

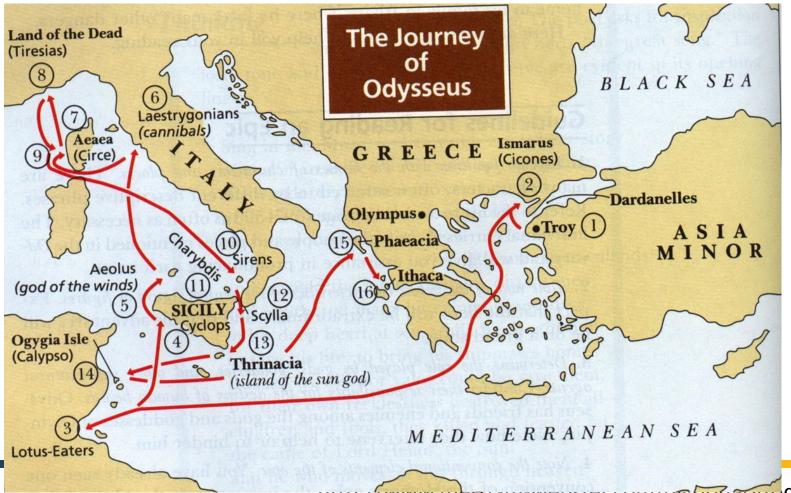
OHDSI's Journey: Where we've been, where we can go

Patrick Ryan, PhD
Janssen Research and Development
Columbia University Medical Center
10 January 2017



Odyssey (noun): \oh-d-si\

1. A long journey full of adventures



IIII.//www.IIIemani-websiei.com/urctionary/odyssey



OHDSI's mission

To improve health, by empowering a community to collaboratively generate the evidence that promotes better health decisions and better care.



OHDSI's values

- Innovation: Observational research is a field which will benefit greatly from disruptive thinking. We actively seek and encourage fresh methodological approaches in our work.
- Reproducibility: Accurate, reproducible, and well-calibrated evidence is necessary for health improvement.
- **Community**: Everyone is welcome to actively participate in OHDSI, whether you are a patient, a health professional, a researcher, or someone who simply believes in our cause.
- **Collaboration**: We work collectively to prioritize and address the real world needs of our community's participants.
- Openness: We strive to make all our community's proceeds open and publicly accessible, including the methods, tools and the evidence that we generate.
- **Beneficence**: We seek to protect the rights of individuals and organizations within our community at all times.



OHDSI's areas of focus

Methodological research

Open-source analytics development

Clinical applications

Observational data management

Clinical characterization

Population-leve estimation

Patient-level prediction



Journey toward best practices in data management

Case Report

Healthc Inform Res. 2016 January,22(1):54-58. http://dx.doi.org/10.4258/hir.2016.22.1.54 pISSN 2093-3681 • etSSN 2093-369X

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Special Communication

Evaluating common data models for use with a longitudinal community registry



Maryam Garza a, Guilherme Del Fiol b, Jessica Tenenbaum c, Anita Walden a,d, Meredith Nahm Zozus c,d,*

Boyce et al.: Preparing Nursing Home Data for Clinical Research

ike City, UT 84108, USA ham, NC 27705, USA

is Drive, Mail Slot # 782, Little Rock, AR 72205, USA



Preparing Nursing Home Data from Multiple Sites for Clinical Research - A Case Study Using Observational Health Data Sciences and Informatics

Richard D. Boyce, PhD; Steven M. Handler, MD, PhD; Jordan F. Karp, MD; Subashan Perera, PhD; Charles F. Reynolds III, MD

determine which is best suited for sharing da t)-based community registry.

nodels in use for clinical research data: Sentir s versions), PCORnet v3.0 (an extension of t k. Each model was evaluated against 11 crites categories: content coverage, integrity, flexible and extent of implementation.

centage of our data elements (76%), fared well age than the other models. Sentinel and PCORn is respectively. Although SDTM accommodated es), 45% of the data elements mapped to SDTN ers, increasing the number of joins required.

or supporting data sharing from longitudir uses and associated data element sets, but to non data model evaluation for other uses.

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ABSTRACT



Journey toward best practices in data quality assessment

Kahn et al.: Harmonized data quality terminology



A Harmonized Data Quality Assessment Terminology and Framework for the Secondary Use of Electronic Health Record Data

Michael G. Kahn, MD, PhD, Tiffany J. Callahan, MPH, Bruce N. Davidson, PhD, Hossein Estiri, PhD, Cars Steven G. Johnson, MS, Siaw-Teng Liaw, MBBS, Phi Daniella Meeker, PhD, Toan C. Ong, PhD, Patrick R. Chunhua Weng, PhD, FACMI Meredith N. Zozus, P.

