Collaborator Showcase: Rapid Fire Presentations

Katia Verhamme, MD, PhD
Associate Professor of Use and Analysis of Observational Data
TOOLS FOR THE COLLABORATIVE MAINTENANCE OF NATIONAL VOCABULARIES AND MAPPINGS

Speaker: Javier Gracia-Tabuenca
Poster 41
Tools for the collaborative maintenance of national vocabularies and mappings

FinOMOP Vocabulary WG
Javier Gracia-Tabuenca
How to get a new vocabulary in the CDM

- **OMOP-vocabulary WG**
  - OMOP-vocabs (<2B)
  - Accessible to everyone
  - Peer-reviewed
  - C&CR
  - Update 6 months

- **FinOMOP**
  - OMOP-vocabs (<2B)
  - Accessible to everyone
  - Peer-reviewed
  - C&CR or STCM
  - Update immediate

- **STCP table**
  - Local OMOP-CDM
  - No concept_ids
  - Accessible only locally
  - Local-review
  - Update immediate
FinOMOP way
FinOMOP way
FinOMOP way

OMOP-vocabs (<2B)
FinOMOP-vocabs (>2B)

main

development

feature_add_ICD10fi_vocabulary

PR?
FinOMOP way
FinOMOP way

- OMOP-vocabs (<2B)
- FinOMOP-vocabs (>2B)

- main
- development

- feature_add_ICD10fi_vocabulary
- feature_update_ICD10fi_mappings
FinOMOP way

main

development

feature_add_ICD10fi_vocabulary

feature_update_ICD10fi_mappings
To know more

For Nordic countries:
Check our dashboard for common vocabularies

For national nodes:
Check an example repository

For developers:
Check our R tools

For everyone:
Come to the poster
IMPLEMENTATION OF THE ARES APPLICATION TO MONITOR NETWORK-WIDE DATA QUALITY AND MAPPING COVERAGE FOR 16 UNIQUE OMOP SOURCES ACROSS RWANDA

Speaker: Jared Houghtaling
Poster 16
Implementation of the ARES application to monitor network-wide data quality and mapping coverage for 16 unique OMOP sources across Rwanda

Jared Houghtaling\textsuperscript{a}, Emma Gesquiere\textsuperscript{a}, Lars Halvorsen\textsuperscript{a}, Marc Twagirumukiza\textsuperscript{b}, and Charles Ruranga\textsuperscript{c}

\textsuperscript{a} edenceHealth NV (Kontich, Belgium)
\textsuperscript{b} University of Gent (Ghent, Belgium)
\textsuperscript{c} University of Rwanda (Kigali, Rwanda)

OHDSI Europe 2023 Symposium – Lightning Talk
Background

• Project underway in 2021

• Collaboration between:
  • Univ. Ghent (BE)
  • Univ. Rwanda
  • Rwanda Biomed. Centre
  • Rwanda MOH
  • edenceHealth (BE)

• Initially aimed at tracking public health response to COVID, has since expanded
Node Installation

- 14 Sites with MacMini configured
- 2 additional national sources (COVID Survey + Case) to augment data sets
- Deployment via Docker
- Automation via SimpleMDM
QC Feedback Loop

Unorthodox CI/CD structure addresses following constraints:
- Poor network quality
  - < 50 kbps
  - Instability
- Issues with GH at sites
- Existing central server config
- SimpleMDM Features

Note that source EHR export process not yet fully automated
### Data Network Overview

<table>
<thead>
<tr>
<th>Data Sources</th>
<th>People</th>
<th>Data Quality Issues</th>
<th>Data Source Releases</th>
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<tr>
<td>14</td>
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### Data Sources

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<tr>
<th>Data Source</th>
<th>Person Count</th>
<th>Start Observed</th>
<th>End Observed</th>
<th>Latest Release</th>
<th>Data Quality Issues</th>
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Acknowledgements

• The many others who have contributed to this work:
  • Ben Burke
  • Lore Vermeylen
  • Frederic Jung
  • Ivo Mbi Kubam
  • Anne Li
  • IT/Data managers at all sites in Rwanda
  • Team at the Rwanda Biomedical Centre
    • Muhammed Semakula
    • Gilbert Rukundo
    • Viviane Akili
    • Laurence Twizeyimana

