OHDSI
OBSERVATIONAL HEALTH DATA SCIENCES AND INFORMATICS

#OHDSICOVID19

OHDSI COVID-19 International Study-A-Thon

The meeting will begin shortly.

Follow our COVID19 Updates
www.ohdsi.org/covid-19-updates
/OHDSI
/company/ohdsi
#JoinTheJourney

Collaborating to design and execute observational research and generate real-world evidence to inform the global pandemic

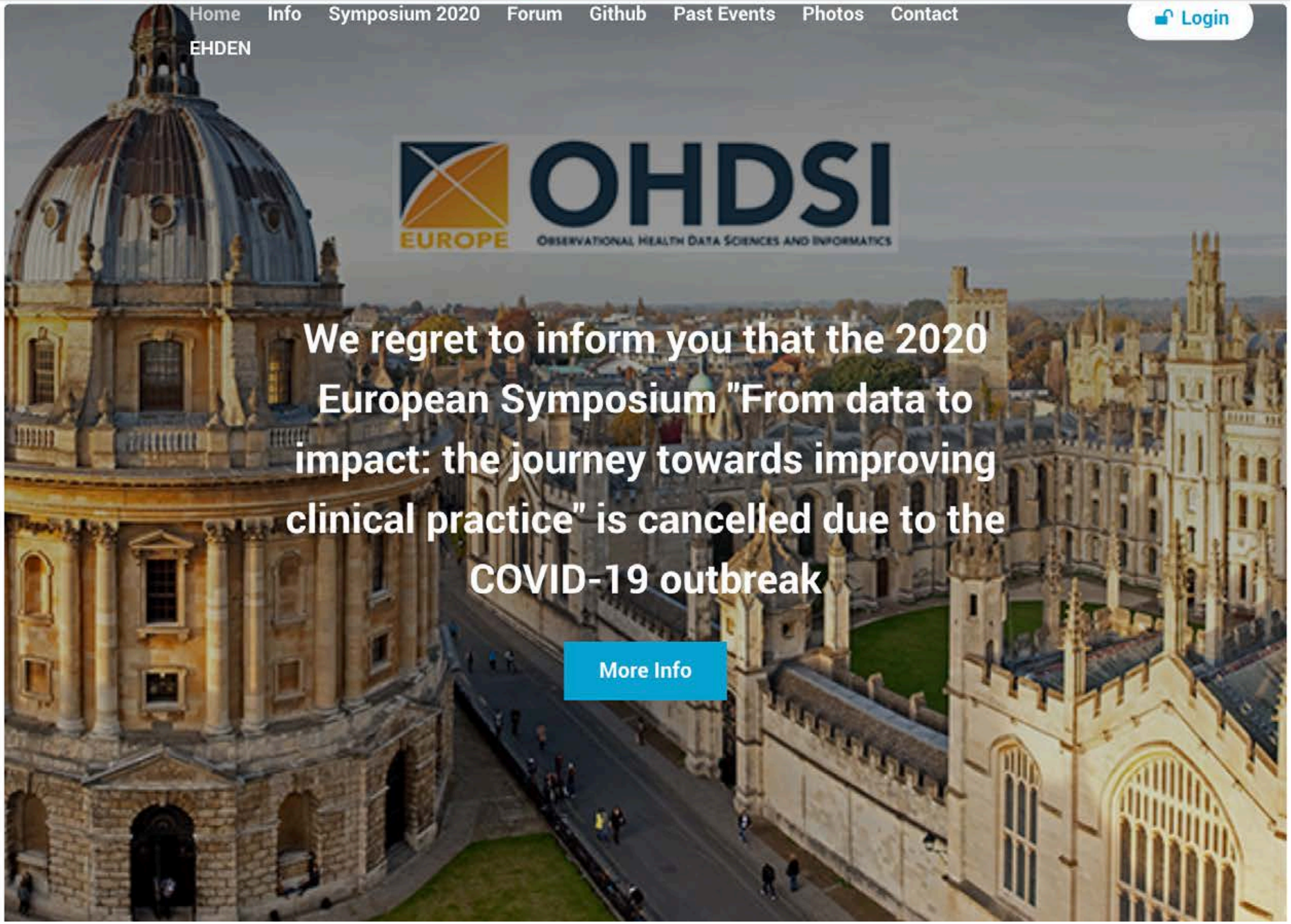
March 26-29, 2020

OHDSI

OBSERVATIONAL HEALTH DATA SCIENCES AND INFORMATICS

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

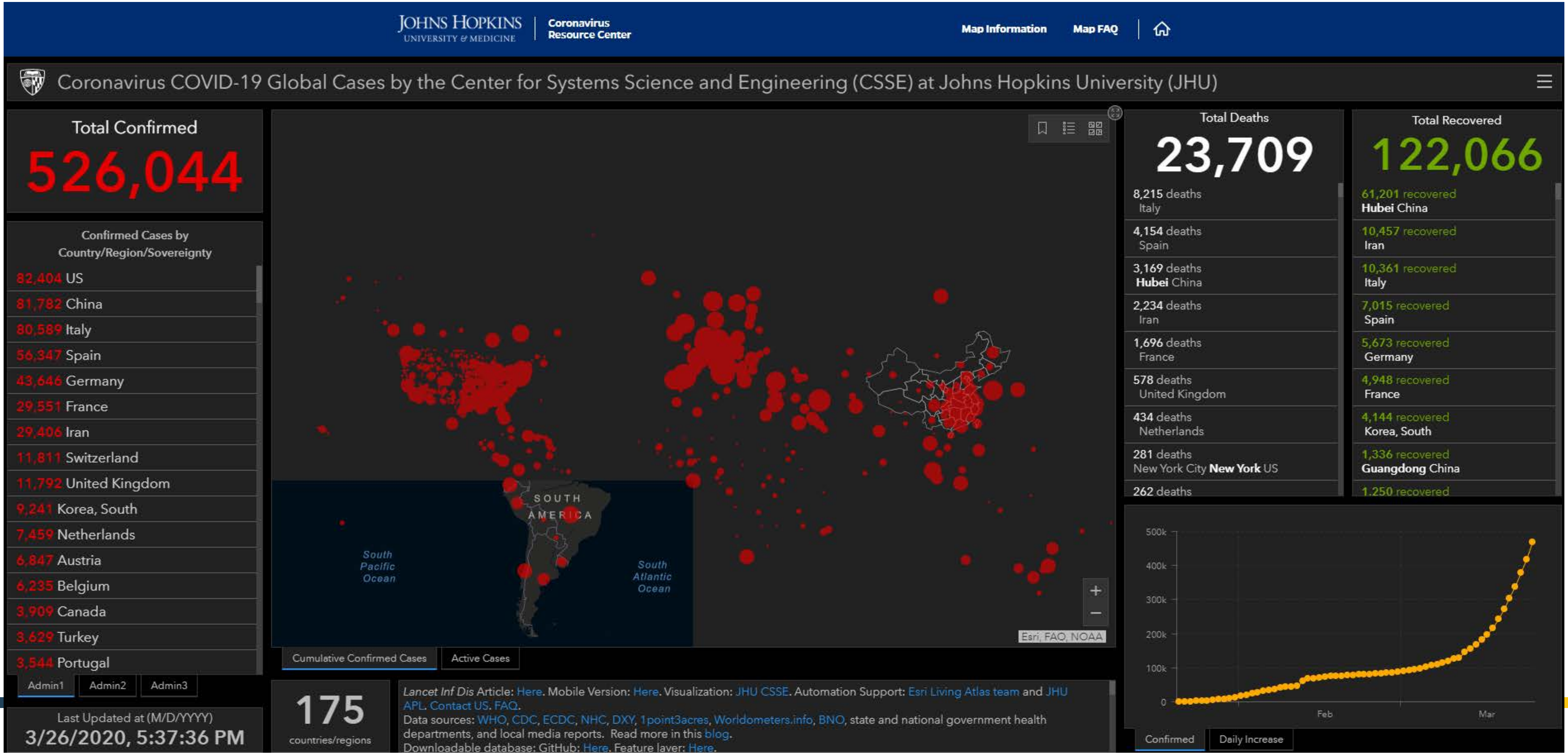
… #flattenthecurve



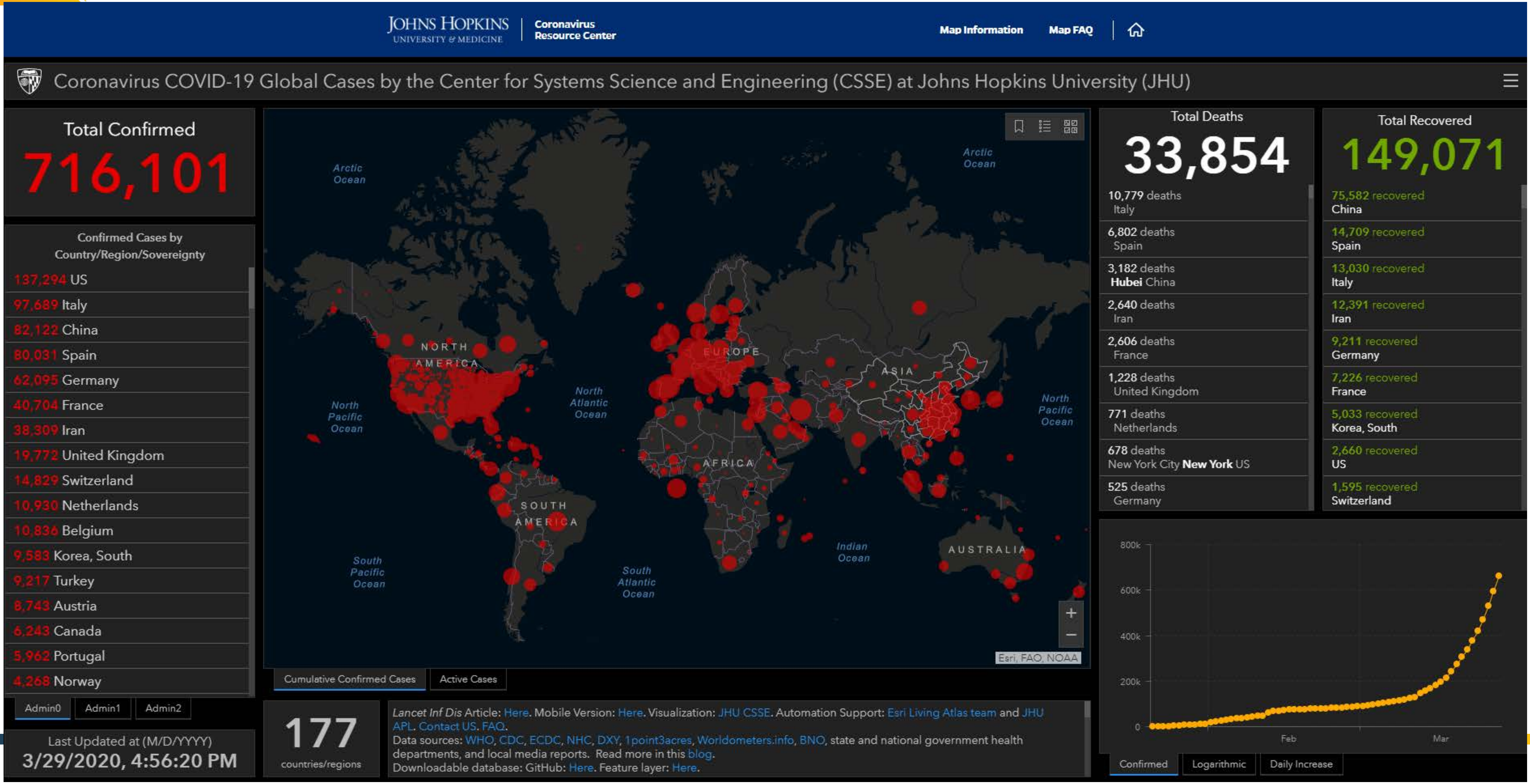
OHDSI COVID-19 Study-a-thon kickoff 26Mar2020 3amEST

https://www.ohdsi.org/covid-19-updates/

When we started on 26 March 2020



29th March 6:00pmEST



Tracking our collaboration 26Mar2020 3amET

OHDSI COVID-19 Study-a-thon Study Tracker

Analytic use case	Study	Lit Review and protocol development	Phenotype development and evaluation	Study package development	Study execution across network	Clinical review and dissemination
Characterization						
	COVID-19 positive patients					
	COVID-19 +ve subgroup analyses					
	Influenza, symptoms, and complications					
	Invasive treatments for respiratory distress					
	other questions?					
Prediction						
	1) Who presenting with flu, symptoms, or complications will be admitted to hospital?					
	2) Who sent home with symptoms will progress to require hospitalizaton?					
	3) Who admitted to hospital will require intensive care services or die?					
	other questions?					
Estimation						
	Effects of hydroxychloroquine					
	Effects of IL6 and JAK inhibitors					
	Effects of HIV protease inhibitors					
	Effects of HepC protease inhibitors					
	Effects of ACE inhibitors					
	other questions?					

