure clinically meaningful **heterogeneity of treatment effects (HTE)**[3]
- HTE on time-to-event outcomes needs **multi-site** data: a single site has limited sample size, sparse events and restricted subgroup representation
- Pooling patient-level data is often infeasible because of privacy, governance and institutional constraints
- **Current Methodological Challenge**
  - Existing federated Cox approaches trade off communication efficiency against statistical fidelity[4,5]:

Approach	One-shot	Lossless (= pooled)	Bias calibration
Fixed-effect meta-analysis	✓	✗	✗
WebDISCO (iterative)	✗	✓	✗
ODACH (surrogate likelihood)	Few rounds	✗	✗
MOCHA (this work)	✓	✓	✓

  - Residual systematic bias (unmeasured confounding, selection, measurement error) can persist after propensity-score (PS) adjustment

Objective: develop a federated TTE framework that reproduces the pooled Cox analysis with a **single round of communication** and calibrates residual bias with **systematic error reference outcome (SEROs)**, enabling HTE estimation without sharing individual-level data

Internal Validation : MOCHA Is Lossless

- Penn Medicine cohort split into **5 hospital-based sites** (1,581-11,741 patients; 144-1,062 events per site); full pooled data = gold standard
- Target: treatment-by-age (<65 vs ≥65) interaction for MACE-4, GLP-1RAs vs SGLT2is

- MOCHA reproduced pooled estimates: max absolute difference 4×10^{-4} (point estimates) and $<2\times10^{-3}$ (SEs)
- Meta-analysis and ODACH diverged, most for **modifier** and **interaction** terms, where sparse site-level events destabilize local estimates

Conclusion

- MOCHA enables **one-shot, pooled-equivalent** Cox analysis for federated TTE of HTE without sharing patient-level data
- **SERO calibration** removes spurious subgroup signals while preserving associations robust to systematic error
- A scalable, reproducible approach for multi-institutional real-world evidence generation

References:
[1] Hernán MA, Robins JM. Am J Epidemiol. 2016;183:758-764.
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Funding: NIH U24MH136069, U24AG098157

Contact: ychen123@pennmedicine.upenn.edu

Method: Framework

- **Model:** stratified Cox with treatment A, effect modifier M and interaction: $\lambda(t \mid A, M) = \lambda_{0[k]}(t)\exp(\beta_1 A + \beta_2 M + \beta_3 AM)$; subgroup effects $\theta = [\beta_1, \beta_1 + \beta_3]$
- **Step 1 - Local sites:** ℓ_1-penalized PS → quintile strata; evaluate stratified risk function $R_k(\beta)$ on a shared 20^3 Chebyshev grid; **tensor-train** compression[6] (rank 5: ~1,500 vs 8,000 entries)
- **Step 2 - One-shot aggregation:** reconstruct the pooled risk function by Chebyshev interpolation → estimates and Hessian-based SEs; converges to the pooled estimator as grid size and TT-rank grow
- **Step 3 - SERO calibration:** bivariate empirical calibration[6,7]: $\tau_q \sim N_2(\mu, \Sigma_q + \Sigma_\varepsilon)$; $\theta^{cal} = \theta - \mu$, $\Sigma^{cal} = \Sigma + \Sigma_\varepsilon$

Real-World Application: GLP-1RAs vs SGLT2is across 5 U.S. Health Systems

- **102,593** adults with T2D initiating GLP-1RAs (n = 56,257) or SGLT2is (n = 46,336), 2019-2024
- **19** prespecified effect modifiers × **6** CV outcomes in one communication round; **85** SEROs for calibration

Health system	N
Mayo Clinic	30,438
YNHHS	26,052
UPHS	21,771
OneFlorida+	14,883
UTSW	9,449