Daniella Meeker, PhD;* Toan C. Ong, PhD;*I Patrick R
Chunhua Weng, PhD, FACMI;*II Meredith N. Zozus, P

ABSTRACT

Objective: Harmonized data quality (DQ) asset establish a common understanding of the stren for operational analytics, quality improvement, to a comprehensive unified terminology with deframework to support a common approach to a

Materials and Methods: DQ publications, infor programs, and operational manuals from sever to identify potential DQ terms and categories. vet an initial set of DQ terms and definitions the Feedback received from data producers and uterms and categories. Multiple rounds of iterat framework consisting of DQ categories, subcaterminology and logical framework's inclusiver

Generating Evidence & Methods to Improve patient outcomes Multisite Evaluation of a Data Quality

Multisite Evaluation of a Data Quality Tool for Patient-Level Clinical Data Sets

Vojtech Huser, MD, PhD;¹⁰ Frank J. DeFalco;¹⁰ Martijn Schuemie, PhD;¹⁰ Patrick B. Ryan, PhD;¹⁰ Ning Shang, PhD;¹⁰ Mark Velez, MD;¹⁰ Rae Woong Park, MD, PhD;¹⁰ Richard D. Boyce, PhD;¹⁰ Jon Duke, MD, MS;¹⁰ Ritu Khare, PhD;¹⁴ Levon Utidjian, MD;¹⁴ Charles Bailey, MD, PhD¹⁶

ABSTRACT

Introduction: Data quality and fitness for analysis are crucial if outputs of analyses of electronic health record data or administrative claims data should be trusted by the public and the research community.

Methods: We describe a data quality analysis tool (called Achilles Heel) developed by the Observational Health Data Sciences and Informatics Collaborative (OHDSI) and compare outputs from this tool as it was applied to 24 large healthcare datasets across seven different organizations.

Huser et al.: Evaluation of Achilles Heel (Data Quality Tool)



Journey toward open data standardization

www.nature.com/scientificdata

SCIENTIFIC DATA

SUBJECT CATEGORIES

» Translational research » Outcomes research

» Adverse effects

» Drug safety

OPEN Data Descriptor: A curated and standardized adverse drug event resource to accelerate drug safety research

Juan M. Banda¹, Lee Evans², Rami S. Vanguri³, Nicholas P. Tatonetti³, Patrick B. Ryan⁴ & Nigam H. Shah1

Received: 17 December 2015 Accepted: 24 March 2016 Published: 10 May 2016

Identification of adverse drug reactions (ADRs) during the post-marketing phase is one of the most important goals of drug safety surveillance. Spontaneous reporting systems (SRS) data, which are the mainstay of traditional drug safety surveillance, are used for hypothesis generation and to validate the newer approaches. The publicly available US Food and Drug Administration (FDA) Adverse Event Reporting System (FAERS) data requires substantial curation before they can be used appropriately, and applying different strategies for data cleaning and normalization can have material impact on analysis results. We provide a curated and standardized version of FAERS removing duplicate case records, applying standardized vocabularies with drug names mapped to RxNorm concepts and outcomes mapped to SNOMED-CT concepts, and pre-computed summary statistics about drug-outcome relationships for general consumption. This publicly available resource, along with the source code, will accelerate drug safety research by reducing the amount of time count performing data management on the course EAEDC counts improving the quality of the



Journey toward leveraging open data to inform new analyses

Journal of Biomedical Informatics 66 (2017) 72-81



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Journal of Biomedical Informatics





Accuracy of an automated knowledge base for identifying drug adverse reactions



E.A. Voss a,b,c,*, R.D. Boyce d,c, P.B. Ryan a,e,c, J. van der Lei b,c, P.R. Rijnbeek b,c, M.J. Schuemie a,c

ARTICLE INFO

Article history: Received 21 July 2016 Revised 8 December 2016 Accepted 10 December 2016 Available online 16 December 2016

Keywords: Pharmacovigilance Adverse drug reaction Machine-learning experiment Knowledge base Health outcome

ABSTRACT

Introduction: Drug safety researchers seek to know the degree of certainty with which a particular drug is associated with an adverse drug reaction. There are different sources of information used in pharmacovigilance to identify, evaluate, and disseminate medical product safety evidence including spontaneous reports, published peer-reviewed literature, and product labels. Automated data processing and classification using these evidence sources can greatly reduce the manual curation currently required to develop reference sets of positive and negative controls (i.e. drugs that cause adverse drug events and those that do not) to be used in drug safety research.