To be done

Completed

Where are we now?

OHDSI COVID-19 Study-a-thon Study Tracker

Analytic use case	Study	Lit Review and protocol development	Phenotype development and evaluation	Study package development	Study execution across network	Clinical review and dissemination
Characterization						
	COVID-19 positive patients					
	COVID-19 +ve subgroup analyses					
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Estimation						
	Effects of hydroxychloroquine					
	Effects of IL6 and JAK inhibitors					
	Effects of HIV protease inhibitors					
	Effects of HepC protease inhibitors					
	Effects of ACE inhibitors					
	other questions?					

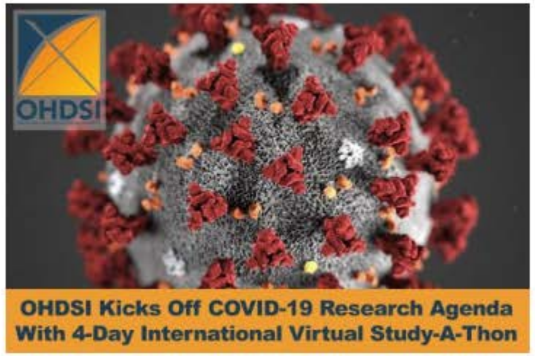
To be done
In progress
Results in, more to come
Completed

OHDSI

OBSERVATIONAL HEALTH DATA SCIENCES AND INFORMATICS

COVID-19 Updates Page

The Observational Health Data Sciences and Informatics (OHDSI) international community will host a COVID-19 virtual study-a-thon this week (March 26-29) to inform healthcare decision-making in response to the current global pandemic.



Day 4

Early Call: Video
Global Call: Video
FINAL CALL: Use This Link To Watch Live (regardless of whether you registered)

Please take a look at the early calls, but we're going to save the exciting study-a-thon updates for our final call tonight! This link will work for anybody, regardless of whether you registered for the study-a-thon. We are so excited to share our studies and early results with the world. Please share this link with people in your networks, so they can see the power of global collaboration in the OHDSI community.

Day 3 Updates

What have we done?

In only **88** hours, we have:

- Convened **351** participants brought together from **30** countries
- Held **12** Global Huddles, **>100** collaborator calls, **>13,000** chat messages
- Engaged **15** concurrent channels
- Reviewed **>10,000** publications
- Drafted **9** protocols
- Released **13** study packages
- Designed **355** cohort definitions
- Assembled a distributed data network with **37** partners signed on to execute studies

https://www.ohdsi.org/covid-19-updates/

3 things that we did in 4 days together that nobody has ever done before

- First large-scale characterization of COVID patients in US and Asia (Ed)
- First prediction model externally validated on COVID patients to support triage to ‘flatten the curve’ (Jenna)
- Largest study ever conducted on the safety of hydroxychloroquine (Dani)

3 things we're about to do that nobody has ever done before

- Designed self-controlled case series to examine safety of IL6 and JAK inhibitors….package is running
- Designed and implemented international study to evaluate protease inhibitors….package is running (Albert)
- Designed and implemented a study to evaluate impact of ACE inhibitor amongst Covid….need more COVID data (Daniel)

Ground rules for presentation

- We will be sharing the journey we’ve been on through all our our studies
  - Celebrate the tremendous progress
  - Highlight the rigorous analytical methods and scientific best practices applied through the week
  - Share ***preliminary*** results, which should not be over-interpreted but provide an exciting view of the journey ahead

Collaborative literature review

Jenny Lane
University of Oxford

Pre Study-a-thon...

AIM TO SUPPORT STUDY TEAMS, ESPECIALLY IN ESTIMATION

DMARDS

ANTIVIRALS

Systematic approach

PubMed
Embase (1974)
Clinicaltrials.gov
ICTRP
BioRxiv & medRxiv

5458 DMARD Articles
(Hydroxychloroquine/ csDMARDs
Biologics- IL6 & JAK inhibitors)

4800 Antiviral Articles
Protease Inhibitors (Lopinavir/ ritonavir)
Hep C/ H1N1 / Ebola/ Influenza

Results

Rayyan (https://rayyan.qcri.org) to collaboratively screen

Data extraction files (efficacy, safety, mechanism of action)

Written summaries for protocols & manuscripts

Updated searches

Chinese clinical trial registry

Clinical guidelines

The Team & Final Products

5 continents; core team 15, 25 in total

Data scientists to clinicians

Teams -> files ->Competency Literature Review -> HCQ / IL6 /HepC Study Channel

BIG thanks to everyone!!

OBSERVATIONAL HEALTH DATA SCIENCES AND INFORMATICS

OHDSI Data Network in Action

Kristin Kostka

IQVIA

United Nations of OMOP (Our Global Network)

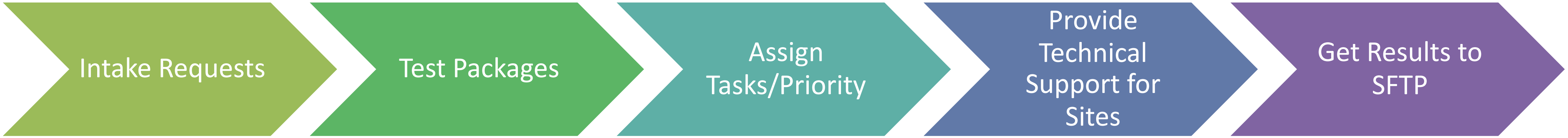
- 37 databases participating
  - Insurance claims, EHRs, Administrative data, Registries
  - 10 countries on 3 continents
- 8 databases with COVID+ patients (and growing)
- Everyone adopted OMOP CDMv5+

Executing 9 OHDSI network studies concurrently...

Expectation

Reality

Process for managing 9 OHDSI network studies concurrently



Mobilizing our action plan

Activity	Shiny App	Data Owners																												
		HIRA	FEEDER-NET COVID Cases (2	Tufts CLAR	CUM	Daegu Catholic University Medical Center--	STARR-OMO	Maine Medical Center	AUSOM	KNUH	WKUH	Seoul National CDM	CCAE (Janssen)	CCAE (UNM)	MDCR (Janssen)	MDCR (UNM)	IPCI	IQVIA UK IMRD	IQVIA DA France	IQVIA DA Belgium	IQVIA DA Germany	IQVIA Hospital CDM	IQVIA US Open Claims	CPRD	JMDC	Optum DOD	Optum PANTHER	SIDIAP	Vanderbilt Synthetic Derivative	MDCD (Janssen)
Pre Work: File Protocol with Local IRB / Go																														
Pre Work: Phenotype Evaluation																														
Cohort Diagnostics of Exposures: Covid19CohortEvalu	https://data.ohdsi.org/Covid19CohortEvaluationExposures/																													
Characterization Runs	TBC																													
COVID-19 positive patients	TBC																													
Run Package																														
Share Results																														
COVID-19 +ve subgroup	TBC																													
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Influenza, symptoms and complications	TBC																													
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Invasive treatments for respiratory distress	TBC																													
Run Package																														
Share Results																														
COVID-19 testing	TBC																													
Run Package																														
Share Results																														
Prediction Studies	_																													
Hospitalization In Sent Home Patients (Internal Validati	_																													
Hospitalization In Sent Home Patients (External Validat	_																													
Installing library into Rstudio																														
Check Cohort Counts																														
Run Package																														
Share Results in OHDSI SFTP																														
Results Published in Shiny App																														
Hospitalization In Symptomatic Patients (External Valid	_													al		l														
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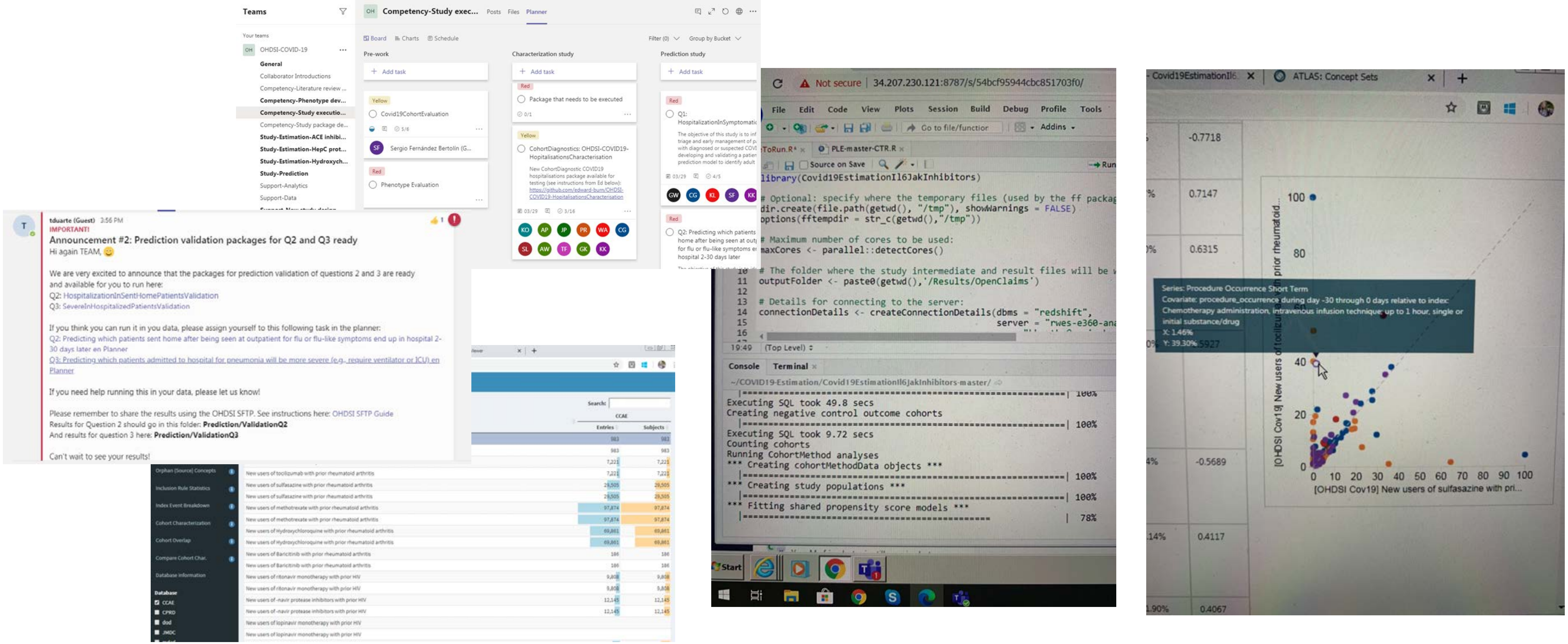
Severe In Hospitalized Patients (Internal Validation)	_																													
Severe In Hospitalized Patients (External Validation)	_																													
Installing library into Rstudio																														
Check Cohort Counts																														
Run Package																														

Thank you HIRA, AUSOM, Tufts, CUMC, Stanford, UC Denver, Vanderbilt, SIDIAP and Veteran's Affairs/VINCI!