- HRs centered near 1 with overlapping CIs → **limited HTE**; MACE-3/MACE-4 modestly favored GLP-1RAs
- **HbA1c <8.5%:** MACE-3 and MACE-4 HR 0.85 (95% CI 0.74-0.97)
- **No lipid-lowering therapy:** MACE-3 HR 0.86 (0.74-0.99), MACE-4 0.85 (0.74-0.99), CV death 0.70 (0.50-0.98)
- **After SERO calibration:** CIs uniformly wider; 5 of 6 significant associations preserved; one boundary signal (MACE-4, no lipid-metabolism disorder) became non-significant

#OHDSISocialShowcase This Week

Thursday

Standardizing Bedside Nursing Narratives for Interoperable Research: An Episode-Based Nursing Observation Extension to the OMOP CDM

(Sujin Gan, Chungsoo Kim, Youngjin Lee, Rae Woong Park)

Standardizing Bedside Nursing Narratives for Interoperable Research

: An Episode-Based Nursing Observation Extension to the OMOP CDM

PRESENTER: Sujin Gan

INTRO:

- Bedside nursing records capture high-frequency assessments, interventions, timestamps, and care context.
- Sequential documentation can show how patient monitoring and responses progress before deterioration.
- We developed **NURSING_EPISODE** and **NURSING_OBSERVATION** to preserve nursing record structure while linking the content to **standard OMOP domains.**

METHODS

1. **Data source and study population**
- Bedside nursing records from adult general-ward inpatients hospitalized ≥24 h at Ajou University Medical Center, 2023–2024
- Included assessments, monitoring, nursing actions, and evaluation results
- **Proof-of-concept cohort**: records within 24 h before rapid response team (RRT) activation

2. **Nursing record standardization**
- **NURSING_EPISODE**: consecutive nursing records within a visit, grouped to preserve temporal organization
- **NURSING_OBSERVATION**: individual nursing records preserving the **original statement, value, timestamp, and record sequence.**
- Mapping initially focused on the **most frequent nursing statements**
- Expert nurses screened clinically informative statements, **excluding routine or non-informative** documentation
- Clinically informative statements were mapped to **SNOMED CT** and **LOINC**, stored in standard OMOP tables, and **linked back to NURSING_OBSERVATION** without duplication.

RESULTS:

1. Nursing records preserved
- **76,152 clinically informative** records from 3,108 patients loaded into **NURSING_OBSERVATION**
- 37,878 **NURSING_EPISODEs** identified, median 10 per admission
- 55.4% shared timestamps with ≥1 other record while preserving within-time order

Preserving ***how*** nursing information was documented, while standardizing ***what*** was clinically documented.

1 Bedside nursing records accumulate over the stay

Row ID	Time	Seq	Statement	Value
3051207	08:15	1	Vital signs measured	BT 38.2, PR 112
3051208	08:15	2	**Fever present**	**BT 38.2°C**
3051209	08:15	3	Physician notified	–
3051216	08:25	1	Acetaminophen given	650 mg PO
3051231	09:30	1	Fever re-evaluated	BT 37.4°C
3051232	09:30	2	Patient resting comfortably	–
3051248	10:30	1	Breath sounds auscultated	clear

NURSING_EPISODE #1001 consecutive records 08:15–08:25

NURSING_EPISODE #1002 09:30

One source record = statement + value + time + sequence

2 OMOP extension: NURSING_EPISODE → NURSING_OBSERVATION

NURSING_EPISODE

Column names	Row values
nursing_episode_id	1001
person_id	12345
visit_occurrence_id	67890
visit_detail_id	5501
episode_number	12
episode_start_datetime	2024-05-01 08:15
episode_end_datetime	2024-05-01 08:25
episode_source_value	consecutive records

1:N

NURSING_OBSERVATION

Column names	Row values 1	Row values 2	Row values 3
nursing_observation_id	2001	2002	2003
nursing_episode_id	1001	1001	1003
observation_sequence	2	2	1
nursing_statement	Fever present	Fever present	Breath sounds auscultated
associated_value	BT 38.2°C	BT 38.2°C	clear
statement_category	assessment	assessment	assessment
source_record_id	3051208	3051208	3051248
nursing_event_sequence	1	2	1
nursing_event_id	3001	4001	5001
nursing_event_field_concept_id	1147138	1147127	1147663