• Funding Agencies:
  • Canada’s International Development Research Centre (IDRC)
  • Swedish International Development Cooperation Agency (Sida)
    under the Global South AI4COVID Program
MULTI-SITE COST-EFFECTIVENESS AND MARKOV CHAIN ANALYSIS OF HEART FAILURE

Speaker: Markus Haug
Poster 88
Multi-site Cost-effectiveness and Markov Chain analysis of heart failure

Markus Haug MSc
University of Tartu
Components for analysis

Markov Chain used for simulation

State costs and initial distribution

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<th>INITIAL DIST.</th>
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Proposed workflow

OMOP CDM → Cohorts → Cohort2Trajectory → Treatment trajectories → TrajectoryMarkovAnalysis → Any study package

- Medical data
- Defined cohorts
- States as cohorts!

Markov model
Treatment cost data
Synthetic treatment trajectories
Treatment trajectories
CSV
Initial state distributions in data sources

Markov chain data source

- EC – Estonia, Covid
- ISS – Spain, Valencia
- ER – Estonia, random 10%
- CU – USA, Columbia University
- ZB – Serbia, Belgrade, tertiary health institution

States: HF0, HF1, HF2, HF3, HFD

Trajectory head prevalence (%): 

- EC: HF0 (88.5), HF1 (8.82), HF2 (1.76), HF3 (0.49), HFD (0.41)
- ISS: HF0 (94.3), HF1 (4.3), HF2 (0.11), HFD (1.19)
- ER: HF0 (80.7), HF1 (7.81), HF2 (4.65), HF3 (2.2), HFD (4.59)
- CU: HF0 (61.3), HF1 (16.9), HF2 (3.85), HF3 (2.12), HFD (15.8)
- ZB: HF0 (50.9), HF1 (4.5), HF2 (0.78), HF3 (0.11), HFD (43.6)
Effect of cost data source

ICER – a metric for comparing how much it costs to how helpful it is.

QALY: Quality-Adjusted Life Year
Acknowledgements

- Team:

- Data partners: Antonio Fernandez (IIS INCLIVA, Spain, Valencia), Thomas Falconer (The Columbia University Irving Medical Center, USA), Ana Danilović, Filip Maljkovic (CHC Zvezdara, Belgrade, Serbia)

JOIN THE STUDY!
DEEP LEARNING COMPARISON

Speaker: Henrik John
Poster 87
Deep Learning Comparison
An OHDSI Network Study
LH John, C Kim, JM Reps, EA Fridgeirsson
Background

Observational healthcare data limit efficacy of deep learning:
- highly sparse
- high-dimensional
- heterogenous

Yang 2022 - Figure 1 - J Am Med Inform Assoc, Volume 29, Issue 5, May 2022, Pages 983–989, https://doi.org/10.1093/jamia/ocac002
Study design

Aims
- Assess the added value of massive observational healthcare data for the development of deep learning models

Prediction methods
- Logistic regression L1
- Gradient Boosting
- ResNet (Gorishniy, 2021)
- FT-Transformer (Gorishniy, 2021)

Prediction problems
- Dementia in persons aged 55 and above
- Lung cancer in persons aged 45 and above
- Bipolar in persons diagnosed with major depressive disorder

Confirmed databases
- Optum SES
- Optum EHR
- IPCI
- AUSOM
## Results

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<tr>
<th>Cohort</th>
<th>Database</th>
<th>Method</th>
<th>AUROC</th>
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<td>ResNet</td>
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<td>Transformer</td>
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</table>
Join The Network Study!

Help us assess the added value of observational data for the development of deep learning models.