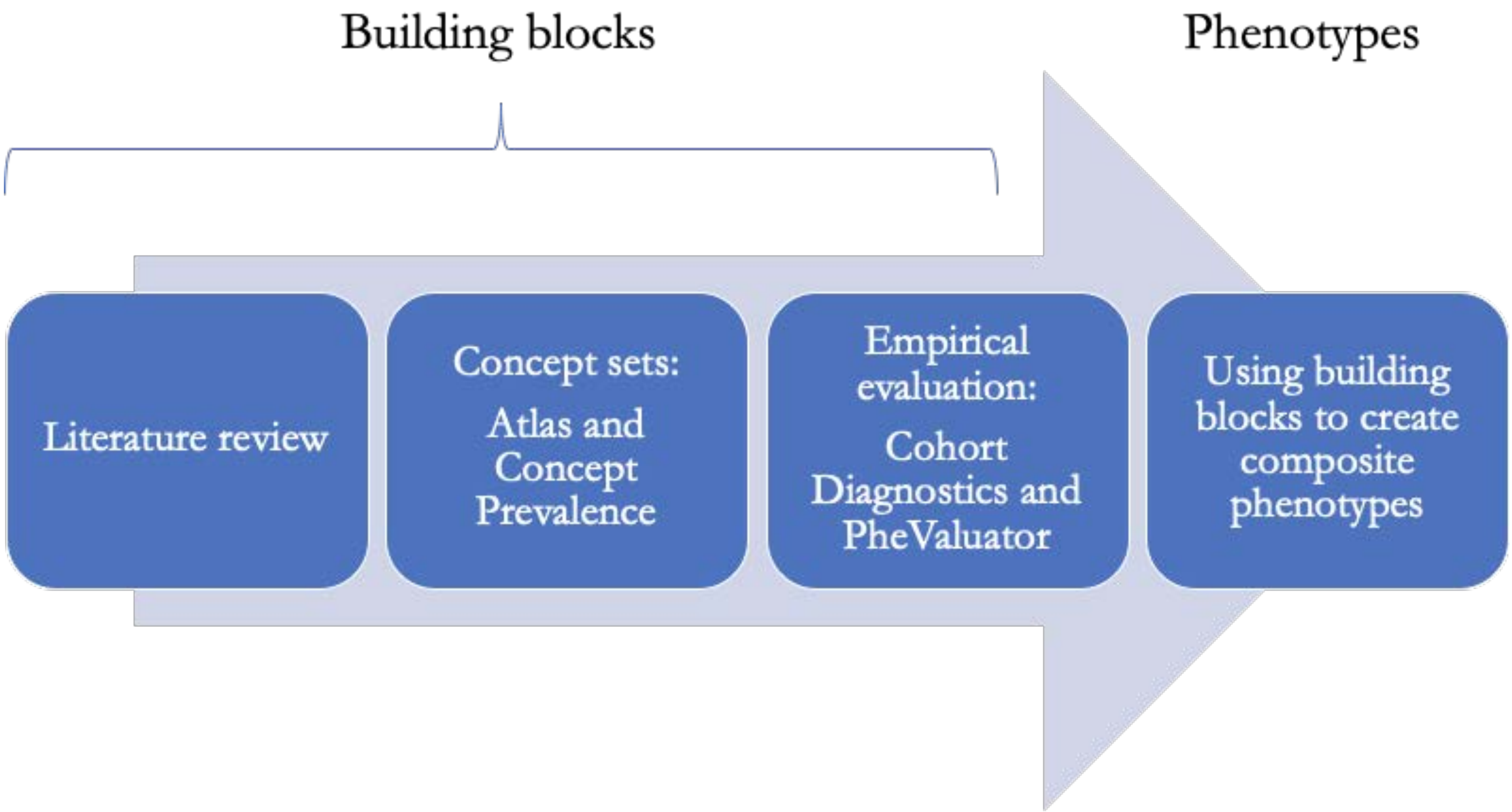
A snapshot of our journey...



Phenotype development and evaluation

Anna Ostropolets
Columbia University

Systematic process we followed



Three lesson we learned

1. To create composite phenotypes we first have to create and validate building blocks.

Example: pneumonia is used in 29 different phenotypes.

2. Phenotypes are driven by their intended use.

Example: how to find influenza?

- Narrow: diagnosis of influenza or test result
- Broad: suspected, confirmed, symptoms (fever AND (cough OR dyspnea OR malaise OR fatigue OR myalgia))

3. Phenotypes require knowledge of the data: data exploration is a must!

Exploring the data: creating comprehensive concept sets

Sepsis

Concept Set Expression | Included Concepts 208 | Included Source Codes | Explore Evidence | Export | Compare

Show 25 entries

Search:

Showing 1 to 15 of 15 entries

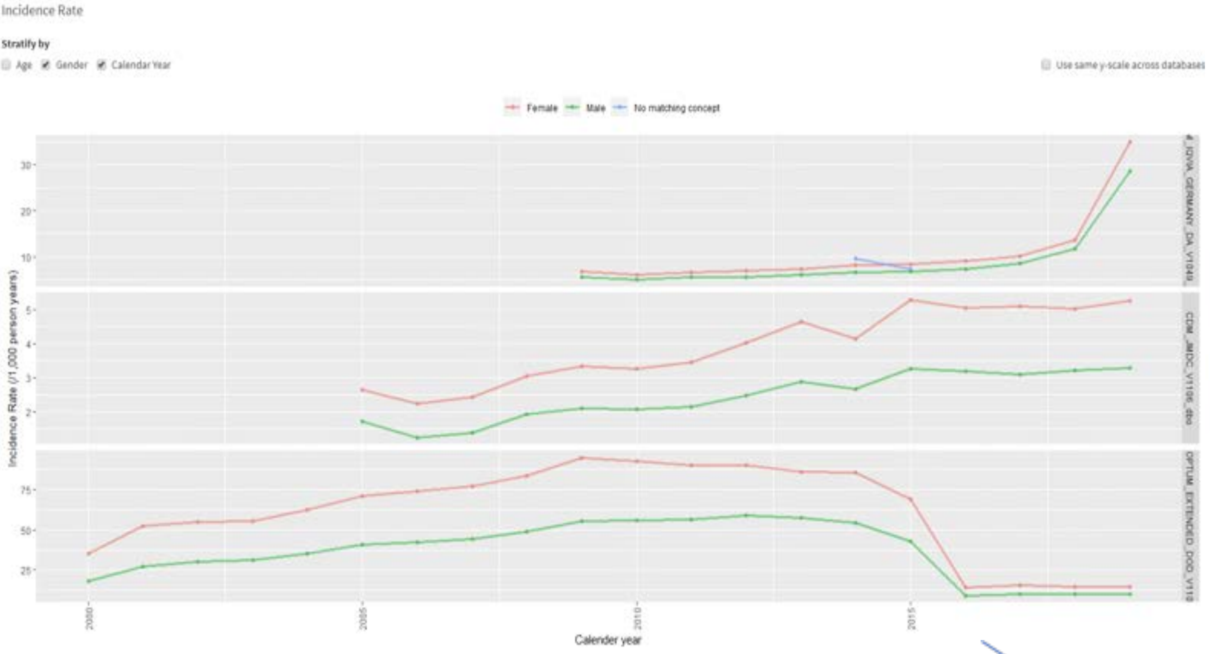
	Concept Id	Concept Code	Concept Name	Domain	Standard Concept Caption	Exclude	Descendants
	37395517	1048491000000106	Acute kidney injury due to acute tubular necrosis due to sepsis	Condition	Standard		✓
	36716312	722278006	Acute kidney injury due to sepsis	Condition	Standard		✓
	132736	5758002	Bacteremia	Condition	Standard		✓
	40487101	447931005	Clinical sepsis	Condition	Standard		✓
	4205449	55528005	Menosepsis	Condition	Standard		✓
	4085627	18613002	Miscarriage with septic shock	Condition	Standard		✓
	4204036	308887002	Postprocedural intra-abdominal sepsis	Condition	Standard		✓
	4066124	200195002	Puerperal septicemia - delivered with postnatal complication	Condition	Standard		✓
	132797	91302008	Sepsis	Condition	Standard		✓
	4029281	238150007	Sepsis syndrome	Condition	Standard		✓
	4046106	230361008	Sepsis-associated encephalopathy	Condition	Standard		✓

Show 25 entries

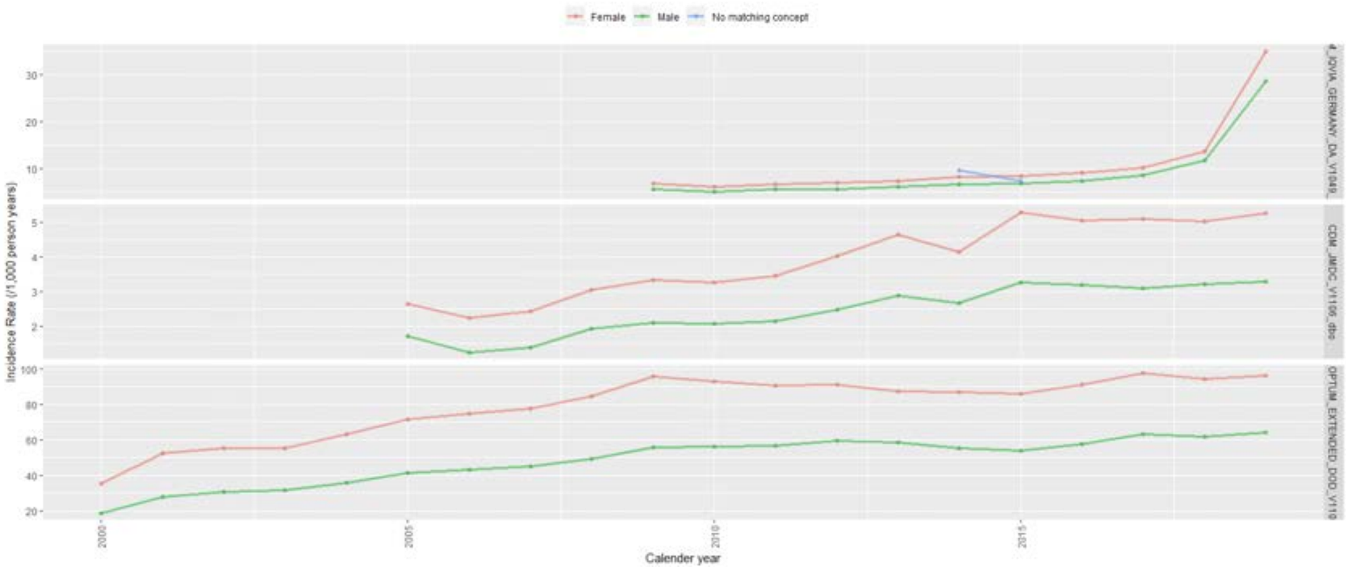
Count	Concept ID	Standard	Vocabulary	Code	Name
160,614	36712860	S	SNOMED	139201000119107	Non-infectious systemic inflammatory response syndrome without acute organ failure
160,614	45539355		ICD10CM	R65.10	Systemic inflammatory response syndrome (SIRS) of non-infectious origin without acute organ dysfunction
131,540	434821	S	SNOMED	238149007	Systemic inflammatory response syndrome
110,914	44826026		ICD9CM	995.90	Systemic inflammatory response syndrome, unspecified

Exploring the data: capturing coding practices

Malaise



Malaise OR (malaise and fatigue)



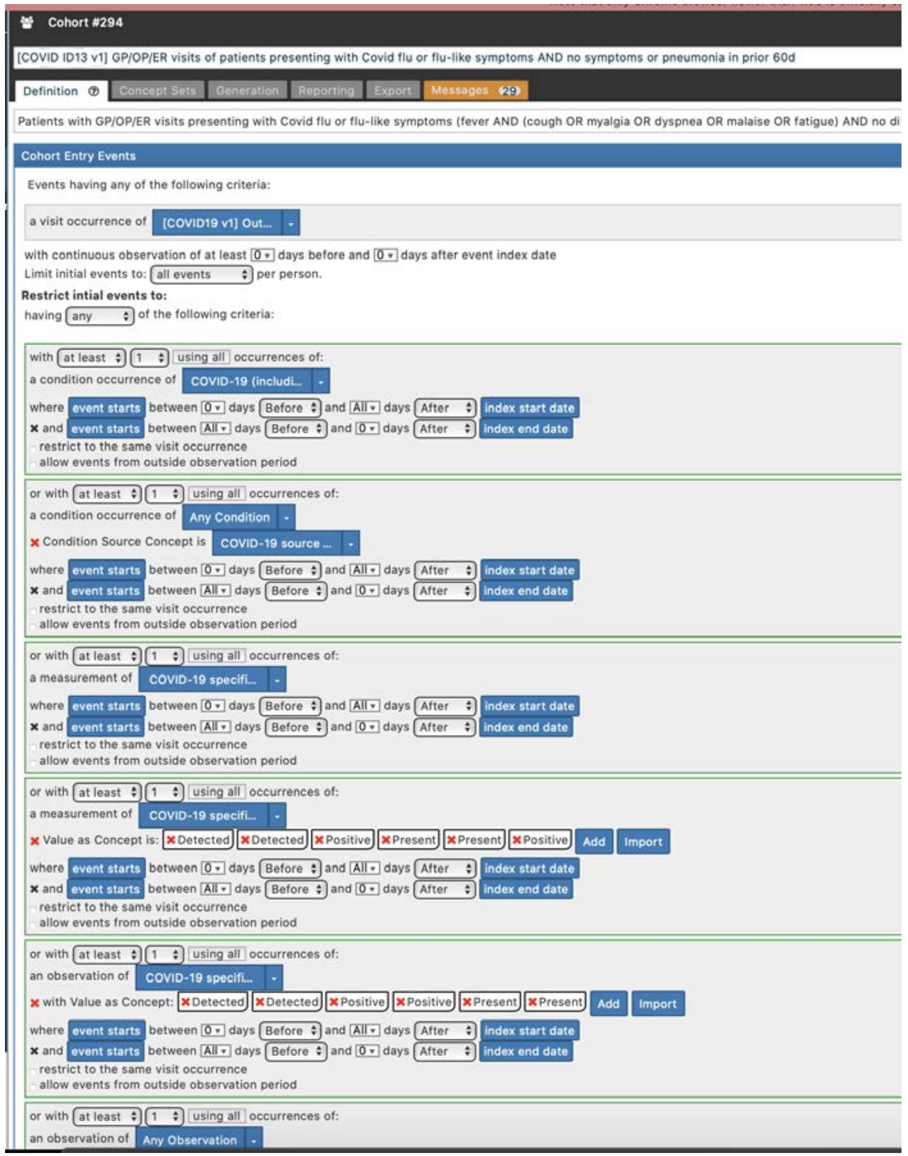
Incidence rate dropped,
need to add fatigue