Methods: In this paper we explore a method for automatically aggregating disparate sources of information together into a single repository, developing a predictive model to classify drug-adverse event relationships, and applying those predictions to a real world problem of identifying negative controls for statistical method calibration.

Results: Our results showed high predictive accuracy for the models combining all available evidence, with an area under the receiver-operator curve of ≥0.92 when tested on three manually generated lists of drugs and conditions that are known to either have or not have an association with an adverse drug event.

Conclusions: Results from a pilot implementation of the method suggests that it is feasible to develop a scalable alternative to the time-and-resource-intensive, manual curation exercise previously applied to develop reference sets of positive and negative controls to be used in drug safety research.

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Journey toward large-scale open science



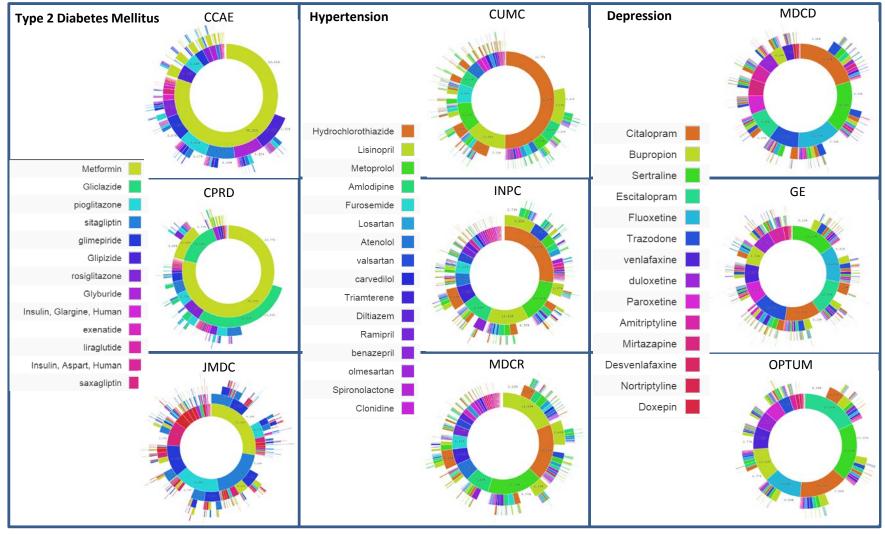
Characterizing treatment pathways at scale using the OHDSI network

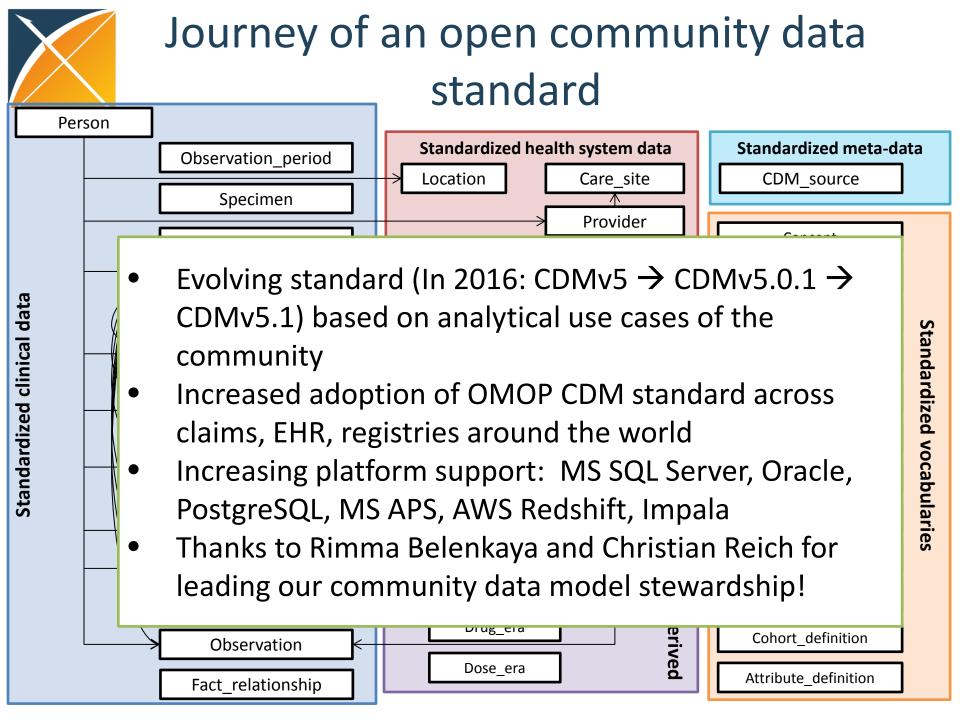
George Hripcsak^{a,b,c,1}, Patrick B. Ryan^{c,d}, Jon D. Duke^{c,e}, Nigam H. Shah^{c,f}, Rae Woong Park^{c,g}, Vojtech Huser^{c,h}, Marc A. Suchard^{c,i,j,k}, Martijn J. Schuemie^{c,d}, Frank J. DeFalco^{c,d}, Adler Perotte^{a,c}, Juan M. Banda^{c,f}, Christian G. Reich^{c,l}, Lisa M. Schilling^{c,m}, Michael E. Matheny^{c,n,o}, Daniella Meeker^{c,p,q}, Nicole Pratt^{c,r}, and David Madigan^{c,s}

