ATLAS/Medical Imaging WG Updates + Phenotype Phebruary Report

OHDSI Community Call

Feb. 22, 2022 • 11 am ET

Future OHDSI Community Calls

Date	Topic
Feb. 22	Workgroup Updates (ATLAS/WebAPI, Medical Imaging), Phenotype Phebruary Report
Mar. 1	Breakout Sessions (Characterization, Estimation, Prediction)
Mar. 8	CDM Workshop (Part 1)
Mar. 15	CDM Workshop (Part 2)
Mar. 22	OHDSI Vocabulary Journey
Mar. 29	Reproducibility

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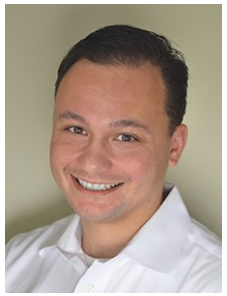
Mar. 29	Reproducibility

March 1 OHDSI Community Call

Breakout Discussions: What Is Happening In OHDSI, And What Comes Next?

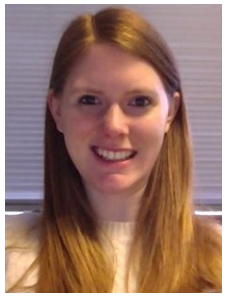



Characterization

Aniek Markus and Anthony Sena


Estimation

Martijn Schuemie and Marc Suchard




Prediction

Jenna Reps and Ross Williams


SAVE
THE
DATE

2022 OHDSI U.S. Symposium

The 2022 OHDSI U.S. Symposium will be held Oct. 14-16. The main symposium day is scheduled to be the 14th, while activities will be held the next two days.

2022 OHDSI U.S. Symposium

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The 2022 OHDSI U.S. Symposium will be held Oct. 14-16. The main symposium day is scheduled to be Friday, Oct. 14, while activities will be held the next two days.

2022 OHDSI U.S. Symposium

Do you want to join the scientific review committee?

Three Stages of The Journey

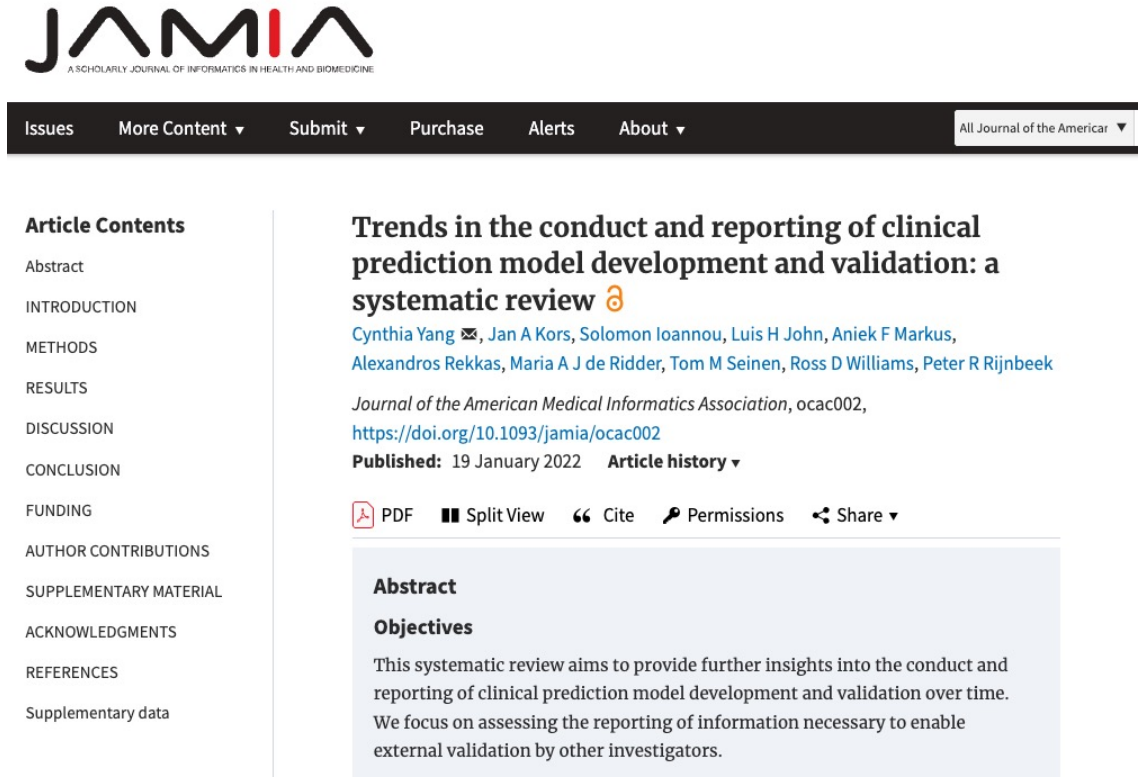
Where Have We Been?

Where Are We Now?

Where Are We Going?

OHDSI Shoutouts!

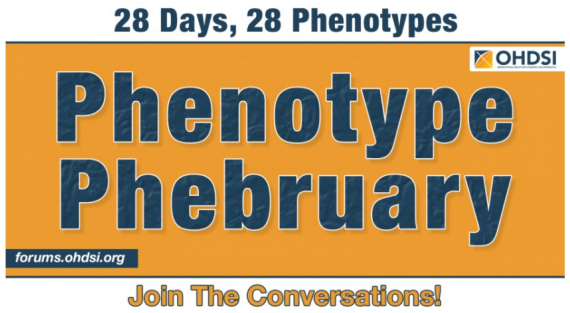
Congratulations to co-authors **Cynthia Yang, Jan Kors, Solomon Ioannou, Luis John, Aniek Markus, Alexandros Rekkas, Maria de Ridder, Tom Seinen, Ross Williams, and Peter Rijnbeek** on the study "**Trends in the conduct and reporting of clinical prediction model development and validation: a systematic review**" which was recently published in JAMIA.