Final Results

- Literature reviews done for 36 phenotypes
- 355 cohorts created in atlas-covid19.ohdsi.org
- 114 validated and reviewed cohorts for prediction,

estimation and characterization on atlas.ohdsi.org

- Results of Covid19CohortEvaluation are posted on data.ohdsi.org



Next Steps

- Complete the remaining cohorts for characterization
- Finalize the CohortEvalution package for all cohorts and run across the OHDSI network
- Write a paper about our phenotyping experience

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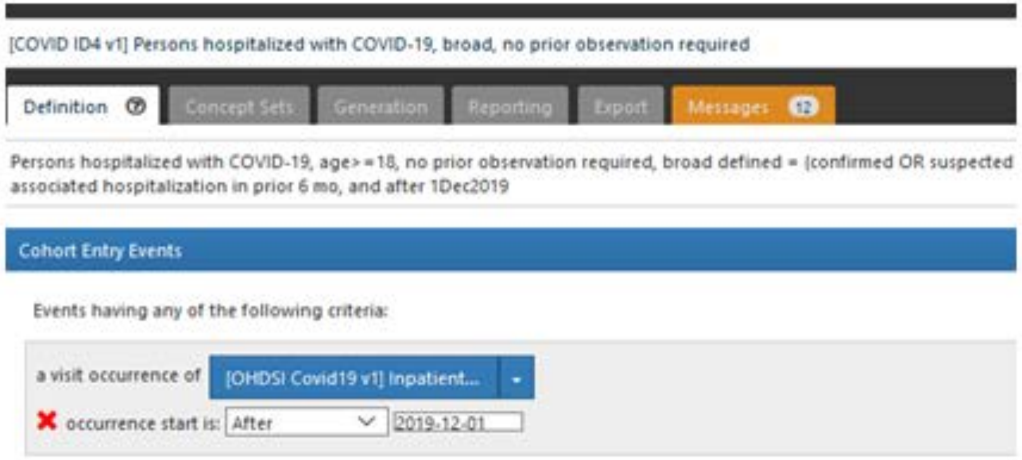
Clinical characterization of COVID-19

Ed Burn

Background

Characterisation in OHDSI: Defining Cohorts

- A cohort is a set of persons who satisfy one or more inclusion criteria for a duration of time



Background

Characterisation in OHDSI: Cohort characterisation

- OHDSI approaches characterization through descriptive statistics of all conditions, drug and device exposures, procedures and other clinical observations that are present in the person's history.


Using FeatureExtraction

Martijn J. Schuemie

2019-08-28

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Background

Characterisation in OHDSI: Incidence

Incidence rates and proportions are statistics that are used in public health to assess the occurrence of a new outcome in a population during a time-at-risk (TAR)

Figure 11.2: Person-level view of incidence calculation components. In this example, time-at-risk is defined to start one day after cohort start, and end at cohort end.

Our to do list

- Elucidating research questions
  - Writing protocols
    - Develop study packages
      - Review results
        - Disseminate results

Research questions

1. Characterizing adults hospitalized with influenza in 2009-2010 and 2014-2019, and COVID-19 in 2019-2020

2. Characterization of individuals tested for COVID-19

3. Characteristics and outcomes of COVID-19 in children

Research questions

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Research questions

1. Characterizing adults hospitalized with influenza in 2009-2010 and 2014-2019, and COVID-19 in 2019-2020

2. Characterization of individuals tested for COVID-19

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Protocols

Research questions

D Protocol template

1. Table of contents
2. List of abbreviations
3. Abstract
4. Amendments and Updates
5. Milestones
6. Rationale and Background
7. Study Objectives
    - Primary Hypotheses
    - Secondary Hypotheses
    - Primary Objectives
    - Secondary Objectives
8. Research methods
    - Study Design
    - Data Source(s)
    - Study population
    - Exposures
    - Outcomes
    - Covariates
9. Data Analysis Plan

Protocols

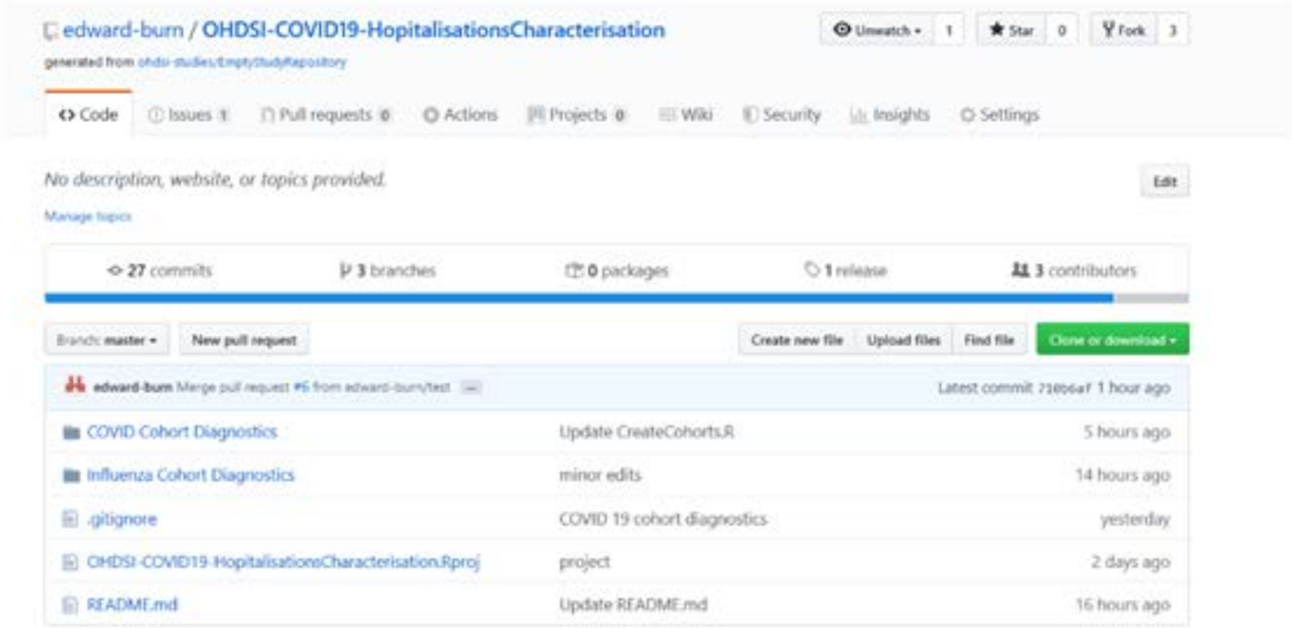
Characterization and outcomes of individuals tested for COVID-19: evidence from the OHDSI network

Characterizing adults hospitalized with influenza in 2009-2010 and 2014-2019, and COVID-19 in 2019-2020: protocol for an OHDSI network study

Protocol

Characteristics and outcomes of COVID-19 in Children in 2019-2020: evidence from the OHDSI network

Preparing study packages



Characteristics of adults hospitalized with influenza

- 2009 vs 2014-2019

Characteristic	Proportion Target	Proportion Comparator	StdDiff
Age group			
15-19	1.8%	0.3%	-0.10
20-24	3.2%	0.9%	-0.11
25-29	5.0%	1.2%	-0.15
30-34	6.3%	1.6%	-0.17
35-39	6.4%	1.7%	-0.17
40-44	7.2%	1.8%	-0.18
45-49	8.5%	2.5%	-0.18
50-54	10.8%	3.7%	-0.19
55-59	9.4%	5.6%	-0.10
60-64	8.5%	7.2%	-0.03
65-69	7.3%	10.9%	0.08
70-74	6.1%	13.7%	0.17
75-79	6.3%	13.7%	0.17
80-84	10.4%	13.0%	0.05
85-89	2.7%	21.0%	0.38
90-94		1.2%	

Characteristics of adults hospitalized with influenza

- 2009 vs 2014-2019

Medical history: General			
Acute respiratory disease	89.8%	74.6%	-0.12
Attention deficit hyperactivity disorder	1.6%	0.8%	-0.05
Chronic liver disease	6.6%	3.8%	-0.09
Chronic obstructive lung disease	26.3%	42.4%	0.19
Crohn's disease	1.2%	0.8%	-0.03
Dementia	5.6%	16.5%	0.23
Depressive disorder	24.1%	28.6%	0.06
Diabetes mellitus	32.4%	42.9%	0.12
Gastroesophageal reflux disease	25.5%	36.5%	0.14
Gastrointestinal hemorrhage	9.2%	8.3%	-0.02
Human immunodeficiency virus infection	1.3%	0.6%	-0.05
Hyperlipidemia	47.0%	66.8%	0.19
Hypertensive disorder	61.5%	80.4%	0.16

Characteristics of adults who have tested positive for COVID-19

Characteristic	Columbia University Irving Medical Center
N	1,076
Age (median [IQR])	67
Gender: female (%)	51.2
Charlson score (median [IQR])	6
Medical history: General	
Acute respiratory disease (%)	29.6
Chronic obstructive lung disease (%)	19.7
Gastroesophageal reflux disease (%)	24.2
Hyperlipidemia (%)	41.8
Hypertensive disorder (%)	60.4
Pneumonia (%)	32.2
Renal impairment (%)	39.7
Urinary tract infectious disease (%)	15.7
Atrial fibrillation (%)	20.4
Heart disease (%)	60.7
Heart failure (%)	30.1
Malignant neoplastic disease (%)	22.2

Characteristics of adults who have tested positive for COVID-19

Characteristic	Columbia University Irving Medical Center
N	1,076
Medication use	
Anti-inflammatory and antirheumatic products (%)	33.2
Antithrombotic agents (%)	77.3
Beta blocking agents (%)	41.1
Calcium channel blockers (%)	36.3
Immunosuppressants (%)	16.1
Lipid modifying agents (%)	46.5

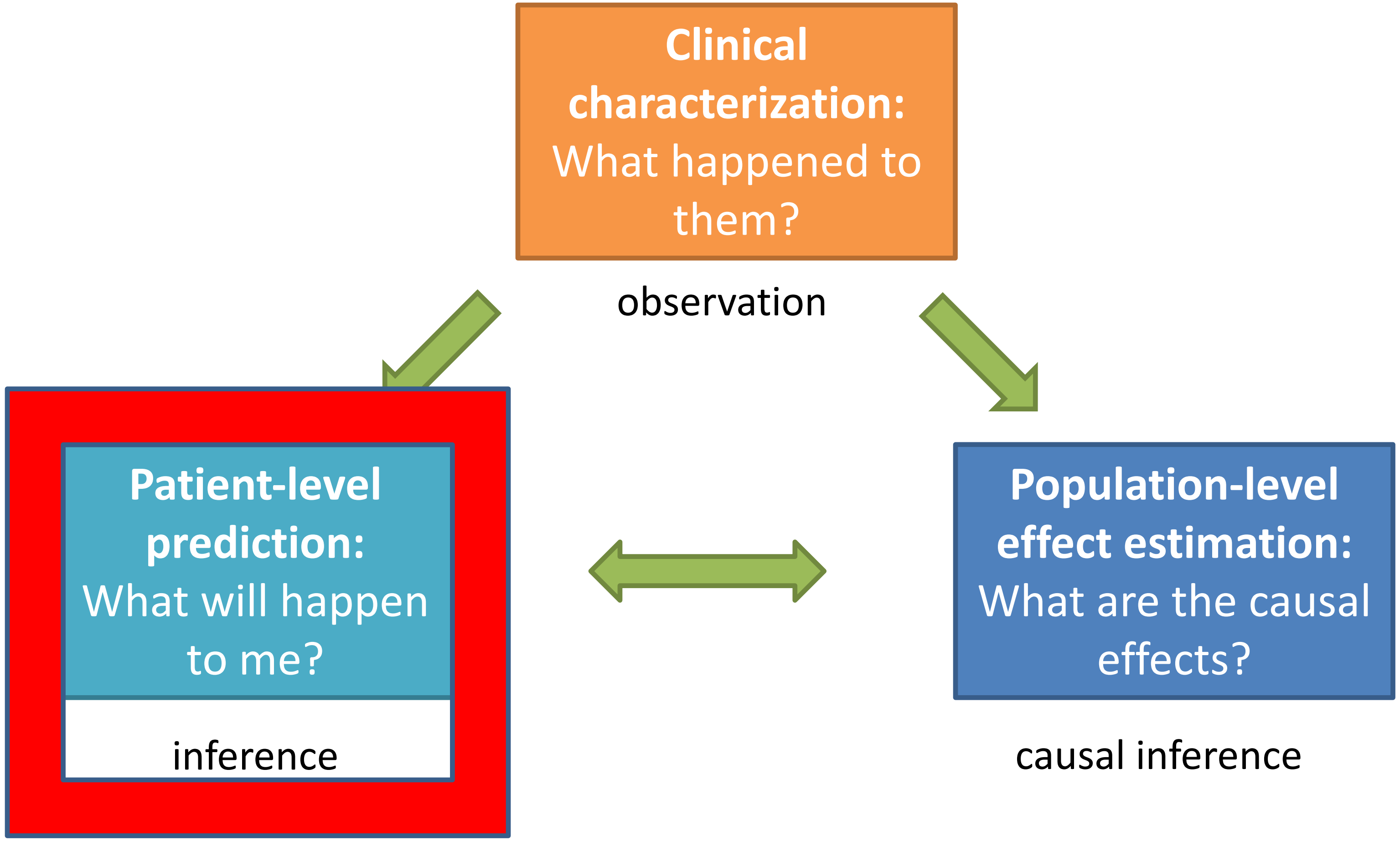
Our to do list

- Elucidating research questions
  - Writing protocols
    - Develop study packages
      - Review results
        - Disseminate results