Head over to https://github.com/ohdsi-studies/DeepLearningComparison or use the QR code.
THE ASSOCIATION OF SHORT-, MEDIUM AND LONG-TERM CARDIOVASCULAR SEQUELAE WITH COVID-19 INFECTION: A MULTINATIONAL PILOT STUDY

Speaker: Ian Wong
Poster 73
The association of short-, medium and long-term cardiovascular sequelae with COVID-19 infection: a multinational pilot study

Ian Chi Kei Wong, BSc (Hons) Pharmacy, MSc, PhD
Lo Shiu Kwan Kan Po Ling Professor in Pharmacy
Head, Department of Pharmacology and Pharmacy, LKS Faculty of Medicine, The University of Hong Kong
Lead Scientist, The Laboratory of Data Discovery for Health (D²4H)
wongick@hku.hk

This work was supported by the Research Grants Council of Hong Kong under the Collaborative Research Fund Scheme (C7154-20G)
Background

• COVID-19 infection is associated with a range of cardiovascular (CV) sequelae and associated mortality.\(^1,2\)

• The risk of CV sequelae remained unclear owing to the large variability in risk estimates from existing studies which differs in study design, population and selection of controls.\(^3\)

• This study aimed to evaluate the risk of short-, medium-, and long-term CV sequelae following COVID-19 using multi-national healthcare data

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Methods

Study design
- Retrospective cohort study
- Propensity score matching

Study population
- Individuals with COVID-19 between December 1st 2019–20 and non-COVID-19 controls

Study outcome
- Incident of nine cardiovascular sequelae

Follow-up
- Short- (Up to 6 months),
- Medium- (6 months to 1 year),
- Long-term (1 to 3 years)

Data source
- Multi-national healthcare databases
- We are calling for your collaborations!
Preliminary findings

Figure 1. Flow diagram on the selection of study population

Figure 2. Hazard ratio and calibrated hazard ratio of cardiovascular sequelae between December 1st, 2019–2022 in Italy LPD IQVIA database
Future plans

1. Further analyses to evaluate the short, medium and long-term risk of cardiovascular sequelae

2. Perform study package in databases mapped to OMOP CDM

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<tr>
<th>Database</th>
<th>Electronic health records</th>
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<td>US Open-claim IQVIA</td>
<td>Pre-adjudicated health insurance claims collected from general practitioners and specialists</td>
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<td>Germany DA IQVIA&lt;sup&gt;a&lt;/sup&gt;, France LPD IQVIA&lt;sup&gt;b&lt;/sup&gt;</td>
<td>Proprietary practice management software used by general practitioners and selected specialists</td>
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<tr>
<td>Italy LPD IQVIA&lt;sup&gt;b&lt;/sup&gt;, UK IMRD IQVIA&lt;sup&gt;c&lt;/sup&gt;</td>
<td>Patient records from general practitioners</td>
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<tr>
<td>Korea HIRA</td>
<td>Health Insurance Review &amp; Assessment Service</td>
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<sup>a</sup> DA = Disease Analyser, <sup>b</sup> LPD = Longitudinal Patient Database, <sup>c</sup> IMRD = IQVIA Medical Research Data
SUPPORTING PHARMACOVIGILANCE SIGNAL VALIDATION AND PRIORITIZATION WITH ANALYSES OF ROUTINELY COLLECTED HEALTH DATA – LESSONS LEARNED FROM AN EHDEN NETWORK STUDY

Speaker: Judith Brand
Poster 56
Supporting pharmacovigilance signal validation and prioritisation with analyses of routinely collected health data

*lessons learned from an EHDEN network study*

Judith Brand

Pharmacovigilance study-a-thon
Uppsala, 5-9 September 2022
How do we identify signals?

VigiBase
> 34M reports
(> 4M drug-event combinations)

Prioritisation

Detection

Validation

Assessment

Strength of evidence
Public health and clinical impact
Novelty

~hrs per signal
~wks per signal

Routine health data
What we did...

- Routine signal validation and prioritisation of statistical signals involving:
  - 200 generic drugs
  - 16 adverse event phenotypes

- On request, characterization analyses with 10 EHDEN data partners to contextualise:
  - Drug
  - Indication(s)
  - Adverse event
What we learned...