Phenotype Phebruary

Phenotype Phebruary Daily Updates

"Phenotype Phebruary" is a community-wide initiative to both develop and evaluate phenotypes for health outcomes that could be investigated by the community. Patrick Ryan introduced this initiative in both a video presentation and a forum post, and each of the conversations around the "28 phenotypes for 28 days" are being held within the OHDSI forums.



This page will provide direct links to each forum post, which is where conversations around each specific phenotype should be held.

Please be active in these discussions. What ways can you contribute?

1. Join the conversation

- Discussions will be here on forums.ohdsi.org
- Each day will be a new thread
  – Ex: Look for: "Phenotype Phebruary Day 1 – Type 2 diabetes mellitus"
- Explore the definitions and review the results provided
- Reply with your thoughts, reflections, insights and question

2. Evaluate the cohort definitions in your data

- Execute cohort definitions and CohortDiagnostics in your CDM
- Share insights you learn from your data on the forums
- Share results to compile across the network on data.ohdsi.org

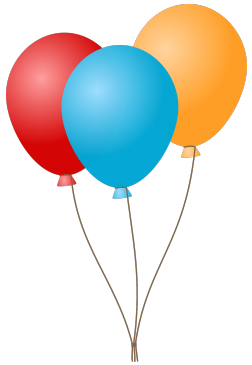
3. Lead a discussion

- Patrick will be leading the discussion for the first 7 days, but if others would like to similarly lead a phenotype development and evaluation activity, contact ryan@ohdsi.org or chat with him in OHDSI MSTeams, tell me your desired phenotype target and calendar date you want to commit to.

Feb. 1 • Type 2 Diabetes Mellitus
Feb. 2 • Type 1 Diabetes Mellitus
Feb. 3 • Atrial Fibrillation
Feb. 4 • Multiple Myeloma
Feb. 5 • Alzheimer's Disease
Feb. 6 • Hemorrhagic Events
Feb. 7 • Neutropenia
Feb. 8 • Kidney Stones
Feb. 9 • Delirium
Feb. 10 • Systemic Lupus Erythematosus
Feb. 11 • Suicide Attempts
Feb. 12 • Parkinson's Disease and Parkinsonism
Feb. 13 • Attention Deficit Hyperactivity Disorder
Feb. 14 • Hypertension *(Video Description)*
Feb. 15 • Acute Myocardial Infarction
Feb. 16 • Heart Failure
Feb. 17 • Cardiomyopathy
Feb. 18 • Multiple Sclerosis
Feb. 19 • Triple Negative Breast Cancer
Feb. 20 • Pulmonary Hypertension
Feb. 21 • Prostate Cancer
Feb. 22 • HIV
Feb. 23 • Hidradenitis Suppurativa
Feb. 24 • Depression
Feb. 25 • COVID-19 Subtypes
Feb. 26 • Non-Small-Cell Lung Cancer
Feb. 27 • Drug-Induced Liver Injury
Feb. 28 • Developmental Disabilities

https://www.ohdsi.org/phenotype-phebruary

OHDSI Shoutouts!



Any shoutouts from the community? Please share and help promote and celebrate OHDSI work!

Have a study published? Please send to sachson@ohdsi.org so we can share during this call and on our social channels.
Let's work together to promote the collaborative work happening in OHDSI!

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	Common Data Model Vocabulary Subgroup
Tuesday	2 pm	Health Equity
Wednesday	7 am	Medical Imaging
Wednesday	11:30 am	Latin America
Wednesday	12 pm	FHIR and OMOP Terminologies Subgroup (Zoom)
Thursday	10 am	Medical Devices
Thursday	11 am	Data Quality Dashboard Development
Friday	10 am	Phenotype Development and Evaluation
Monday	10 am	Healthcare Systems Special Interest Group
Monday	10 am	GIS-Geographical Information System

www.ohdsi.org/upcoming-working-group-calls

Get Access To Different Teams/WGs/Chapters

5. Select the workgroups you want to join (you can refer to the WIKI for work group objectives www.ohdsi.org/web/wiki/doku.php?id=projects:overview)

- [ ] ATLAS
- [ ] Clinical Trials
- [ ] Common Data Model
- [ ] Data Quality Dashboard Development
- [ ] Early-stage Researchers
- [ ] Education Work Group
- [ ] FHIR and OMOP
- [ ] Geographic Information System (GIS)
- [ ] HADES Health Analytics Data-to-Evidence Suite
- [ ] Healthcare Systems Interest Group (formerly EHR)
- [ ] Health Equity
- [ ] Latin America
- [ ] Medical Devices
- [ ] Medical Imaging
- [ ] Natural Language Processing
- [ ] OHDSI APAC
- [ ] OHDSI APAC Steering Committee
- [ ] OHDSI Steering Committee
- [ ] Oncology
- [ ] Open-source Community
- [ ] Phenotype Development and Evaluation
- [ ] Population-Level Effect Estimation / Patient-Level Prediction
- [ ] Psychiatry
- [ ] Registry (formerly UK Biobank)
- [ ] Surgery and Perioperative Medicine
- [ ] Vaccine Evidence
- [ ] Vaccine Vocabulary