3 Each record is linked to standardized OMOP records

Row values 1 · nursing_event_id 3001 → MEASUREMENT: measurement_id 3001; Body temperature 38.2 ° C; LOINC 8310-5 · concept 3020891

Row values 2 · nursing_event_id 4001 → CONDITION_OCCURRENCE: condition_occurrence_id 4001; Fever; SNOMED CT 386661006 · concept 437663

Row values 3 · nursing_event_id 5001 → PROCEDURE_OCCURRENCE: procedure_occurrence_id 5001; Auscultation; SNOMED CT 37931006 · concept 4243768

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2. Linkage to standard OMOP
- Of 6,962 unique statements, the top **473 (69.0% of records)** were mapped; **86.0%** of their records linked: MEASUREMENT 64.0%, OBSERVATION 13.0%, PROCEDURE 5.5%, CONDITION 3.5%.
- **14.0% unlinked**, mostly template headers

NURSING_EPISODE

nursing_episode_id	PK
person_id	FK → PERSON
visit_occurrence_id	FK → VISIT_OCCURRENCE
visit_detail_id	FK → VISIT_DETAIL
episode_number	order within the visit
episode_start_datetime	first record
episode_end_datetime	last record
episode_type_concept_id	32817 = EHR
episode_source_value	grouping rule

NURSING_OBSERVATION

nursing_observation_id	PK
nursing_episode_id	FK → NURSING_EPISODE
person_id	FK → PERSON
observation_datetime	documented time
observation_sequence	order within timestamp
nursing_statement	statement as written
associated_value	paired value
statement_category	assessment / action type
source_record_id	EHR record key
nursing_event_sequence	1..n per record
nursing_event_id	linked OMOP record ID
nursing_event_field_concept_id	target table.field

CONCLUSON
- This OMOP extension makes bedside nursing narratives usable for sequence-aware research while preserving the original documentation structure and compatibility with standard OMOP domains.

FUTURE DIRECTIONS:
- Analyze sequence-based care patterns, such as abnormal finding followed by physician notification
- Extend from RRT patients to all inpatients
- Further map lower-frequency and drug-related records
- Validate across other hospitals, including non-Korean settings