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Journey to clinical characterization insights required network research







OHDSI's standardized vocabularies

- 69 Vocabularies across 25 domains
 - Thank you Christian and the Odysseus team for
 - continue to steward, maintain, and improve this invaluable resource for the entire community!
- 3,526,752 concepts
 - 1,174,628 standard concepts
 - 1,418,696 source codes
 - 323,159 classification concepts
- 24,064,798 concept relationships



Our journey as a community of collaborators



OHDSI Collaborators:

- >140 researchers in academia, industry, government, health systems
- >20 countries
- Multi-disciplinary expertise: epidemiology, statistics, medical informatics, computer science, machine learning, clinical sciences

Databases converted to OMOP CDM within OHDSI Community:

- >50 databases
- >660 million patients



Forums.ohdsi.org

- 361 distinct users who have posted
- 5,823 posts on 1,100 topics
- Active discussions across all categories:
 - Implementers, Developers, Researchers, CDM Builders, Vocabulary users

Thank you Christian Reich, Lee Evans, and Chris Knoll for being our most diligent community responders!



Journey toward open-source analytics development

- 61 developers on OHDSI GitHub repositories
- Applications in development or released for:
 - CDM ETL design and implementation
 - Clinical characterization (ACHILLES, ATLAS)
 - Population-level effect estimation (CohortMethod)
 - Patient-level prediction
 - OHDSI network studies (protocol + source code)



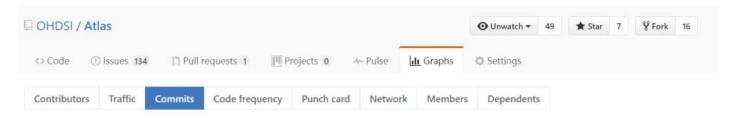
Journey toward open-source analytics development



ATLAS – a single community platform for:

- -vocabulary browsing
- -database characterization
- -cohort definition
- -incidence rate
- -patient profiles
- -population-level effect estimation study design

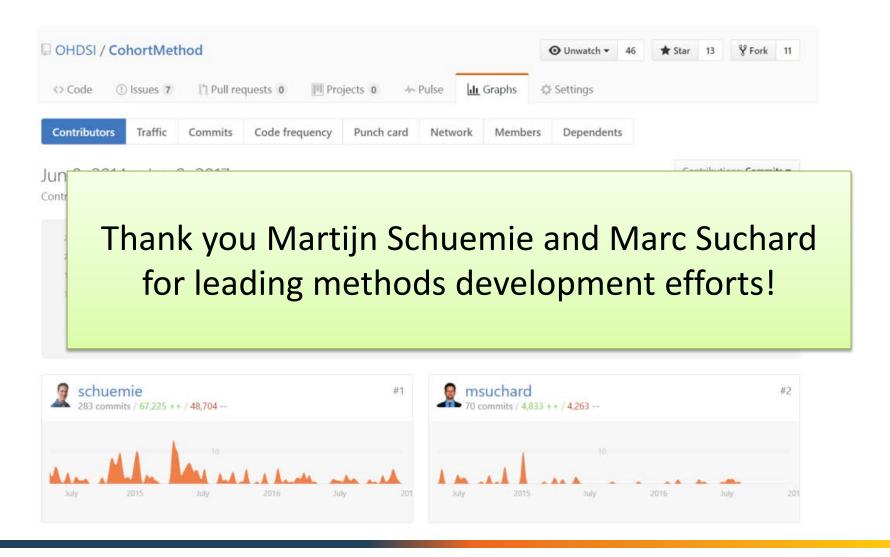
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Thank you Frank DeFalco for leading the OHDSI architecture workgroup!