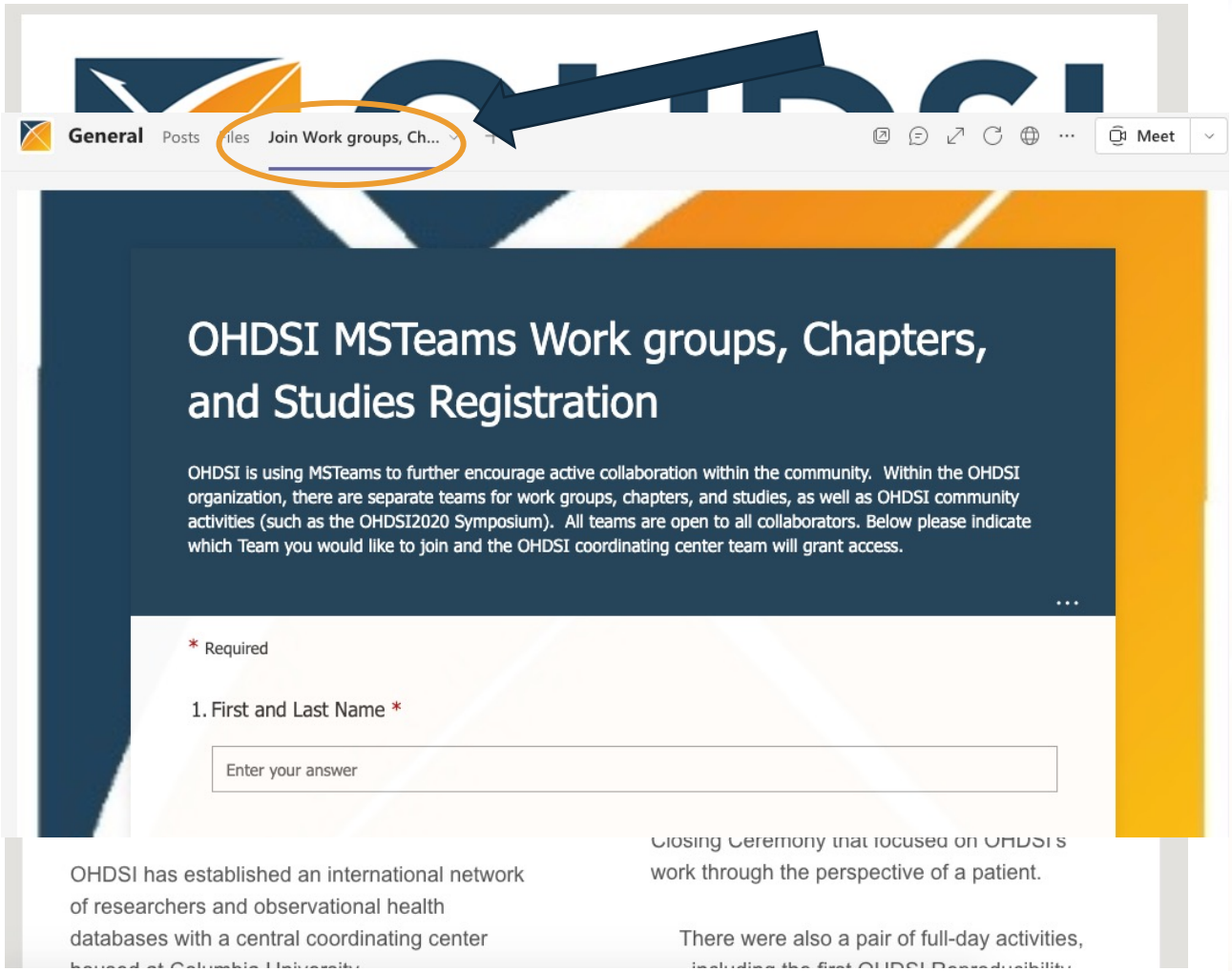
6. Select the chapter(s) you want to join

- [ ] Africa
- [ ] Australia
- [ ] China
- [ ] Europe
- [ ] Japan
- [ ] Korea
- [ ] Singapore
- [ ] Taiwan

7. Select the studies you want to join

- [ ] HERA-Health Equity Research Assessment
- [ ] PIONEER for Prostate Cancer (study-a-thon ended)
- [ ] SCYLLA (SARS-Cov-2 Large-scale Longitudinal Analyses)

Get Access To Different Teams/WGs/Chapters



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- ☐ Clinical Trials
- ☐ Common Data Model
- ☐ Data Quality Dashboard Development
- ☐ Early-stage Researchers
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- ☐ FHIR and OMOP
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- ☐ SCYLLA (SARS-Cov-2 Large-scale Longitudinal Analyses)

Learn More About Workgroup 2022 OKRs

OHDSI Workgroups

OHDSI's central mission is to improve health by empowering a community to collaboratively generate the evidence that promotes better health decisions and better care. We work towards that goal in the areas of data standards, methodological research, open-source analytics development, and clinical applications.

Our workgroups present opportunities for all community members to find a home for their talents and passions, and make meaningful contributions. We are always looking for new collaborators. Learn more about these workgroups by checking out this page. Any workgroup that provided a community call update is highlighted in the top section.

See an area where you want to contribute? Please Join The Journey!

Join Our Workgroup Efforts!

Form To Join Workgroups In MSTeams | **Weekly Workgroup Meeting Schedule**

Get To Know The OHDSI Workgroups

Asia-Pacific (APAC)
Current Participants: 228
Lead: Mui Van Zandt
2022 OKRs

ATLAS/WebAPI
Current Participants: 228
Lead: Anthony Sena
2022 OKRs

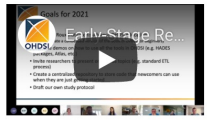
No Workgroup Update Yet

Clinical Trials
Current Participants: 201
Leads: Mike Hamidi, Lin Zhen
2022 OKRs

Common Data Model
Current Participants: 449
Lead: Clair Blacketer
2022 OKRs

Data Quality Dashboard Development
Current Participants: 174
Lead: Clair Blacketer
2022 OKRs

Early-Stage Researchers
Current Participants: 113
Leads: Faaizah Arshad, Ross Williams
2022 OKRs



Education
Current Participants: 73
Lead: Nigel Hughes
2022 OKRs

FHIR and OMOP
Current Participants: 100
Leads: Jon Duke, Christian Reich, Dana Stephenson
2022 OKRs

No Workgroup Update Yet

Geographic Information System (GIS)
Current Participants: 106
Leads: Robert Miller, Andrew Williams
2022 OKRs

HADES (Health Analytics Data-to-Evidence Suite)
Current Participants: 190
Lead: Martijn Schuemie
2022 OKRs