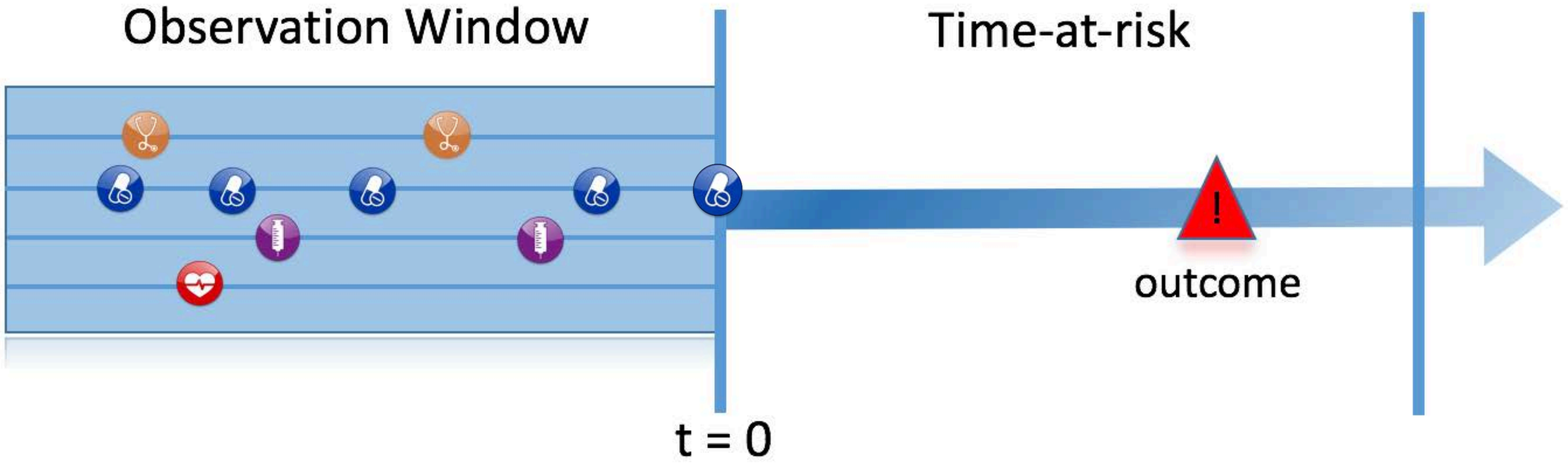
The journey through patient-level prediction

Peter Rijnbeek
Erasmus MC

Complementary evidence to inform the patient journey



Prediction Problem Definition



Among a target population (T), we aim to predict which patients at a defined moment in time (t=0) will experience some outcome (O) during a time-at-risk
Prediction is done using only information about the patients in an observation window prior to that moment in time.

Important questions to ask!

- What decision is the prediction model intended to inform?
- When is the decision made in the context of the patient's health experience and interaction with the healthcare system?
- Who is the decision-maker, and from which stakeholder vantage point are we evaluating the decision?
- What is the trade-off between True Positive, False Positive, True Negative, False Negative?
- Etc.

OHDSI Mission for Patient-Level Prediction

OHDSI aims to develop a systematic process to learn and evaluate large-scale patient-level prediction models using observational health data in a data network

Evidence Generation → Evidence Evaluation → Evidence Dissemination

OHDSI's Patient-Level Prediction Framework

JAMIA
A SCHOLARLY JOURNAL OF INFORMATICS IN HEALTH AND BIOMEDICINE

Design and implementation of a standardized framework to generate and evaluate patient-level prediction models using observational healthcare data

Jenna M Reps, Martijn J Schuemie, Marc A Suchard, Patrick B Ryan, Peter R Rijnbeek

Journal of the American Medical Informatics Association, Volume 25, Issue 8, August 2018, Pages 969–975, https://doi.org/10.1093/jamia/ocy032

Published: 27 April 2018 **Article history** ▾

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Abstract

Objective

To develop a conceptual prediction model framework containing standardized steps and describe the corresponding open-source software developed to consistently implement the framework across computational environments and observational healthcare databases to enable model sharing and reproducibility.

R-package

www.github.com/OHDSI/PatientLevelPrediction

- Vignettes
- Videos
- Online training material

Book-of-OHDSI
https://ohdsi.github.io/TheBookOfOhdsi/

Study Results
www.data.ohdsi.org

The prediction chapter and the publication are added on top of our channel in Teams

The Journey: Problem Definition

Problem Definition → Data Extraction → Training → Internal Validation → External Validation → Dissemination

Problem pre-specification. A study protocol should unambiguously pre-specify the planned analyses.

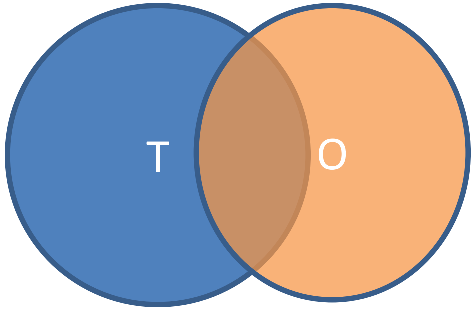
Transparency. Others should be able to reproduce a study in every detail using the provided information. All analysis code should be made available as open source on the OHDSI Github.

Team Effort:

- Problem Definition + Questions
- Literature Research -> Prior work, Rationale
- Study Protocol Development

The Journey: Data Extraction

Problem Definition → Data Extraction → Training → Internal Validation → External Validation → Dissemination



We extract data for the patients in the Target Cohort (T) and we select <u>all</u> patients that experience the outcome (O)

The Target Cohort (T) and Outcome Cohort (O) can be defined using ATLAS or custom code (see later today).

For model development all outcomes (O) of patients in the Target Cohort (T) are used.

Team Effort:
- Literature Review
- Cohort Definition

Work done with the phenotype group

The Journey: Model Development

Problem Definition → Data Extraction → Training → Internal Validation → External Validation → Dissemination

Age	Gender	Var 1	...	Var n	Stroke
34	M	1	0	1	1
50	F	0	0	0	1
24	M	0	1	0	0
67	F	1	1	0	0
34	F	0	0	0	0
65	M	1	0	0	1
34	F	0	0	0	0
40	M	0	1	1	0

Data is extracted from the OMOP CDM using the Feature Extraction R-Package.

This allows for specification of the candidate predictors and time windows.

Team effort:
Cohort Diagnostics Package

Work done with other channels

The Journey: Model Development

Model training and **Internal validation** is done using a train test split:

1. Person split: examples are assigned randomly to the train or test set, or

2. Time split: a split is made at a moment in time (temporal validation)

Train set | Test set

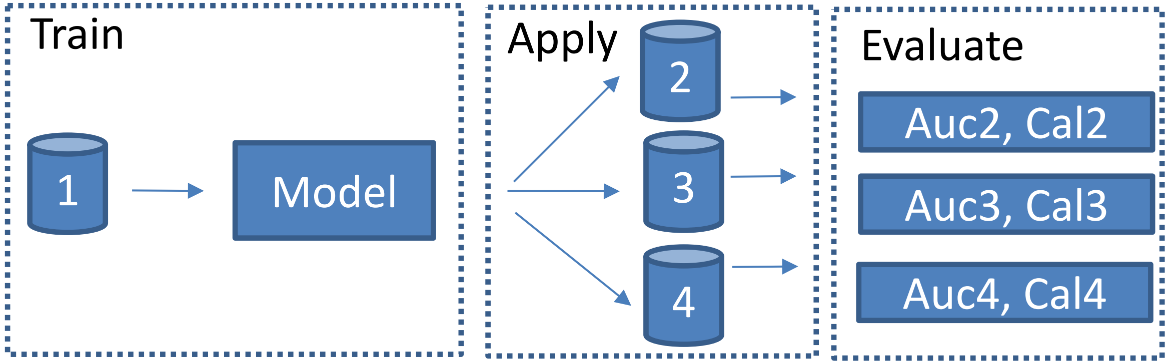
2014-01-15

- Study Package Development
- Study Execution

The Journey: External Validation

Problem Definition → Data Extraction → Training → Internal Validation → **External Validation** → Dissemination

External validation is performed using data from multiple populations not used for training.



- Data Partners

The Journey: Dissemination

Dissemination of study results should follow the minimum requirements as stated in the Transparent Reporting of a multivariable prediction model for Individual Prognosis Or Diagnosis (TRIPOD) statement [1].

- Internal and external validation
- Sharing of full model details
- Sharing of all analyses code to allow full reproducibility

Website to share protocol, code, models and results for all databases

[1] Moons, KG et al. Ann Intern Med. 2015;162(1):W1-73

PLP Aims Study-A-Thon

Build and evaluate models developed on Flu patients to:

1) Test them on COVID patients if data becomes available
2) Have tools ready to learn on COVID patients

And,

Replicate some of the models found in literature

Team Effort

51 Participants in our channel and literature study

Thank you all for the great collaboration in the PLP team

Patient-level prediction #1:
Amongst patients presenting with COVID-19, influenza, or associated symptoms, who are most likely to be admitted to hospital in next 30d?

Jenna Reps
Janssen Research and Development

Background

- Can we predict who is going to be hospitalized at the point they have their first outpatient visit with flu/covid19 or flu-like symptoms?

- This could be used to aid the **'do I hospitalize or send this patient home?'** decision that doctors will need to make
- Simple model could potentially be used for phone screen (patient calls medical staff and model answers questions)

Methods

T1: GP/OP/ER visits of patients presenting with Covid-19, flu or flu-like symptoms AND no symptoms or pneumonia in prior 60d

O1: Hospitalizations with pneumonia **(narrow)**

O2: Hospitalizations with pneumonia or ARDS or sepsis or AKI **(broad)**

O3: Hospitalizations with pneumonia or ARDS or sepsis or AKI requiring intensive services or resulting in death in 30d **(severe)**

O4: Death **(severe)**

TAR: 0-30d

Preliminary results

Analysis	Dev	Val	T	O	Model	TAR start	TAR end	AUC	AUPRC	T Size	O Count	O Incidence (%)
Analysis_2	optumDod	optumDod	[COVID ID13 v1] GP/OP/ER visits of patients presenting with Covid flu or flu-like symptoms AND no symptoms or pneumonia in prior 60d	[COVID19 ID26 V1] Hospitalizations with pneumonia or ARDS or sepsis or AKI	Lasso Logistic Regression	0	30	0.8721	0.3542	37500	2617	6.9787
Analysis_6	optumDod	optumDod	[COVID ID13 v1] GP/OP/ER visits of patients presenting with Covid flu or flu-like symptoms AND no symptoms or pneumonia in prior 60d	[COVID19 ID26 V1] Hospitalizations with pneumonia or ARDS or sepsis or AKI	Lasso Logistic Regression	0	30	0.8387	0.2625	37499	2616	6.9762
Analysis_2	optumDod	ccae	[COVID ID13 v1] GP/OP/ER visits of patients presenting with Covid flu or flu-like symptoms AND no symptoms or pneumonia in prior 60d	[COVID19 ID26 V1] Hospitalizations with pneumonia or ARDS or sepsis or AKI	Lasso Logistic Regression	0	30	0.7876	0.1358	3146729	53842	1.711
Analysis_2	optumDod	HIRA	[COVID ID13 v1] GP/OP/ER visits of patients presenting with Covid flu or flu-like symptoms AND no symptoms or pneumonia in prior 60d	[COVID19 ID26 V1] Hospitalizations with pneumonia or ARDS or sepsis or AKI	Lasso Logistic Regression	0	30	0.74	0.082	6011	165	2.745
Analysis_2	optumDod	ipci	[COVID ID13 v1] GP/OP/ER visits of patients presenting with Covid flu or flu-like symptoms AND no symptoms or pneumonia in prior 60d	[COVID19 ID26 V1] Hospitalizations with pneumonia or ARDS or sepsis or AKI	Lasso Logistic Regression	0	30	0.76241	0.00585	27610	36	0.13039
Analysis_2	optumDod	jmdc	[COVID ID13 v1] GP/OP/ER visits of patients presenting with Covid flu or flu-like symptoms AND no symptoms or pneumonia in prior 60d	[COVID19 ID26 V1] Hospitalizations with pneumonia or ARDS or sepsis or AKI	Lasso Logistic Regression	0	30	0.679683	0.006628	1276478	1011	0.079202
Analysis_2	optumDod	mdcd	[COVID ID13 v1] GP/OP/ER visits of patients presenting with Covid flu or flu-like symptoms AND no symptoms or pneumonia in prior 60d	[COVID19 ID26 V1] Hospitalizations with pneumonia or ARDS or sepsis or AKI	Lasso Logistic Regression	0	30	0.819	0.307	536410	53319	9.94
Analysis_2	optumDod	mdcr	[COVID ID13 v1] GP/OP/ER visits of patients presenting with Covid flu or flu-like symptoms AND no symptoms or pneumonia in prior 60d	[COVID19 ID26 V1] Hospitalizations with pneumonia or ARDS or sepsis or AKI	Lasso Logistic Regression	0	30	0.709	0.351	248964	48170	19.348

Discussion and next steps

- Made a simple score model: 7 variables + age + gender model - shiny: https://data.ohdsi.org/Covid19PredictionSimpleHospitalizationModel/

- External validation of OHDSI score model

- External validation existing risk models

Patient-level prediction #2: Amongst patients at GP presenting with virus or associated symptoms with/without pneumonia who are sent home, who are most likely to require hospitalization in next 30d?