Journey toward open-source analytics development





OHDSI Symposium 2016

• 410 registrants from 11 countries, 27 US states

Congratulations to Christophe Lambert, Sigfried Gold, and Rupa Makadia on winning the OHDSI Best Poster awards!

 48 poster presentations in observational data management, methodological research, analytics technology and infrastructure, and clinical applications

Thank you OHDSI tutorial faculty!









CDM/ETL: Rimma Belenkaya, Karthik Natarajan, Mark Velez, Erica Voss





Technology stack: Taha Abdul-Basser, Lee Evans, Karthik Natarajan, Mark Velez





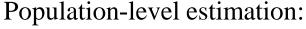




Cohort definition: Juan Banda, Jon Duke, Chris Knoll, Nigam Shah

Vocabulary:

Frank DeFalco, George Hripcsak, Christian Reich



David Madigan, Martijn Schuemie, Marc Suchard







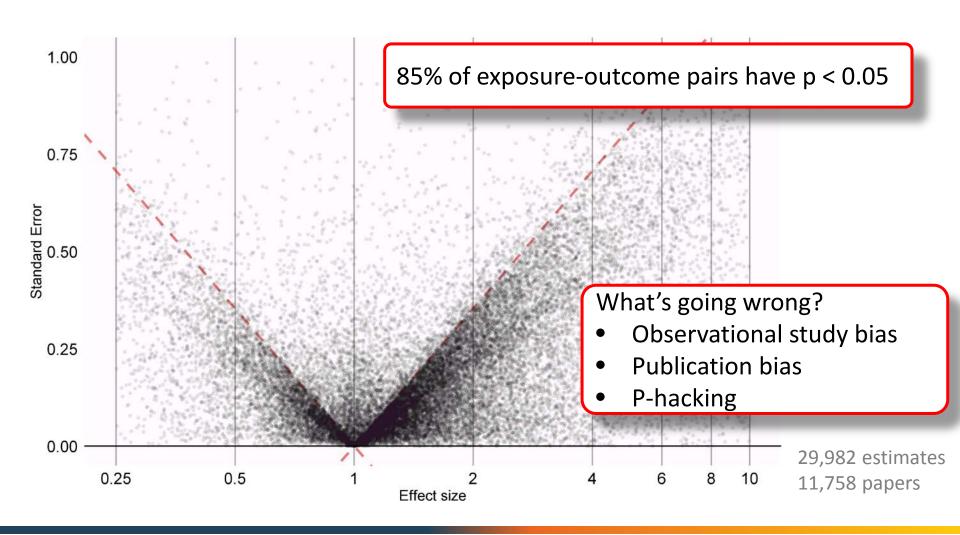






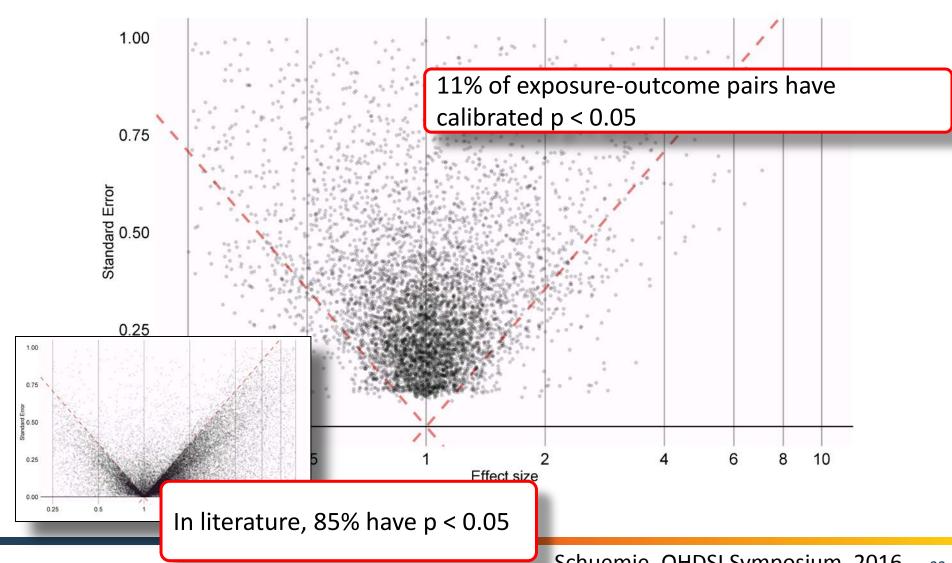


Observational research results in literature





Large-scale analysis can start to produce reliable evidence to enable an honest learning healthcare system