Feasible in given time limits

Useful for understanding potential:
- Bias and confounding
- Public health and clinical impact

Rapid feasibility assessment of follow-up pharmacoepi analysis

Multidisciplinary team

Large and diverse data network

Wide range of phenotypes for adverse events

Effective bridges between source vocabularies

Precomputation and standardisation of code

Data governance supporting PV use case
Advancing medicines safety together

Thanks to all who made this event possible!

julie.henderson@who-umc.org

Uppsala Monitoring Centre (UMC)
Box 1051, SE-751 40 Uppsala, Sweden
Email: info@who-umc.org, www.who-umc.org
PATTERN OF LONG COVID SYMPTOMS AND CONDITIONS: CLUSTERING ANALYSIS BASED ON LARGE MULTINATIONAL COHORTS AS PART OF AN EHDEN STUDY-A-THON

Speaker: Marti Catala Sabate
Poster 77
Pattern of Long COVID Symptoms and Conditions: Clustering Analysis Based on Large Multinational Cohorts as part of an EHDEN Study

MOTIVATION

OBJECTIVES

OBJECTIVE 1
To describe the epidemiology of long COVID.

OBJECTIVE 2
To characterise populations with long COVID.

OBJECTIVE 3
To identify long COVID subgroups.

STUDY-A-THON
17th to 21st April 2023
13 database partners from 9 countries

Adaptation of Long COVID definition for our study

1. Covid diagnosis OR positive test
2. Relevant symptoms persisting for >3 months after #1 (>4 weeks)
3. Lack of previous symptoms or condition/s that cause similar symptoms

RESULTS FOR OBJECTIVE 3
Latent Class Analysis: 4 subgroups, 1+ symptoms

(i) Mostly defined by one predominant symptom, which could also be common in the whole population
(ii) A lot of heterogeneity in general across databases and healthcare settings
RESULTS FOR OBJECTIVE 3
Latent Class Analysis: 4 subgroups, 3+ symptoms

(i) More combinations of multiple predominant symptoms, potentially clinically more relevant
(ii) Some clusters repeated across databases (for 2+, 3+ symptoms): anxiety-depression, dyspnea-cough, gastrointestinal-abdominal pain...
(iii) A lot of heterogeneity in general across databases and healthcare settings
Thank you for your attention!

Any questions?

Contact kim.lopez@spc.ox.ac.uk
EVALUATION OF TREATMENT EFFECT HETEROGENEITY IN THE LEGEND-HYPERTENSION STUDY

Speaker: Alexandros Rekkas
Poster 52
Evaluation of treatment effect heterogeneity in the LEGEND-Hypertension study

Alexandros Rekkas, Jenna M. Reps, Peter R. Rijnbeek, David van Klaveren
Methods

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- Stratification on acute MI risk (below 1%, between 1% and 1.5%, above 1.5%)
- Evaluation of preference score distributions, covariate balance, and negative control outcomes
- Estimation of relative treatment effects within risk strata using Cox proportional hazards regression
- Estimation of absolute risk differences within risk strata from the differences between the Kaplan-Meier curves on day 730 from treatment initiation
Results

Risk differences of acute MI within risk groups of acute MI in MDCD

Risk differences of acute MI within risk groups of acute MI in CCAE
More results

Results can be explored here:

https://arekkas.shinyapps.io/legend_htn_hte
Characteristics and Outcomes of >1M Inflammatory Bowel Disease Patients

Chen Yanover, KI Research Institute, Israel
Background, Goal

• Crohn's disease (CD) and ulcerative colitis (UC) are chronic inflammatory bowel diseases (IBD) with consistently increasing incidence rates. These conditions significantly impact the quality of life of patients and families.

⇒ Characterize IBD, CD, UC disease trajectory
  • Risk factors, symptoms, associated comorbidities, treatment pathways, outcomes
Methods

• Study design: A multinational cohort study using routinely collected healthcare data from 16 OMOPed DBs
  • USA, France, Germany, the UK, Korea, Japan, Australia

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<td>IQVIA™ Medicare Research Data – UK</td>
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<td>IQVIA™ Disease Analyzer – France</td>
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<td>IQVIA™ Disease Analyzer – Germany</td>
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<tr>
<td>IQVIA Australian Longitudinal Patient Data</td>
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</tbody>
</table>