Ross D. Williams
Erasmus MC

Background

A large proportion of patients presenting with symptoms will be sent home

Some of these patients will go on to experience disease progression

This model can act as a safety net for a clinician and reassurance for patient.

Methods

T1: Visit with COVID or Influenza or flu-like symptoms and with NO pneumonia and NO admission

T2: same as T1 except WITH pneumonia

O1: Hospitalizations with pneumonia or ARDS or sepsis or AKI requiring intensive services

O2: Hospitalizations with pneumonia or ARDS or sepsis or AKI requiring intensive services or resulting in death in 30d

TAR: 2-30d

Preliminary results

Analysis	Dev	Val	T	O	Model	TAR start	TAR end	AUC	AUPRC	T Size	O Count	O Incidence (%)
Analysis_1	optumDod	optumDod	[COVID ID14 v1] GP/OP/ER visits of patients presenting with Covid flu or flu-like symptoms with pneumonia and no admission	[COVID19 ID27 V1] Hospitalizations with pneumonia or ARDS or sepsis or AKI requiring intensive services or resulting in death in 30d	Lasso Logistic Regression	2	30	0.75216	0.03286	25282	115	0.45487
Analysis_2	optumDod	optumDod	[COVID ID15 v1] GP/OP/ER visits of patients presenting with Covid flu or flu-like symptoms with no pneumonia and no admission	[COVID19 ID27 V1] Hospitalizations with pneumonia or ARDS or sepsis or AKI requiring intensive services or resulting in death in 30d	Lasso Logistic Regression	2	30	0.8643	0.03104	74826	109	0.14567
Analysis_3	optumDod	optumDod	[COVID ID14 v1] GP/OP/ER visits of patients presenting with Covid flu or flu-like symptoms with pneumonia and no admission	[COVID19 ID26 V1] Hospitalizations with pneumonia or ARDS or sepsis or AKI	Lasso Logistic Regression	2	30	0.72116	0.08942	25283	827	3.27097
Analysis_4	optumDod	optumDod	[COVID ID15 v1] GP/OP/ER visits of patients presenting with Covid flu or flu-like symptoms with no pneumonia and no admission	[COVID19 ID26 V1] Hospitalizations with pneumonia or ARDS or sepsis or AKI	Lasso Logistic Regression	2	30	0.8374	0.1153	74826	788	1.0531
			[COVID ID14 v1] GP/OP/ER visits of	[COVID19 ID27 V1] Hospitalizations with	Lasso							

Discussion and next steps

COVID-19 validation and external validation

Model parsimonisation

Tool creation

– how can we best present the model for application?

Model dissemination

Patient-level prediction #3:
Amongst patients hospitalized with pneumonia, who are most likely to require intensive services or die?

Aniek Markus
Erasmus MC

Background

- Lack of evidence of factors associated with disease severity
- Enables close monitoring of high risk patients
- Indicator for short-term demand of intensive services

Methods

- T [IV]: Hospitalization with pneumonia
- T [EV]: Hospitalization with COVID-19

- O1: Patients requiring intensive services* or death
- O2: Death

* Includes ventilation, intubation, tracheotomy, or ECMO.

Preliminary results

Analysis	Dev	Val	T	O	Model	TAR start	TAR end	AUC	AUPRC	T Size	O Count	O Incidence (%)
Analysis_1	optumDod	optumDod	[COVID19 ID29 V1] Hospitalizations with pneumonia, age>=18	[COVID19 ID27 V1] Hospitalizations with pneumonia or ARDS or sepsis or AKI requiring intensive services or resulting in death in 30d	Lasso Logistic Regression	0	30	0.642	0.322	37499	8062	21.499
Analysis_2	optumDod	optumDod	[COVID19 ID29 V1] Hospitalizations with pneumonia, age>=18	[COVID19 ID28 v1] persons who die	Lasso Logistic Regression	0	30	0.72077	0.1743	37500	2783	7.42133
Analysis_3	optumDod	optumDod	[COVID19 ID29 V1] Hospitalizations with pneumonia, age>=18	[COVID19 ID27 V1] Hospitalizations with pneumonia or ARDS or sepsis or AKI requiring intensive services or resulting in death in 30d	Lasso Logistic Regression	0	30	0.538	0.236	37499	8062	21.499
Analysis_4	optumDod	optumDod	[COVID19 ID29 V1] Hospitalizations with pneumonia, age>=18	[COVID19 ID28 v1] persons who die	Lasso Logistic Regression	0	30	0.6305	0.1106	37499	2782	7.4189

Discussion and next steps

- Developing more parsimonious models
  - easier to use and understand in practice

- External validation in COVID-19 data

- In the future: also train models in COVID-19 data

Population-level Estimation #1: Hydroxychloroquine

Dani Prieto-Alhambra
University of Oxford

BACKGROUND
What have we achieved?

TWO RQs

1. What is the safety profile of hydroxychloroquine?

2. What is its potential anti-viral efficacy?

METHODS

DESIGN

1. Comparative cohort HCQ (t) vs SSZ (o) in RA patients
2. SCCS (regardless of indication)

PARTICIPANTS

1. RA diagnosis + new use of HCQ or SSZ
2. HCQ use (on/off) + outcome of interest (“case”)

METHODS (2)

OUTCOMES

1. Serious adverse events, including: arrhythmia, cv disease, vte, liver failure, kidney failure, GI bleeds, mortality
2. Flu/viral infections, hospitalized pneumonia (not in SCCS)

ANALYSES

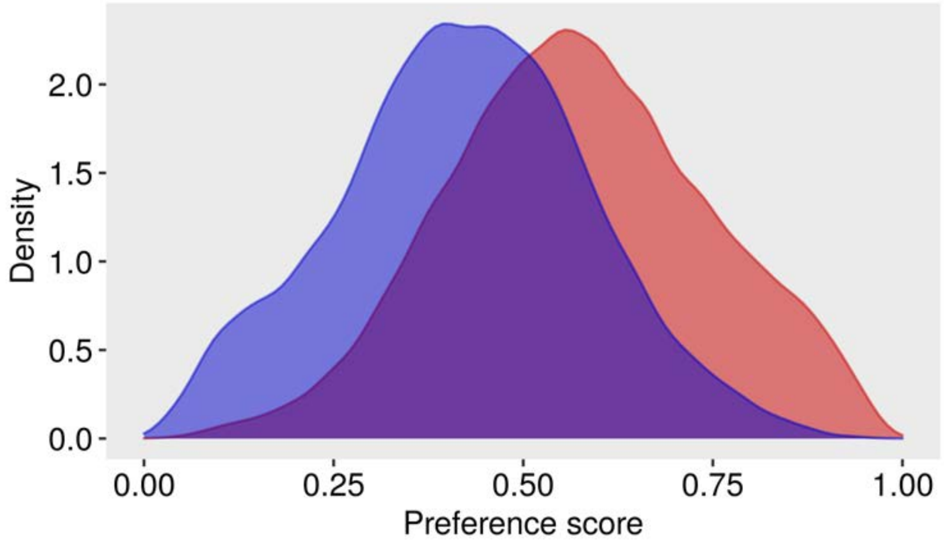
1. PS stratification + negative control outcome calibration
   - On treatment and ITT (up to 5y)
2. Age and season-adjusted SCCS

RESULTS (VTE)

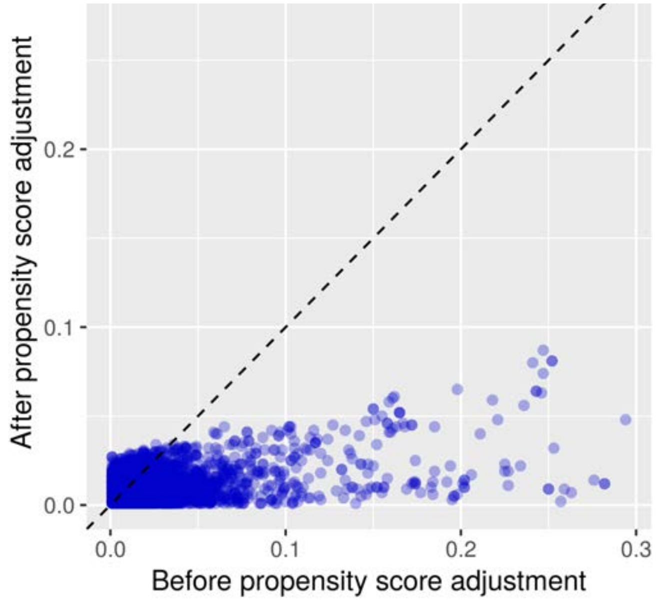
Power

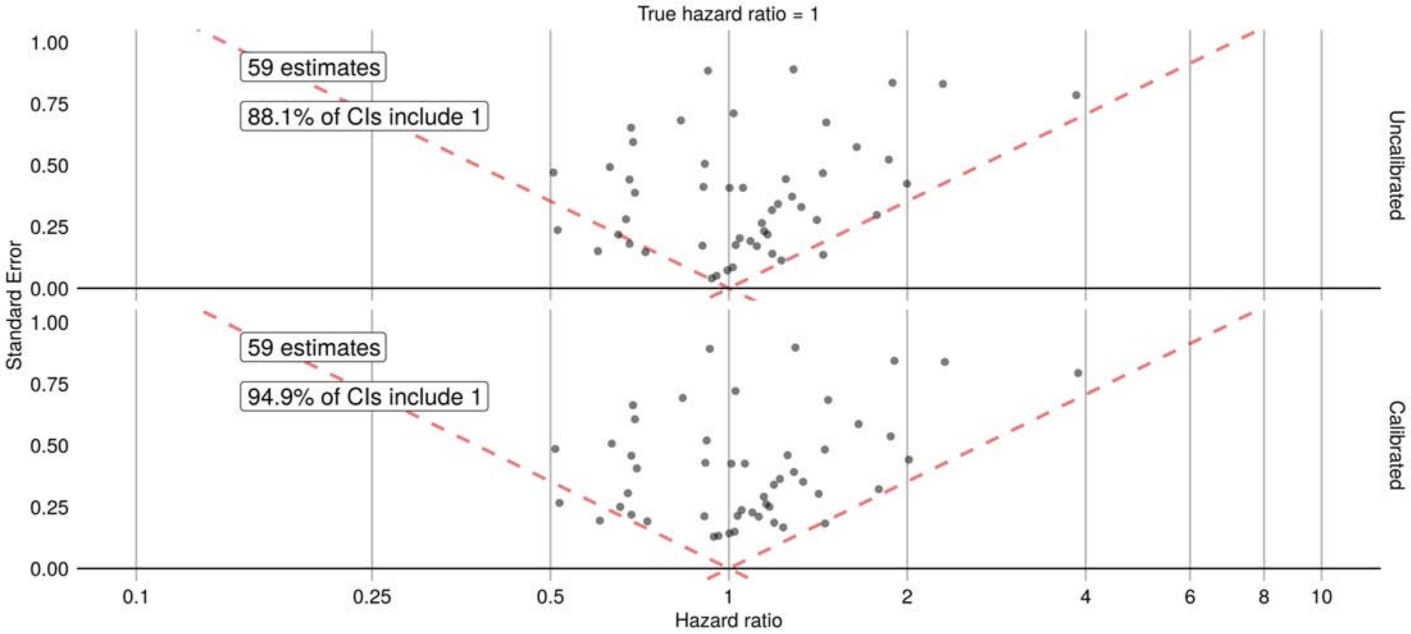
DATA SOURCE	N HCQ	N SSZ	T events HCQ	C events SSZ
CCAE	66,162	23,319	641	159
CPRD	9,134	11,401	131	176
IQVIA-DE	3,898	5,052	34	47
OPTUM	51,288	17,464	946	209
TOTAL	**130,482**	**57,236**	**1,752**	**591**