Healthcare Systems (formerly EHR)
Current Participants: 304
Lead: Melanie Philofsky
2022 OKRs

Health Equity
Current Participants: 183
Lead: Jake Gillberg
2022 OKRs

Latin America
Current Participants: 30
Lead: Jose Posada
2022 OKRs

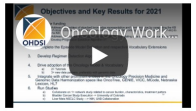
Medical Devices
Current Participants: 102
Leads: Vojtech Huser, Asiyah Lin
2022 OKRs

Medical Imaging
Current Participants: 28
Leads: Paul Nagy, Seng Chan You
2022 OKRs

No Workgroup Update Yet

Natural Language Processing
Current Participants: 317
Lead: Hua Xu
2022 OKRs

Oncology
Current Participants: 209
Lead: Asieh Golozar
2022 OKRs



Open-Source Community
Current Participants: 18
Leads: Adam Black, Paul Nagy
2022 OKRs

Patient-Level Prediction
Current Participants: 287
Leads: Jenna Reps, Peter Rijnbeek
2022 OKRs

Phenotype Development & Evaluation
Current Participants: 180
Lead: Gowtham Rao
2022 OKRs

Population-Level Estimation
Current Participants: 287
Leads: Martijn Schuemie, Marc Suchard
2022 OKRs

Psychiatry
Current Participants: 101
Leads: Dmitry Dymshyts, Andrew Williams
2022 OKRs

Registry (formerly UK Biobank)
Current Participants: 92
Lead: Maxim Moinat
2022 OKRs

Steering Group
Current Participants: 59
Lead: Patrick Ryan
2022 OKRs

No Workgroup Update Yet

Surgery and Perioperative Medicine
Current Participants: 28
Lead: Evan Minty
2022 OKRs

No Workgroup Update Yet

Vaccine Vocabulary
Current Participants: 76
Lead: Adam Black
2022 OKRs

ohdsi.org/ohdsi-workgroups

Learn More About Workgroup 2022 OKRs

Workgroup name: HADES

Workgroup lead: Martijn Schuemie

1. Objective 1: Enable the OHDSI community to perform observational research following OHDSI best practices for characterization, population-level estimation, and patient-level prediction by providing a cohesive set of open-source analytic software.

2022 Key Results:

1. Quarterly releases of Hydra
2. Develop R packages for characterization, incidence rates, treatment pathways & drug utilization (KR not finalized, subject to change)
3. Make all skeletons modular: ability to combine different study types into a single package (with single Shiny app) (KR not finalized , subject to change)

WG Name: OHDSI Steering Workgroup

WG Lead: Patrick Ryan

1. Objective 1 : enable the community to collaboratively generate evidence and the scientific work products necessary to generate evidence

1Q2022 Key results:

1. 100% of active workgroups have defined OKRs to transparently communicate activities and encourage contributions
2. Convene one OHDSI Workgroup Leader Summit to ensure appropriate communicate across collaborative activities
3. Release a OHDSI community dashboard to allow for regular monitoring the health and progress of our community
4. Produce a document to communicate connections between OHDSI workgroups and partnerships with other organizations and initiatives

ohdsi.org/ohdsi-workgroups

Next CBER Best Seminar

Speaker: Dr. Nicole Pratt
Professor, University of South Australia

Description: As recently approved COVID-19 vaccines are rolled out globally, safety signals will be identified from spontaneous reports and other data sources. Although some work has been done to assess the validity of methods for vaccine safety surveillance, discussion remains on the best way to perform analyses in real-world data to ensure rigorous and rapid identification of safety signals. In this talk, we will discuss the "Evaluating Use of Methods for Adverse Event Under Surveillance (for vaccines) (EUMEAUS)" task force and its findings on the comparative performance of different analytical methods for the assessment of comparative vaccine safety. We will discuss our findings to-date describing our evaluation of different surveillance methods (historic rate, cohort, self-controlled, etc).

Feb 23, 2022 11:00 AM in Eastern Time (US and Canada)

Speakers

Dr. Nicole Pratt

Deputy Director of the Quality Use of Medicines and Pharmacy Research Centre @University of South Australia

Dr. Nicole Pratt is the Deputy Director of the Quality Use of Medicines and Pharmacy Research Centre, University of South Australia. She is a member of the Drug Utilisation Subcommittee (DUSC) of the Australian Department of Health Pharmaceutical Benefits Advisory Committee (PBAC). She has a particular interest in new statistical methodologies to study the effectiveness and safety of medicine use and in the development of tools for post-marketing surveillance of medicines. Nicole leads the evaluation of the Department of Veterans Affairs, Veterans' Medicines Advice and Therapeutics Education Service (Veterans' MATES) program which uses administrative claims data to develop and evaluate interventions to improve use of medicines in the veteran population in Australia. She was a chief investigator of an NHMRC Cenre of Research Excellence in post-market surveillance of medicines and medical devices.

Wed., Feb. 23, 11 am ET

Next APAC Community Call

Next community call on Feb 24
- CDM workshop Part II by Clair Blacketer

Clair Blacketer is an Associate Director in the Observation Health Data Analytics group at Janssen Research & Development, a Johnson & Johnson company. She received her Bachelor of Science in Biology from James Madison University and her Master in Public Health from Eastern Virginia Medical School.

Clair Blacketer is a subject matter expert on licensed observational databases and leads for managing the overall process used to update all CDM databases across J&J. And she has been a leader in the OHDSI CDM and Vocabularies Working Group from 2017. She redesigned the organizational structure and issue tracking of the CDM to allow for better communication between the community and working group around needs the OMOP Common Data Model was not addressing.

ohdsi.org/apac/

Job Opening

Manager, Observational Health Data Analytics

Apply

Location Titusville, New Jersey; Horsham, Pennsylvania; Raritan, New Jersey
Category R&D
Req ID: 2206005052W

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Get future jobs matching this search **Login** or **Register**

Job Description

Janssen Research & Development, L.L.C., a division of Johnson & Johnson's Family of Companies is recruiting for a Manager, Observational Health Data Analytics. The preferred position location includes Horsham, PA; Titusville, NJ; or Raritan, NJ. Remote work options in the United States may be considered on a case-by-case basis and if approved by the Company.