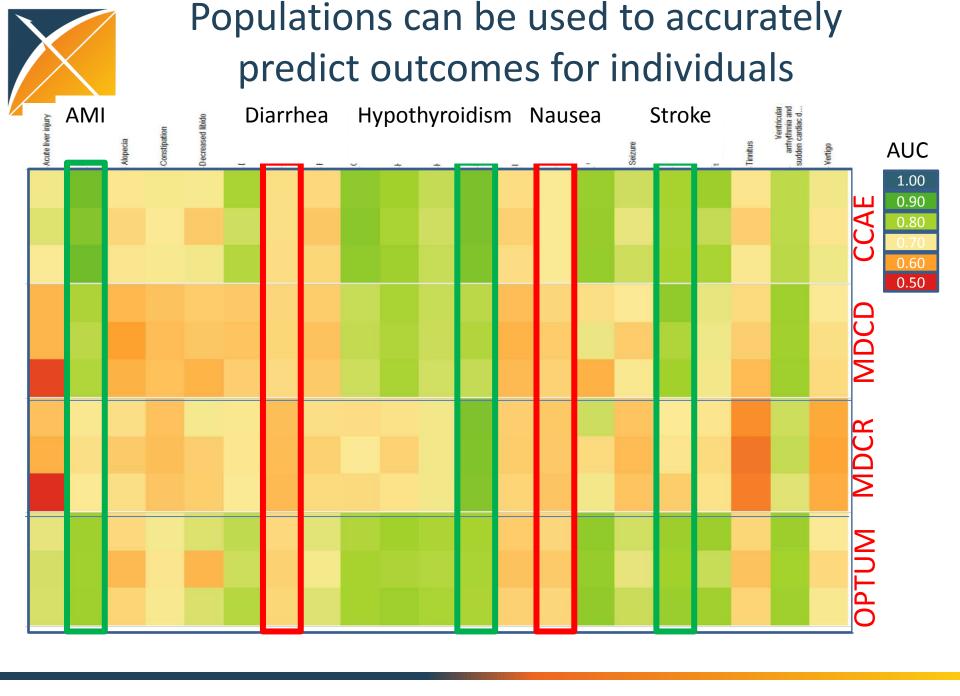
OHDSI's recommended best practices for population-level effect estimation

Evidence Generation Evidence Evaluation Evidence
Dissemination

- Write and share protocol
- Open source study code
- Use validated software
- Replicate across databases

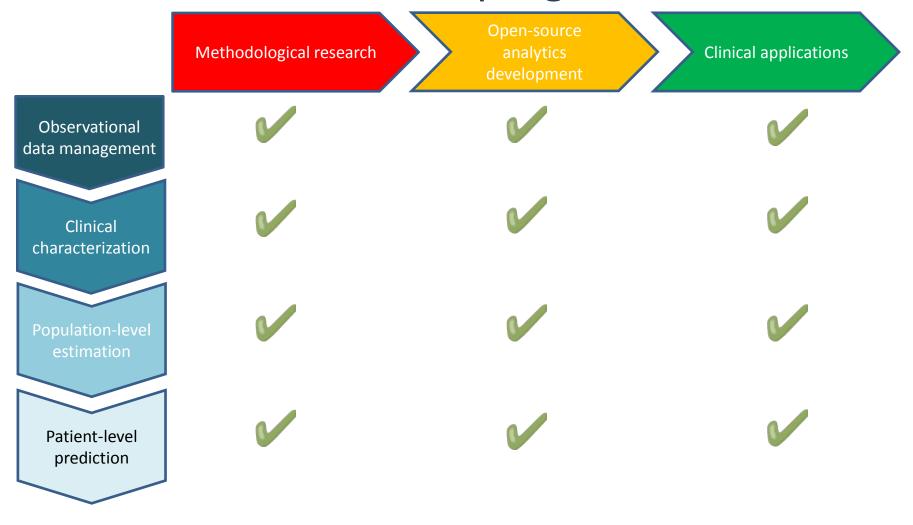
- Produce standard diagnostics
- Include negative controls
- Create positive controls
- Calibrate confidence interval and pvalue