RESULTS (VTE)
Diagnostics (CCAE)



- ✓ PS overlap
- ✓ Covariate balance
- ✓ Negative control outcomes





RESULTS (3)

Risk estimates

data.ohdsi.org/Covid19EstimationHydroxychloroquine/

Apps EUADRSharePoint EU-ADR Home EMIF EMIF Catalogue AppsSIDIAP Revalidation AEMPS-CIMA NHS_e_Learning Variables SIDIAP Sampsize

OHDSI COVID-19 Studyathon: Hydroxychloroquine population-level effect estimation

About | Explore results

Target

[OHDSI Cov19] New users of Hydroxychloroquine with prior rheumatoid arthritis

Comparator

[OHDSI Cov19] New users of sulfasazine with prior rheumatoid arthritis

Outcome

[LEGEND HTN] Venous thromboembolic (pulmonary embolism and deep vein thrombosis) events

Data source

- [x] CCAE
- [x] CPRD
- [x] IQVIA_GERMANY
- [x] OptumDOD

Show 15 **entries**

Analysis	Data source	HR	LB	UB	P	Cal.HR	Cal.LB	Cal.UB
No prior outcome in last 30d, 5 PS strata, TAR on-treatment+14d	CCAE	0.99	0.82	1.20	0.92	1.00	0.74	1.35
No prior outcome in last 30d, 5 PS strata, TAR on-treatment+14d	CPRD	1.06	0.81	1.38	0.66	1.01	0.52	1.98
No prior outcome in last 30d, 5 PS strata, TAR on-treatment+14d	IQVIA_GERMANY	0.98	0.58	1.63	0.94	0.72	0.42	1.23
No prior outcome in last 30d, 5 PS strata, TAR on-treatment+14d	OptumDOD	1.04	0.89	1.22	0.64	1.06	0.84	1.32
No prior outcome in last 30d, 5 PS strata, TAR intent-to-treat 5yr	CCAE	0.97	0.87	1.07	0.51	0.98	0.88	1.10
No prior outcome in last 30d, 5 PS strata, TAR intent-to-treat 5yr	CPRD	0.99	0.83	1.19	0.94	1.01	0.83	1.23
No prior outcome in last 30d, 5 PS strata, TAR intent-to-treat 5yr	IQVIA_GERMANY	0.86	0.65	1.14	0.30	0.76	0.57	1.02
No prior outcome in last 30d, 5 PS strata, TAR intent-to-treat 5yr	OptumDOD	0.95	0.87	1.04	0.24	0.97	0.88	1.07

Showing 1 to 8 of 8 entries

Previous

RESULTS (3)

Risk estimates

Analysis	Data source	HR	LB	UB	P	Cal.HR	Cal.LB	Cal.UB	Cal.P
No prior outcome in last 30d, 5 PS strata, TAR on-treatment+14d	CCAE	0.99	0.82	1.20	0.92	1.00	0.74	1.35	0.88
No prior outcome in last 30d, 5 PS strata, TAR on-treatment+14d	CPRD	1.06	0.81	1.38	0.66	1.01	0.52	1.98	0.83
No prior outcome in last 30d, 5 PS strata, TAR on-treatment+14d	IQVIA_GERMANY	0.98	0.58	1.63	0.94	0.72	0.42	1.23	0.28
No prior outcome in last 30d, 5 PS strata, TAR on-treatment+14d	OptumDOD	1.04	0.89	1.22	0.64	1.06	0.84	1.32	0.69
No prior outcome in last 30d, 5 PS strata, TAR intent-to-treat 5yr	CCAE	0.97	0.87	1.07	0.51	0.98	0.88	1.10	0.77
No prior outcome in last 30d, 5 PS strata, TAR intent-to-treat 5yr	CPRD	0.99	0.83	1.19	0.94	1.01	0.83	1.23	0.73
No prior outcome in last 30d, 5 PS strata, TAR intent-to-treat 5yr	IQVIA_GERMANY	0.86	0.65	1.14	0.30	0.76	0.57	1.02	0.09
No prior outcome in last 30d, 5 PS strata, TAR intent-to-treat 5yr	OptumDOD	0.95	0.87	1.04	0.24	0.97	0.88	1.07	0.56

DISCUSSION

COMPLETED

✓ The biggest study to date on the safety of HCQ

✓ Reassuringly, no consistent signals found

WORK IN PROGRESS

- Running across the whole network (where possible)
- SCCS

OUTSTANDING

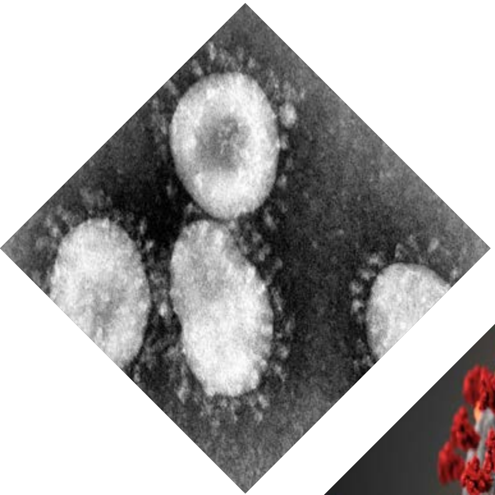
- Anti-viral efficacy (new user design in COVID19 infectees)

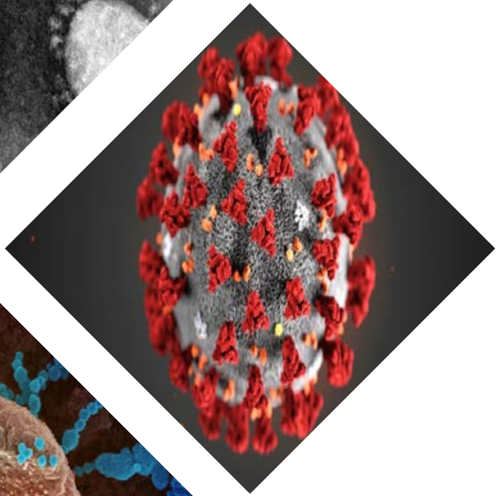
Population-level Estimation #1: Safety of HIV/HepC protease inhibitors

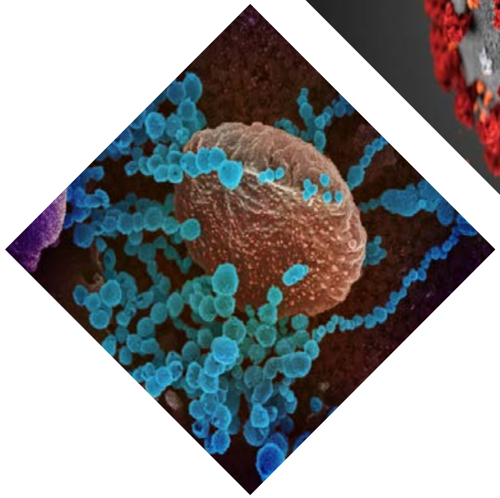
Albert Prats
University of Oxford

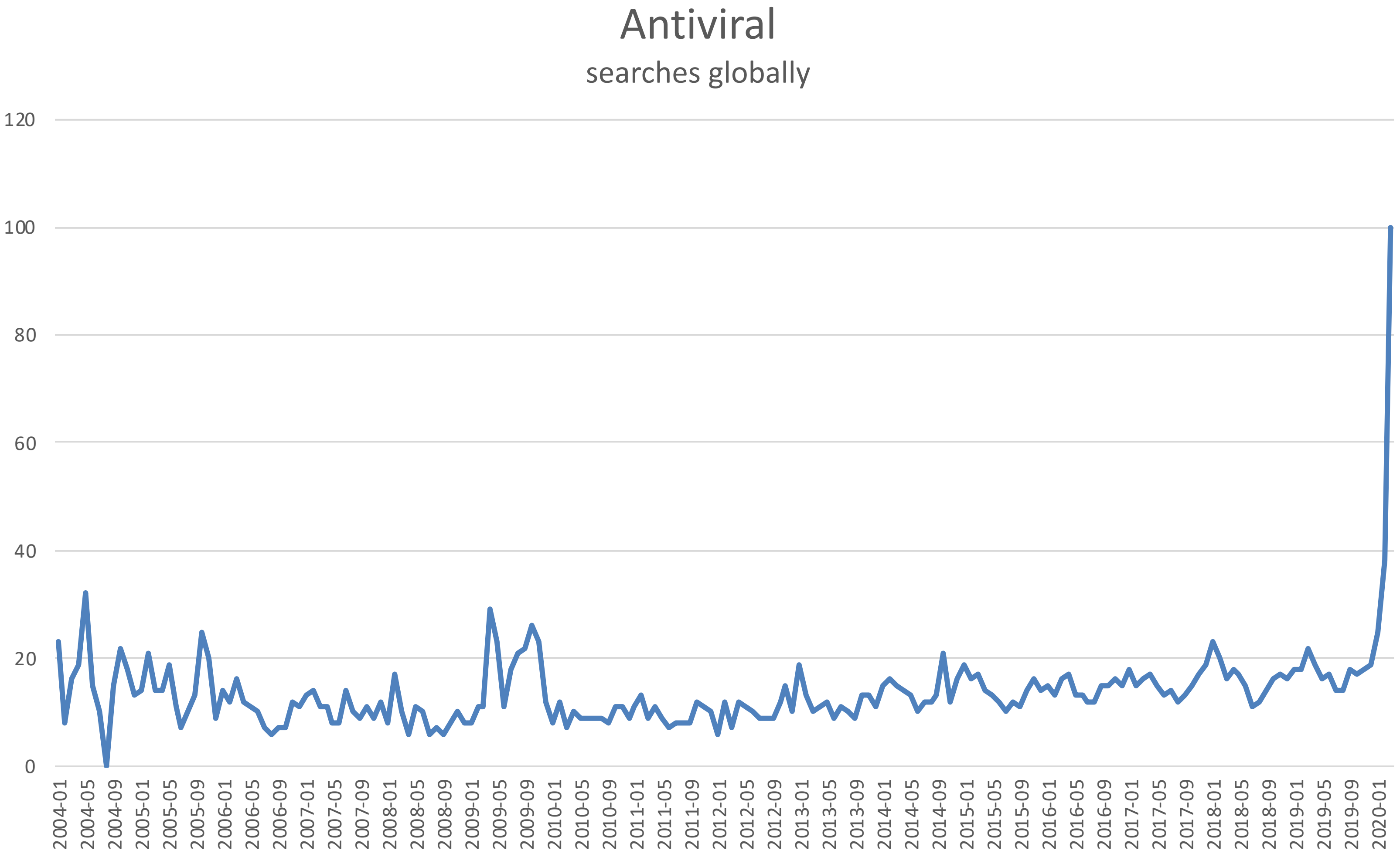
SARS-**CoronaVirus**-2

A little piece of enveloped RNA!



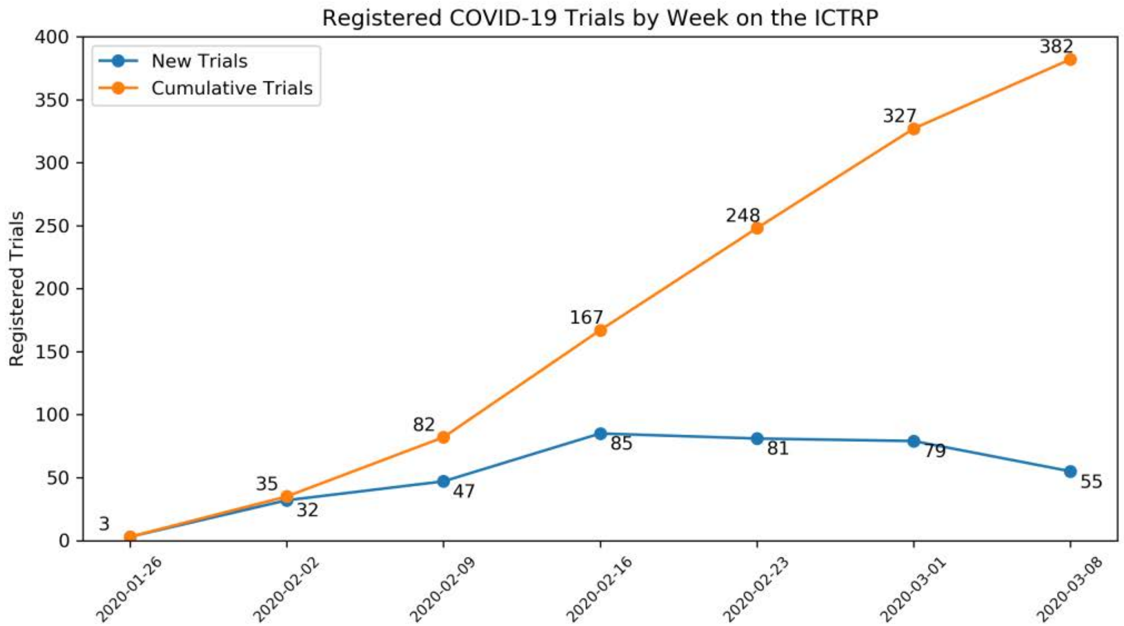






SARS-CoV-2 Antiviral Trials

COVID Treatments being tested!