At the Janssen Pharmaceutical Companies of Johnson & Johnson, we are working to create a world without disease. Transforming lives by finding new and better ways to prevent, intercept, treat and cure disease inspires us. We bring together the best minds and pursue the most promising science. We are Janssen. We collaborate with the world for the health of everyone in it. Learn more at www.janssen.com and follow us @JanssenGlobal. Janssen Research & Development, LLC is part of the Janssen Pharmaceutical Companies.

#OHDSISocialShowcase This Week

Title: Attention based deep neural networks in patient level prediction

PRESENTER: **Egill Fridgeirsson**

INTRO:

- Recently there have been rapid advances using attention-based models in deep learning[1]
- In attention the model learns relations between representations of the input features
- Here we test whether attention-based models can outperform strong linear and non-linear baselines on a diverse set of tasks

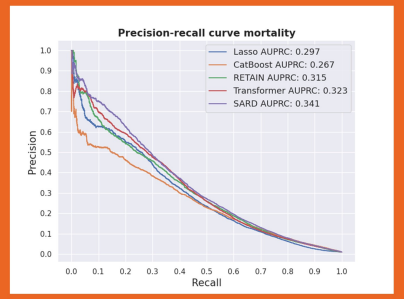
METHODS

1. We test two models, RETAIN[2] which is a recurrent neural network with attention on the hidden states.
2. We also test a transformer which is a pure attention-based model
3. We test a transformer both from scratch and using reverse distillation (SARD) where it learns from a strong linear baseline model[3].
4. The two baselines are an L1 regularized linear model (LASSO) and gradient boosted trees (catboost)
5. We test on three tasks on data from the IPCI (www.ipci.nl) database from the Netherlands:
    1. Mortality within 30 days from GP visits of patients older than 60.
    2. Dementia in next 5 years after a GP visit in 2012-2014 of patients aged between 50-79
    3. Readmission within 30 days after an inpatient visit of adults.
6. Conditions, procedures and drug exposure are extracted from the year before the index visit.
7. We use the PatientLevelPrediction[4] (PLP) package to extract features, we remove features occurring in less than 0.1% of patients/visits and normalize continuous features.
8. We use a 50-25-25 split for training-validation-test sets
    1. For Lasso we use a grid search with variances from 0.01-20.
    2. For all other models we use a randomized search with 100 iterations to select best hyperparameters on validation set

AUC (95% CI)	Mortality	Readmission	Dementia
LASSO	0.902 (0.001)	0.636 (0.07)	**0.869 (0.1)**
Catboost	0.931 (0.003)	0.635 (0.007)	0.865 (0.01)
RETAIN	0.923 (0.003)	0.632 (0.07)	0.857 (0.02)
Transformer	0.926 (0.003)	0.643 (0.007)	0.860 (0.01)
SARD	0.931 (0.003)	**0.644 (0.007)**	**0.869 (0.01)**

AUPRC	Mortality	Readmission	Dementia
LASSO	0,297	0,176	**0,088**
Catboost	0,267	0,175	0,082
RETAIN	0,315	0,166	0,075
Transformer	0,323	0,179	0,08
SARD	**0,341**	**0,183**	0,084

- Overall the performance is similar (< 1%) with regards to the AUC
    - Except LASSO is worse in mortality prediction
- The deep learning models are competitive to the baselines and SARD is either equal or slightly better than the baselines in terms of AUC.
- Reverse distillation improves the model over training from scratch
- With regards to the AUPRC which better reflects performance for the outcome (minority) class SARD is better than others in mortality prediction
- Overall the baselines are competitive but there seems to be slight improvements in precision recall with SARD



Refs

1. Vaswani A, Shazeer N, Parmar N, Uszkoreit J, Jones L, Gomez AN, et al. Attention is all you need. Adv. Neural Inf. Process. Syst., vol. 2017- Decem, 2017,p. 5999–6009. https://doi.org/1706.03762v5
2. Choi E, Bahadori MT, Kulas JA, Schuetz A, Stewart WF, Sun J. RETAIN: An Interpretable Predictive Model for Healthcare using Reverse Time Attention Mechanism. Adv Neural Inf Process Syst 2016;3512–20
3. Kodialam RS, Boiarsky R, Lim J, Dixit N, Sai A, Sontag D. Deep Contextual Clinical Prediction with Reverse Distillation. Proc AAAI Conf Artif Intell 2020;35:249–58.
4. Reps JM, Schuemie MJ, Suchard MA, Ryan PB, Rijnbeek PR. Design and implementation of a standardized framework to generate and evaluate patient-level prediction models using observational healthcare data. J Am Med Informatics Assoc 2018;25:969–75. https://doi.org/10.1093/jamia/ocy032

Data information

	Mortality	Readmission	Dementia
Target cohort	3.802.717 visits	220.580 visits	169.595 patients
Outcome (%)	36.922 (1%)	25.163 (11.4%)	2370 (1.4%)
Index event	GP visit after 60	Inpatient visit of adults	GP visit in 2012-2014 of patients aged 50-79
Time-at-risk	30 days	30 days	5 years
Observation window	1 year prior to index	1 year prior to index	1 year prior to index

- We use the same train-test splits from the PLP package for all models
- Non temporal features are concatenated to visit embeddings for the deep models
- The transformer uses sinusoidal position embeddings

Code available at:
https://github.com/mi-erasmusmc/Sard

Work will eventually be part of the deepPLP package at:
https://github.com/OHDSI/DeepPatientLevelPrediction/

AUTHORS: Egill Fridgeirsson, David Sontag, Peter Rijnbeek

Erasmus MC

OHDSI

MONDAY

Attention based deep neural networks in patient level prediction

Authors: Egill Fridgeirsson, David Sontag, Peter Rijnbeek

#OHDSISocialShowcase This Week

REDCap2OMOP:
A platform for ETLing REDCap projects into the OMOP CDM

PRESENTER: **Michael Gurley**

INTRO:

- Many REDCap proejcts want to convert their data to the OMOP CDM to make their REDCap[1] data comparable to other data assets and use OHDSI's readymade suite of analytic tools and methods libraries.
- The CCC19[2] registry has developed an open source MIT-licensed platform, REDCap2OMOP[3], to handle the conversion of REDcap data to the OMOP CDM.