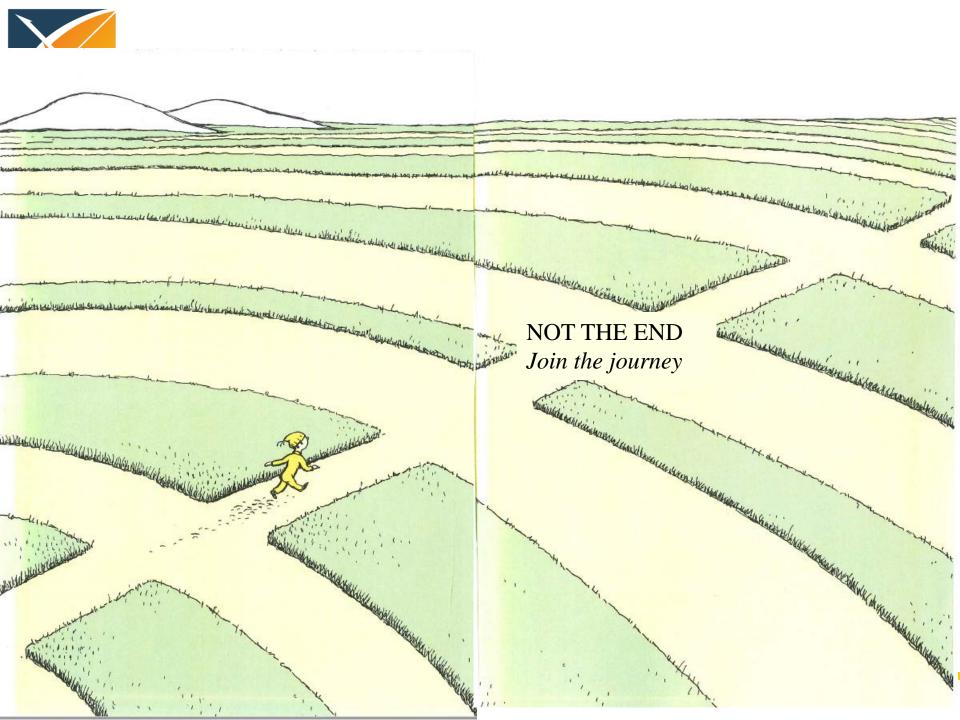
- Don't provide only the effect estimate
- Also share protocol, study code, diagnostics and evaluation
- Produce evidence at scale

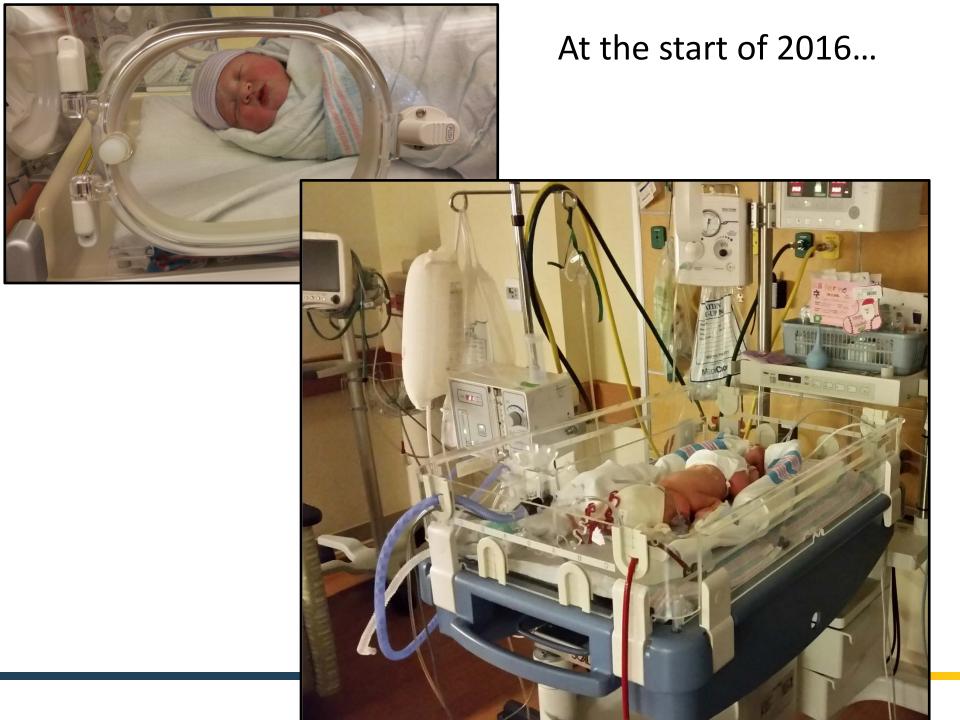




OHDSI's areas of focus: A look back on progress from 2016...