• Disease cohorts defined using IBD, CD, UC Dx, Rx
• Characteristics, outcomes: Predefined features, +100 IBD–specific features during subjects’ entire history, 1Y, 1M before index date; 1M, 1, 3, 5, 10Y and all–time following index date.
Result Teaser

• Age at diagnosis, by index year
• Hospitalization cumulative rate
• Treatment, by age group

CD diagnosis age decreases over time

* median age group; ‖ interquartile range; ◆ estimated average
Challenges, Limitations

• Potential differences in coding, reporting across DBs
• Vocabulary updates render concept sets outdated
• HUGE amounts of data (>2G), challenging to view, handle
• Only binary attributes; no cross-strata info

THANK YOU!
PREDICTION OF 30-DAY, 90-DAY AND 1 YEAR MORTALITY AFTER COLORECTAL CANCER SURGERY USING A DATA-DRIVEN APPROACH

Speaker: Ismail Gögenur
Poster 70
Prediction of 30-day, 90-day and 1 year mortality after colorectal cancer surgery using a data-driven approach
Clinical problem

Risk factors

Key outcomes

Risk factors

Key outcomes
Using an OMOP based big data platform to aid clinical decision support

Registry Data

Patient profile + Key Outcomes

New patient

Prediction of mortality as an aid in clinical decision support!

Decision

Prehabilitation

Revised surgery

Oncological treatment

Medical treatment

No treatment
Overview of the CDM creation at CSS

**MERGE DATASOURCES**

- DCCG
- LPR
- MED
- LAB
- COVID
- DID
- DAD
- CAR
- DAR
- PAT

**ATLAS platform**

**BEDSIDE APPLICATION**

- Clinical research Area
- Decision support
- Cohorts
- Predictions
- Characterizations

**MDT**

- Decision support
Results for the mortality models

365-days mortality

<table>
<thead>
<tr>
<th>Subgroup</th>
<th>Incidence of outcomes</th>
<th>AUROC</th>
<th>Calibration slope</th>
<th>Intercept</th>
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</thead>
<tbody>
<tr>
<td>Elective</td>
<td>10.1 %</td>
<td>0.854</td>
<td>1.10</td>
<td>0.16</td>
</tr>
<tr>
<td>Emergency</td>
<td>37.8 %</td>
<td>0.852</td>
<td>1.13</td>
<td>0.05</td>
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<tr>
<td>Curative</td>
<td>9.0 %</td>
<td>0.850</td>
<td>1.07</td>
<td>0.11</td>
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<tr>
<td>Palliative</td>
<td>46.6 %</td>
<td>0.812</td>
<td>1.03</td>
<td>0.08</td>
</tr>
</tbody>
</table>
Implementing AI based prediction models in clinical practice

- **PATIENT CATEGORY**
  - **LAV RISIKO** (1-5% mortality)
  - **MIDDEL RISIKO** (5-15% mortality)
  - **HØJT RISIKO** (>15% mortality)
  - **MEGET HØJT RISIKO** (>15% mortality)

- **IMPROVED RECOVERY TRAJECTORIES**
  - **PRE-OP**
    - Patientschool
    - Short fasting
    - Oral carbohydrate
  - **OPERATION**
    - Minimally invasive surgery
    - Multimodal analgesia
  - **POST-OP**
    - Ambulation day of surgery
    - Early oral nutrition
  - **POST-DIS**

- **Specialty experts**

- **Expanded MDT**

- **AI Based prediction model**

- **Improved patient care!**
  - ↓ Complications
  - ↑ Empowerment
  - ↑ Cure Rate
  - ↓ Readmissions
  - ↑ Quality of life
  - ↑ Oncol treatment
  - ↓ Mortality
Early results and conclusion

- N=80
- Reduction in length of stay after surgery
- Reduction in morbidity
- Reduction in readmissions after surgery

Early results indicate that decision support tools based on an OMOP based data infrastructure can be feasible in a clinical setting and improve clinical outcomes.
Collaborator Showcase: Rapid Fire Presentations

THANK YOU!
Lunch, Collaborator Showcase, and Early Investigator meetings

The Collaborator Showcase is made possible with the help of MTG and IOMED

Early Investigators mentor meetings in the Queen’s Lounge

Led by Ross Williams