METHODS

The REDCap2OMOP platform consists of two primary components;

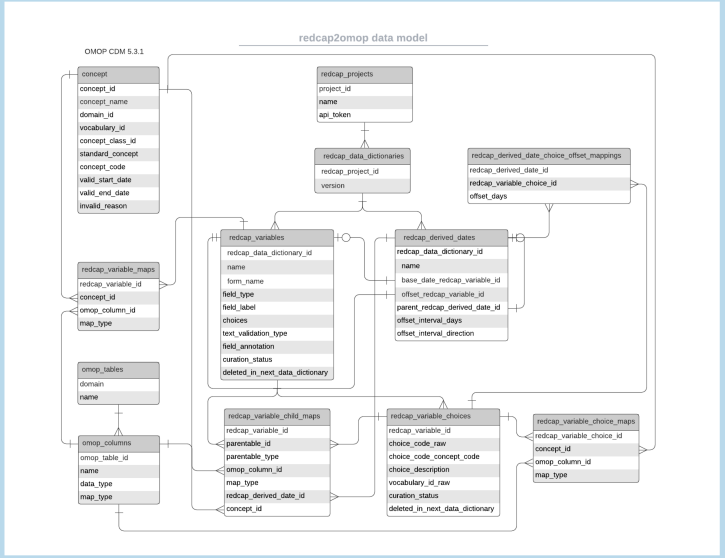
1. A browser-based interface (**Curator**) for managing REDCap data dictionary versions, OMOP vocabulary mappings and time point designations.
2. ETL code (**Converter**) that applies these mappings and designations to a REDCap data export to populate an OMOP 5.3.1 instance.

RESULTS

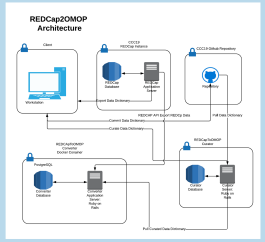
- **Curator** ingests data dictionary versions, computes a delta, creates a new version if necessary, migrates prior mappings and supports the curation of new items in a user interface.
- **Convertor** pulls the curated mappings from **Curator** via a RESTful API, imports REDCap data from a REDCap project via the REDCap API and uses the mappings to ETL into an OMOP 5.3.1 instance.

Footnotes

1. REDCap Research Electronic Data Capture https://www.project-redcap.org/
2. The COVID-19 and Cancer Consortium: https://ccc19.org/
3. REDCap2OMOP: https://github.com/NUARIG/redcap2omop



Take a picture to download the full paper



ETL Logic

- People, Providers and Death are handled separately. Must have enough variables to create people.
- Clinical Domain entities built from REDCap Variable or REDCap variable choices mapped to standard concepts. Subsidiary columns handled by child maps.
- CCC19 REDCap project does not support dates. Derived date logic was added.
- REDCap Variable map types:
  - OMOP Column
  - OMOP concept
  - OMOP concept choice
- REDCap Variable Choice map types:
  - OMOP concept

Take away

The REDCap2OMOP platform provides for a robust solution to the challenge of managing the ETL of evolving REDCap projects across newly published versions of REDCap data dictionaries to the OMOP CDM.

Jeremy Warner
Yulia Bushmanova
Firas Wehbe

TUESDAY

REDCap2OMOP: A platform for ETLing REDCap projects into the OMOP CDM

Authors: Michael J. Gurley, Jeremy Warner, Yulia Bushmanova, Firas Wehbe

#OHDSISocialShowcase This Week

Trends in the development and validation of patient-level prediction models using electronic health record data:
a systematic review

PRESENTER: Cynthia Yang

INTRO:

- The aim of this systematic review is to provide further insights in the development of the field over time, with a focus on the transparent reporting of model development and validation using electronic health record (EHR) data to enable external validation by other investigators.

METHODS:

1. We searched Embase, Medline, Web-of-Science, Cochrane Library and Google Scholar. The search was limited to papers written in English and published between January 1, 2009, and November 15, 2019.
2. We included all papers that described the development of one or more multivariable prognostic prediction models using EHR data.
3. To investigate trends, we assessed differences in items between the periods 2009-2014 and 2015-2019.

RESULTS:

1. Our literature search resulted in a total of 9,942 papers. After deduplication, 6,235 titles and abstracts were screened. From this, 1,075 potentially eligible papers were identified. Upon full text inspection, 422 papers were eventually included for synthesis. In total, we extracted items for 579 models from 422 papers (1 to 6 models per paper). We observed an increase from 135 models in 101 papers in the period 2009-2014 to 444 models in 321 papers in the period 2015-2019.

We found limited improvement in the methodological conduct and reporting of prognostic model development and validation using EHR data in the period 2009-2019.

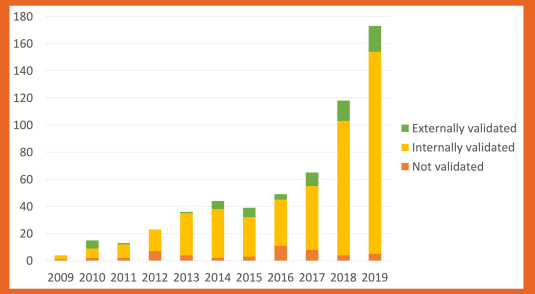


Figure 1. Reporting of validation results

Scan the QR code to access the brief report.