Indication

Synagis® (palivizumab) is a prescription medication that is used to help prevent a serious lung disease caused by respiratory syncytial virus (RSV) in children at high risk for severe lung disease from RSV.

Select Safety Information

Common side effects of Synagis include fever and rash. Other possible side effects include skin reactions around the area where the shot was given (like redness, swelling, warmth, or discomfort).

Please see complete Important Safety Information on pages 22-24 and accompanying full Prescribing Information, including Patient Information.

Doctor X: "This paper says there's side effects, but I've never seen them happen"



SYNAGIS- palivizumab injection, solution MedImmune, LLC

HIGHLIGHTS OF PRESCRIBING INFORMATION

These highlights do not include all the information needed to use SYNAGIS safely and effectively. See full prescribing information for SYNAGIS.

SYNAGIS® (palivizumab) injection, for intramuscular use

Initial U.S. Approval: 1998

------ INDICATIONS AND USAGE

Synagis is a respiratory syncytial virus (RSV) F protein inhibitor monoclonal antibody indicated for the prevention of serious lower respiratory tract disease caused by RSV in children at high risk of RSV disease.

- Safety and efficacy were established in children with bronchopulmonary dysplasia (BPD), infants with a history of
 premature birth (less than or equal to 35 weeks gestational age), and children with hemodynamically significant
 congenital heart disease (CHD).
- · The safety and efficacy of Synagis have not been established for treatment of RSV disease. (1)

······DOSAGE AND ADMINISTRATION ······

15 mg per kg of body weight, administered intramuscularly prior to commencement of the RSV season and remaining doses administered monthly throughout the RSV season. (2.1)

Children undergoing cardio-pulmonary bypass should receive an additional dose of Synagis as soon as possible after the cardio-pulmonary bypass procedure (even if sooner than a month from the previous dose). Thereafter, doses should be administered monthly as scheduled. (2.1, 12.3)

----- DOSAGE FORMS AND STRENGTHS

Single-dose liquid solution vials: 50 mg per 0.5 mL and 100 mg per 1 mL. (3)

------CONTRAINDICATIONS ------

Previous significant hypersensitivity reaction to Synagis. (4)

------ WARNINGS AND PRECAUTIONS ------

- Anaphylaxis and anaphylactic shock (including fatal cases), and other severe acute hypersensitivity reactions have been reported. Permanently discontinue Synagis and administer appropriate medications if such reactions occur. (5.1)
- As with any intramuscular injection, Synagis should be given with caution to children with thrombocytopenia or any coagulation disorder. (5.2)
- Palivizumab may interfere with immunological-based RSV diagnostic tests such as some antigen detection-based assays. (5.3, 12.4)

-----ADVERSE REACTIONS ------

Adverse reactions occurring greater than or equal to 10% and at least 1% more frequently than placebo are fever and rash. (6.1)







In the middle of 2016...







At the end of 2016...





Why our journey isn't finished yet

- No patient should have to wonder "what's the chance that this event might happen to me?"
- All patients deserve to have reliable evidence about the safety and comparative effectiveness of alternative treatments when making medical decisions
- The potential for a 'learning healthcare system' can only be realized if we agree to learn together and collaborate to build a system



Building the LHC of observational research?





OHDSI's areas of focus: A look forward at 2017...

Methodological research

Open-source analytics development

Clinical applications

Observational data management

Clinical characterization

Population-level estimation

Patient-level prediction

- Generate and disseminate more clinical evidence
- Maintain and evolve open community data and vocabulary standards
- Develop and improve tools to enable large-scale analysis
- Establish and promote community best practices
- Strengthen and expand collaborations across OHDSI research network
- Advance scholarship in observational data science through publication, presentations, and education
- Generate and disseminate more clinical evidence



Join the journey

Discussion / questions / comments



ryan@ohdsi.org