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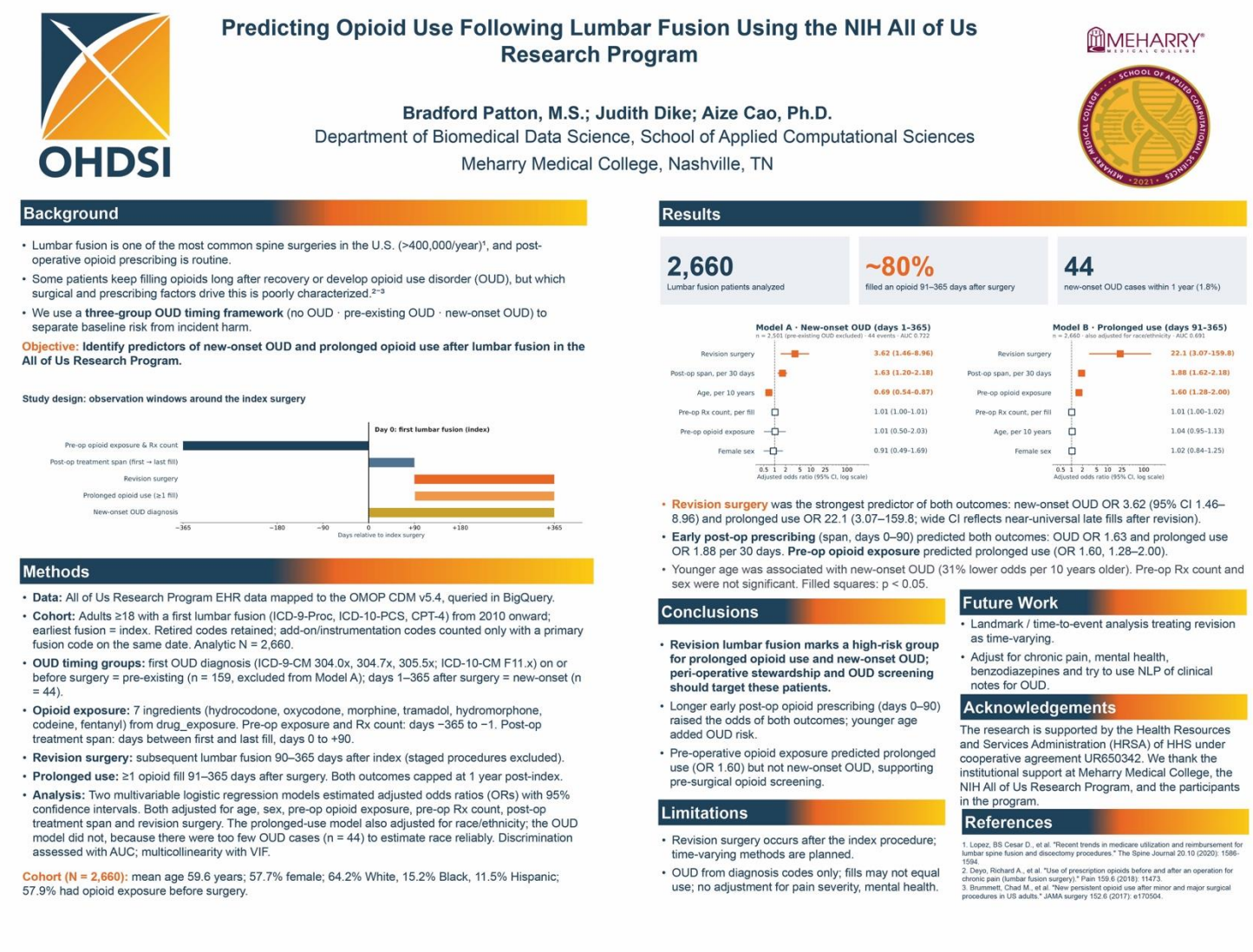
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#OHDSISocialShowcase This Week

Friday

Adapting, Extending, and Reimagining the OHDSI Ecosystem for Pediatric Research: The PEDSnet Experience

(Hanieh Razzaghi, Charles Bailey)



Predicting Opioid Use Following Lumbar Fusion Using the NIH All of Us Research Program

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Background

- Lumbar fusion is one of the most common spine surgeries in the U.S. (>400,000/year)[1], and post-operative opioid prescribing is routine.
- Some patients keep filling opioids long after recovery or develop opioid use disorder (OUD), but which surgical and prescribing factors drive this is poorly characterized.[2–3]
- We use a **three-group OUD timing framework** (no OUD · pre-existing OUD · new-onset OUD) to separate baseline risk from incident harm.

Objective: Identify predictors of new-onset OUD and prolonged opioid use after lumbar fusion in the All of Us Research Program.