Main findings:

1. The percentage of models for which code lists were provided to define the target population, outcome, and candidate predictors was very low and remained below 20% over time. In both periods, the prediction horizon was reported for 84% of all models. The percentage of models for which the time window for candidate predictor measurement was reported increased from 46% to 50%, while the percentage of models for which the final model was completely presented decreased from 49% to 39%.
2. External validation increased from 10% to 12%, internal validation only increased from 76% to 81%, and no validation decreased from 13% to 7% (see Figure 1). The percentage of externally validated models that were validated using data from a different country increased from 7% to 9%.

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WEDNESDAY

Trends in the development and validation of patient-level prediction models using electronic health record data: a systematic review

Authors: Cynthia Yang, Jan A. Kors, Solomon Ioannou, Luis H. John, Aniek Markus, Alexandros Rekkas, Maria de Ridder, Tom Seinen, Ross Williams, Peter Rijnbeek

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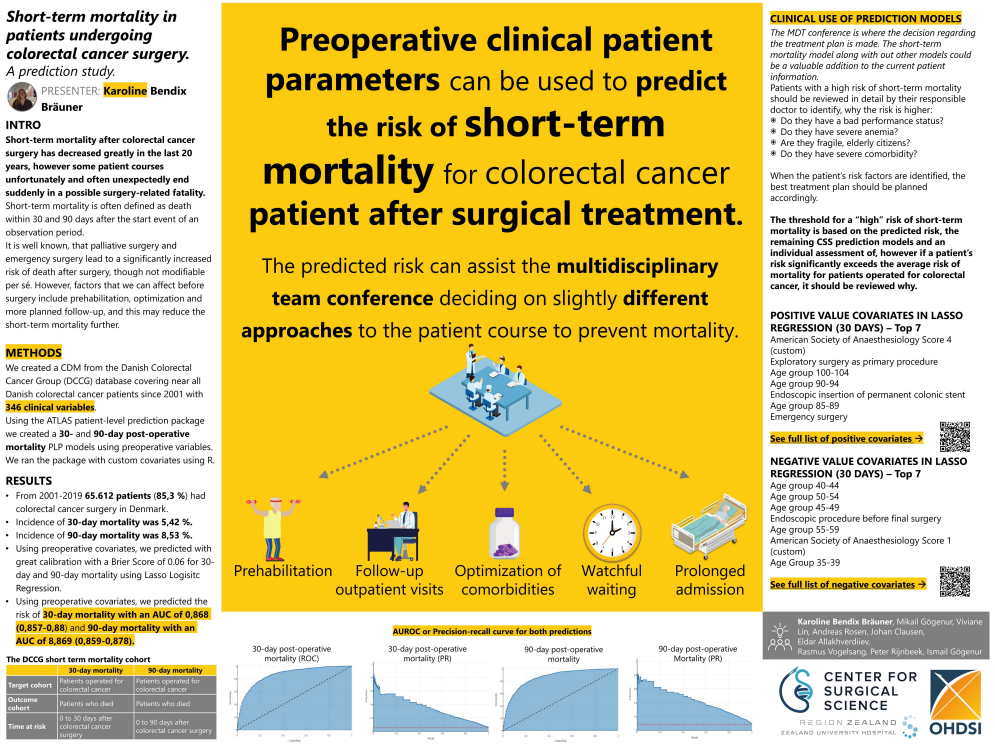

Short-term mortality in patients undergoing colorectal cancer surgery.
A prediction study.

PRESENTER: **Karoline Bendix Bräuner**

INTRO

Short-term mortality after colorectal cancer surgery has decreased greatly in the last 20 years, however some patient courses unfortunately and often unexpectedly end suddenly in a possible surgery-related fatality.
Short-term mortality is often defined as death within 30 and 90 days after the start event of an observation period.
It is well known, that palliative surgery and emergency surgery lead to a significantly increased risk of death after surgery, though not modifiable per sé. However, factors that we can affect before surgery include prehabilitation, optimization and more planned follow-up, and this may reduce the short-term mortality further.

METHODS

We created a CDM from the Danish Colorectal Cancer Group (DCCG) database covering near all Danish colorectal cancer patients since 2001 with **346 clinical variables**.
Using the ATLAS patient-level prediction package we created a **30-** and **90-day post-operative mortality** PLP models using preoperative variables. We ran the package with custom covariates using R.

RESULTS

- From 2001-2019 **65.612 patients** (**85,3 %**) had colorectal cancer surgery in Denmark.
- Incidence of **30-day mortality was 5,42 %.**
- Incidence of **90-day mortality was 8,53 %.**
- Using preoperative covariates, we predicted with great calibration with a Brier Score of 0.06 for 30-day and 90-day mortality using Lasso Logisitc Regression.
- Using preoperative covariates, we predicted the risk of **30-day mortality with an AUC of 0,868 (0,857-0,88)** and **90-day mortality with an AUC of 8,869 (0,859-0,878).**

The DCCG short term mortality cohort

	30-day mortality	90-day mortality
Target cohort	Patients operated for colorectal cancer	Patients operated for colorectal cancer
Outcome cohort	Patients who died	Patients who died
Time at risk	0 to 30 days after colorectal cancer surgery	0 to 90 days after colorectal cancer surgery

Preoperative clinical patient parameters can be used to **predict the risk of short-term mortality** for colorectal cancer **patient after surgical treatment.**

The predicted risk can assist the **multidisciplinary team conference** deciding on slightly **different approaches** to the patient course to prevent mortality.

Prehabilitation | Follow-up outpatient visits | Optimization of comorbidities | Watchful waiting | Prolonged admission

AUROC or Precision-recall curve for both predictions

30-day post-operative mortality (ROC) | 30-day post-operative mortality (PR) | 90-day post-operative mortality | 90-day post-operative Mortality (PR)

CLINICAL USE OF PREDICTION MODELS

The MDT conference is where the decision regarding the treatment plan is made. The short-term mortality model along with out other models could be a valuable addition to the current patient information.
Patients with a high risk of short-term mortality should be reviewed in detail by their responsible doctor to identify, why the risk is higher:
- Do they have a bad performance status?
- Do they have severe anemia?
- Are they fragile, elderly citizens?
- Do they have severe comorbidity?

When the patient's risk factors are identified, the best treatment plan should be planned accordingly.

The threshold for a "high" risk of short-term mortality is based on the predicted risk, the remaining CSS prediction models and an individual assessment of, however if a patient's risk significantly exceeds the average risk of mortality for patients operated for colorectal cancer, it should be reviewed why.

POSITIVE VALUE COVARIATES IN LASSO REGRESSION (30 DAYS) – Top 7
American Society of Anaesthesiology Score 4 (custom)
Exploratory surgery as primary procedure
Age group 100-104
Age group 90-94
Endoscopic insertion of permanent colonic stent
Age group 85-89
Emergency surgery

See full list of positive covariates →

NEGATIVE VALUE COVARIATES IN LASSO REGRESSION (30 DAYS) – Top 7
Age group 40-44
Age group 50-54
Age group 45-49
Endoscopic procedure before final surgery
Age group 55-59
American Society of Anaesthesiology Score 1 (custom)
Age Group 35-39

See full list of negative covariates →

Karoline Bendix Bräuner, Mikail Gögenur, Viviane Lin, Andreas Rosen, Johan Clausen, Eldar Allakhverdiiev, Rasmus Vogelsang, Peter Rijnbeek, Ismail Gögenur

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OHDSI

THURSDAY

Short-term mortality in patients undergoing colorectal cancer surgery: A prediction study

Authors: Karoline Bendix Bräuner, Mikail Gögenur, Viviane Annabelle Lin, Andreas Weinberger Rosen, Johan Clausen, Eldar Allakhverdiiev, Rasmus Peuliche Vogelsang, Ismail Gögenur

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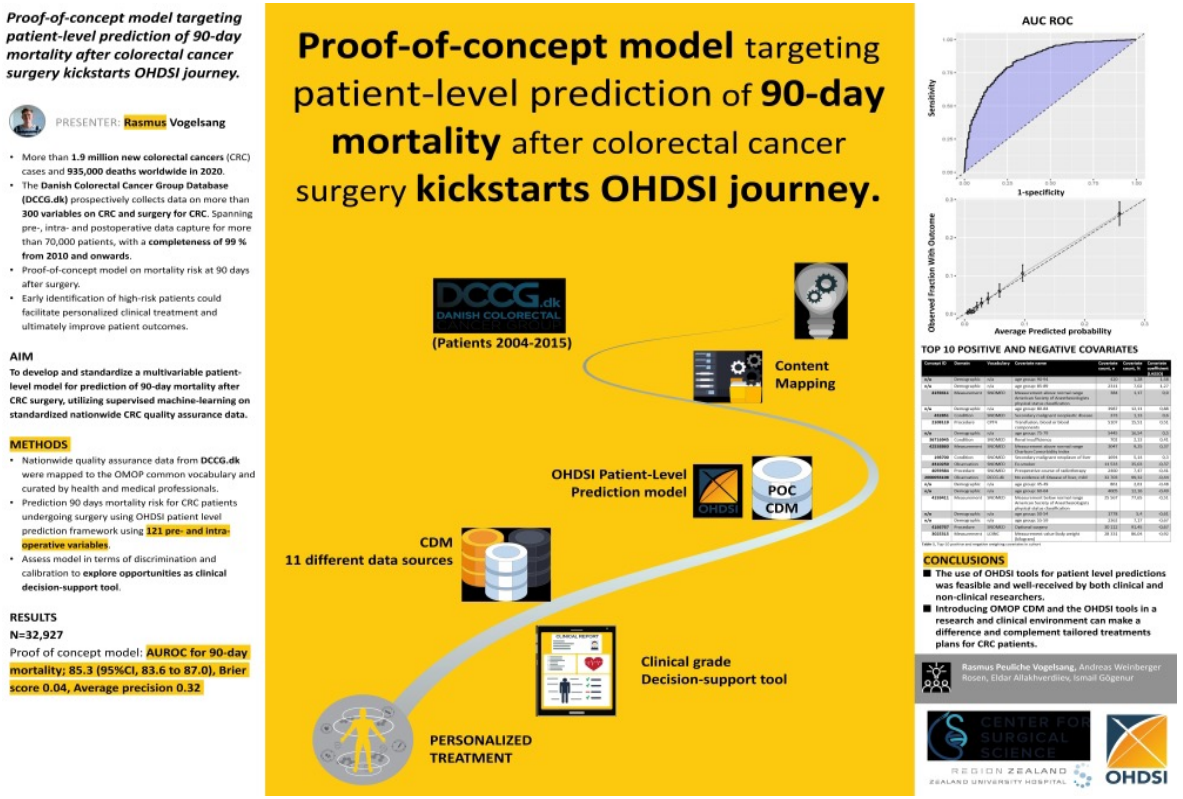

FRIDAY

Proof-of-concept model targeting patient-level prediction of 90-day mortality after colorectal cancer surgery kickstarts OHDSI journey

Authors: Rasmus Peuliche Vogelsang, Andreas Weinberger Rosen, Eldar Allakhverdiiev, Ismail Gögenur

Where Are We Going?

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

Welcome To OHDSI Newcomers

Are there any new people to the OHDSI community call who would like to introduce themselves?

Please raise your hand and share why you are interested in joining the OHDSI community.

Three Stages of The Journey

Where Have We Been?

Where Are We Now?

Where Are We Going?

February 22 OHDSI Community Call

ATLAS/Web API Workgroup Update

Anthony Sena

Medical Imaging Workgroup Update

Paul Nagy

Phenotype Phebruary Update #3

Patrick Ryan