Study design: observation windows around the index surgery

Methods

- **Data:** All of Us Research Program EHR data mapped to the OMOP CDM v5.4, queried in BigQuery.
- **Cohort:** Adults ≥18 with a first lumbar fusion (ICD-9-Proc, ICD-10-PCS, CPT-4) from 2010 onward; earliest fusion = index. Retired codes retained; add-on/instrumentation codes counted only with a primary fusion code on the same date. Analytic N = 2,660.
- **OUD timing groups:** first OUD diagnosis (ICD-9-CM 304.0x, 304.7x, 305.5x; ICD-10-CM F11.x) on or before surgery = pre-existing (n = 159, excluded from Model A); days 1–365 after surgery = new-onset (n = 44).
- **Opioid exposure:** 7 ingredients (hydrocodone, oxycodone, morphine, tramadol, hydromorphone, codeine, fentanyl) from drug_exposure. Pre-op exposure and Rx count: days −365 to −1. Post-op treatment span: days between first and last fill, days 0 to +90.
- **Revision surgery:** subsequent lumbar fusion 90–365 days after index (staged procedures excluded).
- **Prolonged use:** ≥1 opioid fill 91–365 days after surgery. Both outcomes capped at 1 year post-index.
- **Analysis:** Two multivariable logistic regression models estimated adjusted odds ratios (ORs) with 95% confidence intervals. Both adjusted for age, sex, pre-op opioid exposure, pre-op Rx count, post-op treatment span and revision surgery. The prolonged-use model also adjusted for race/ethnicity; the OUD model did not, because there were too few OUD cases (n = 44) to estimate race reliably. Discrimination assessed with AUC; multicollinearity with VIF.

Cohort (N = 2,660): mean age 59.6 years; 57.7% female; 64.2% White, 15.2% Black, 11.5% Hispanic; 57.9% had opioid exposure before surgery.

Results

2,660	~80%	44
Lumbar fusion patients analyzed	filled an opioid 91–365 days after surgery	new-onset OUD cases within 1 year (1.8%)

- **Revision surgery** was the strongest predictor of both outcomes: new-onset OUD OR 3.62 (95% CI 1.46–8.96) and prolonged use OR 22.1 (3.07–159.8; wide CI reflects near-universal late fills after revision).
- **Early post-op prescribing** (span, days 0–90) predicted both outcomes: OUD OR 1.63 and prolonged use OR 1.88 per 30 days. **Pre-op opioid exposure** predicted prolonged use (OR 1.60, 1.28–2.00).
- Younger age was associated with new-onset OUD (31% lower odds per 10 years older). Pre-op Rx count and sex were not significant. Filled squares: $p < 0.05$.

Conclusions

- **Revision lumbar fusion marks a high-risk group for prolonged opioid use and new-onset OUD; peri-operative stewardship and OUD screening should target these patients.**
- Longer early post-op opioid prescribing (days 0–90) raised the odds of both outcomes; younger age added OUD risk.
- Pre-operative opioid exposure predicted prolonged use (OR 1.60) but not new-onset OUD, supporting pre-surgical opioid screening.

Limitations

- Revision surgery occurs after the index procedure; time-varying methods are planned.
- OUD from diagnosis codes only; fills may not equal use; no adjustment for pain severity, mental health.

Future Work

- Landmark / time-to-event analysis treating revision as time-varying.
- Adjust for chronic pain, mental health, benzodiazepines and try to use NLP of clinical notes for OUD.

Acknowledgements

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References

1. Lopez, BS Cesar D., et al. "Recent trends in medicare utilization and reimbursement for lumbar spine fusion and discectomy procedures." The Spine Journal 20.10 (2020): 1586-1594.
2. Deyo, Richard A., et al. "Use of prescription opioids before and after an operation for chronic pain (lumbar fusion surgery)." Pain 159.6 (2018): 11473.
3. Brummett, Chad M., et al. "New persistent opioid use after minor and major surgical procedures in US adults." JAMA surgery 152.6 (2017): e170504.

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?

OHDSI2026 Software Demos



Peter Hoffmann

Data4Life

Pythia: An LLM-Powered Study Design Advisor for ATLAS v3.0



Griffin Weber

Harvard Medical School

Argos: Simple Cohort Builder and Analysis Tool for Federated Networks Using OMOP



Georgina Kennedy

University of New South Wales

Groundworkers: Concept Grounding and Graph Traversal for Agents



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-2026



Find your workgroup.

Fuel our mission.

ohdsi.org/workgroups