	Antiviral drugs, non-specific	
Interferons	Activate cytoplasmic enzymes affecting viral messenger RNA translation and protein synthesis; evidence of minor efficacy in MERS-CoV in combination with ribavirin	4
	Antiviral drugs, antiretrovirals	
ASC09	**HIV** protease inhibitor; to be used in combination with ritonavir	4
Azvudine	Azidocytidine nucleoside analogue; **HIV** reverse transcriptase inhibitor	4
Danoprevir	**Hepatitis C** virus NS3 protease inhibitor; to be used in combination with ritonavir	1
Darunavir	**HIV** protease inhibitor; used in combination with cobicistat, a CYP3A inhibitor	2
Lopinavir + ritonavir	Both **HIV** reverse transcriptase inhibitors; ritonavir is mainly used to enhance the action of other drugs by inhibition of CYP3A4; in vitro and possible clinical efficacy in SARS-CoV	2
Remdesivir	Nucleotide analogue; inhibitor of RNA-dependent RNA polymerase; used to treat Ebola and Marburg viruses; effective in vitro against SARS-CoV-1 and MERS and blocks infection with 2019-nCoV in vitro	2

Adapted from: https://www.cebm.net/covid-19/registered-trials-and-analysis/ at 29-March

Antivirals Background

Effectiveness
Does it work?

Safety
Does it harm patients?

HIV antivirals

SARS

? COVID

Gastrointestinal events

Liver Injury

Pancreatitis

etc ...

Hepatitis C antivirals

in-vitro

X SARS

? COVID

Arrythmia

Liver Injury

Hematologic

etc ...

Safety
Does it harm patients?

HIV Antivirals Estimation

Ritonavir/lopinavir

All HIV protease inhibitors

VS

NNRTIs

Integrase inhibitors

SCCS

Cohort study

of HIV treatment naïve patients

(PS stratification)

Effectiveness
Does it work?

HIV Antivirals Estimation

Cohort study

of SARS-CoV-2 Patients

(PS stratification)

Ritonavir/lopinavir

All HIV protease inhibitors

Hospital treated

VS

pneumonia

Hydroxychloroquine

Poor outcomes

Safety
Does it harm patients?

Hep C Antivirals Estimation

Hepatitis C protease inhibitors

SCCS

Peginterferon alfa-2b

Ribavirin

Cohort study

Pairwise Comparisons

(PS stratification)

Effectiveness
Does it work?

Hep C Antivirals Estimation

Hepatitis C protease inhibitors

Peginterferon alfa-2b

Ribavirin

Hydroxychloroquine

Cohort study pairwise comparisons

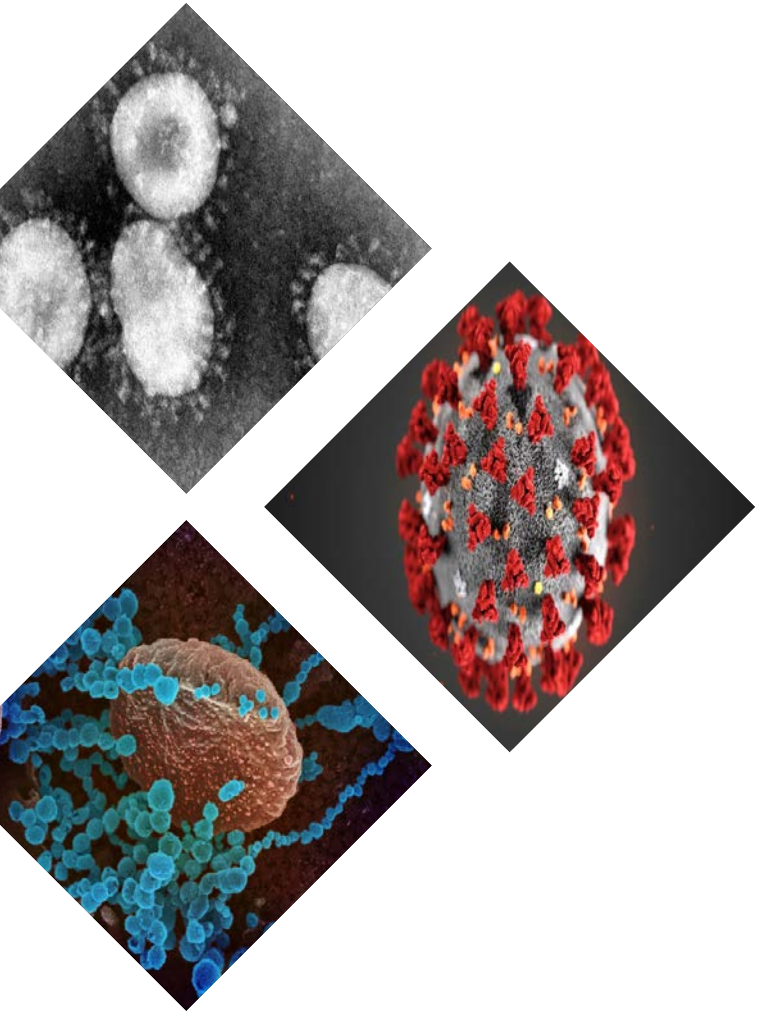
of SARS-CoV-2 Patients

(PS stratification)

Hospital treated pneumonia

Poor pneumonia outcomes

Progress



Protocol	Done!
Safety Analyses	SCCS Cohorts
Effectiveness Analyses	Cohorts
Paper writing	Background and methods

OHDSI

OBSERVATIONAL HEALTH DATA SCIENCES AND INFORMATICS

Population-level Estimation #3: Association of angiotensin converting enzyme (ACE) inhibitors and angiotensin II receptor blockers (ARB) on COVID incidence and complications

Daniel Morales
University of Dundee

Background

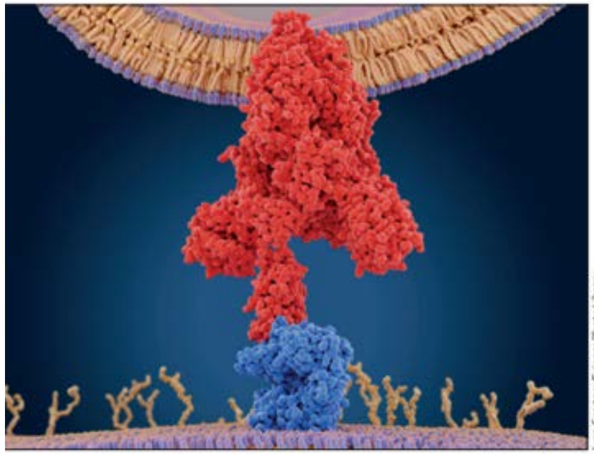
Authors	COVID Patients	Location	Key Content
Guan et al	1099	China	24% HTN in severe disease (vs 13%)
Zhou	191	China	HTN Univariate OR 3.1 (1.6-6.0) for death
Wang et al	138	China	HTN admissions 31%, HTN ICU 58%
Wu et al	201	China	HTN admissions 19%, HTN ARDS 27%

- People with hypertension (HTN) have worse COVID-19 outcomes
- Speculation that ACE/ARBs taken for HTN may be detrimental
  - Coronaviruses interact with RAS ACE-2 receptor, allowing them to enter the cell
  - ACE & ARBs upregulate ACE-2 receptors (limited data)
  - RAS ACE-2 expressed in lung, kidney, heart, GI tract
- Speculation that ARBs may be protective
  - Prevent the angiotensin I receptor from being stimulated
  - Regulate ACE-2 and reduce angiotensin production by ACE and increase production of the vasodilator angiotensin(1-7)

Are patients with hypertension and diabetes mellitus at increased risk for COVID-19 infection?

The most distinctive comorbidities of 32 non-survivors from a group of 52 intensive care unit patients with novel coronavirus disease

inhibitors and ARBs, which results in an upregulation of ACE2.[5] ACE2 can also be increased by thiazolidinediones and ibuprofen. These data suggest that ACE2 expression is increased in diabetes and treatment with ACE inhibitors and ARBs increases ACE2 expression. Consequently, the increased expression of ACE2 would facilitate infection with COVID-19. We therefore hypothesise that diabetes and hypertension treatment with



Fang et. Al. Lancet Resp Medicine 11 March 2020

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EMA advises continued use of medicines for hypertension, heart or kidney disease during COVID-19 pandemic

Share

Press release 27/03/2020

EMA is aware of recent media reports and publications which question whether some medicines, for instance angiotensin converting enzyme (ACE) inhibitors and angiotensin receptor blockers (ARBs, or sartan medicines), could worsen coronavirus disease (COVID-19). ACE inhibitors and ARBs are most commonly used for treating patients with high blood pressure, heart failure or kidney disease.

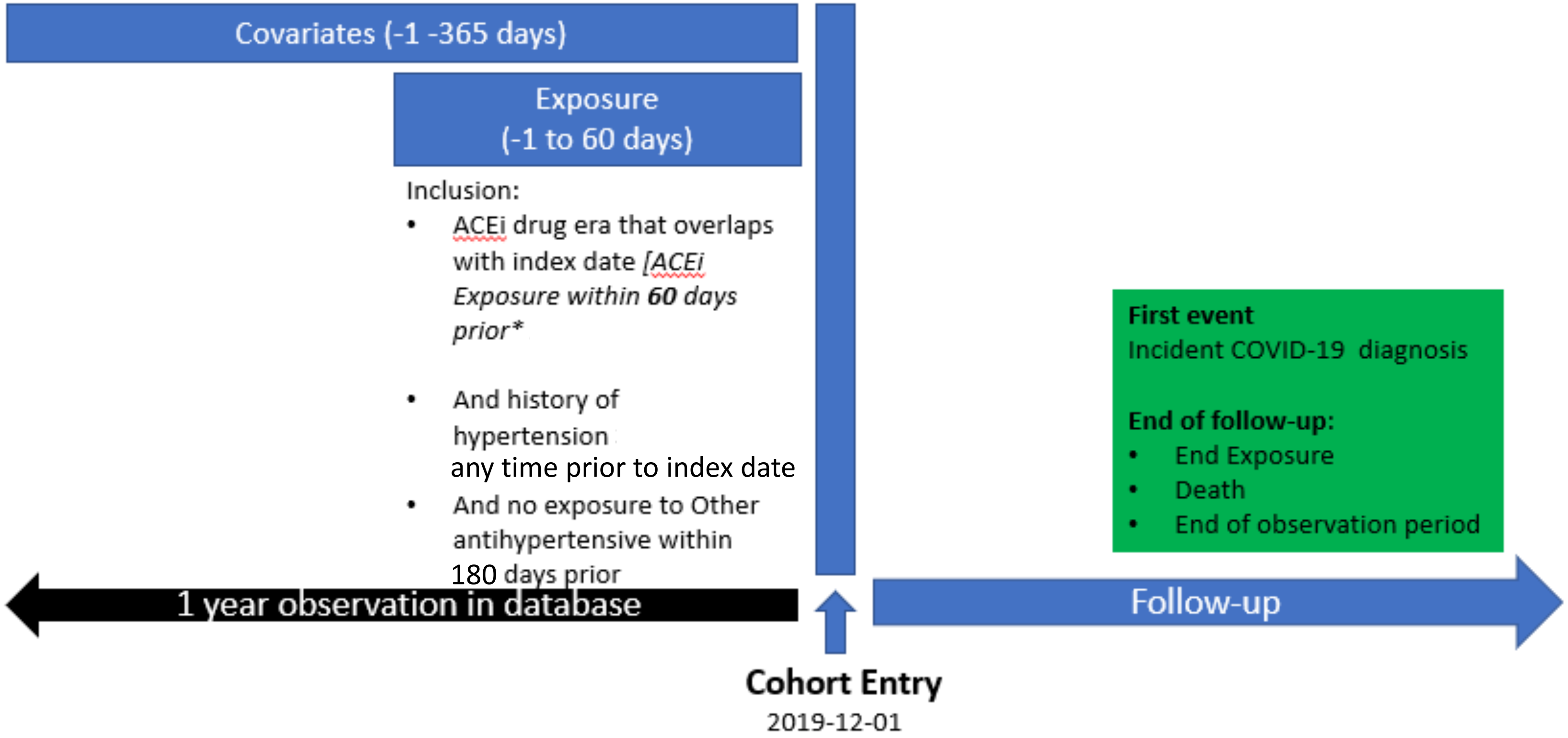
https://www.ema.europa.eu/en/news/ema-advises-continued-use-medicines-hypertension-heart-kidney-disease-during-covid-19-pandemic

Clinical Hypotheses

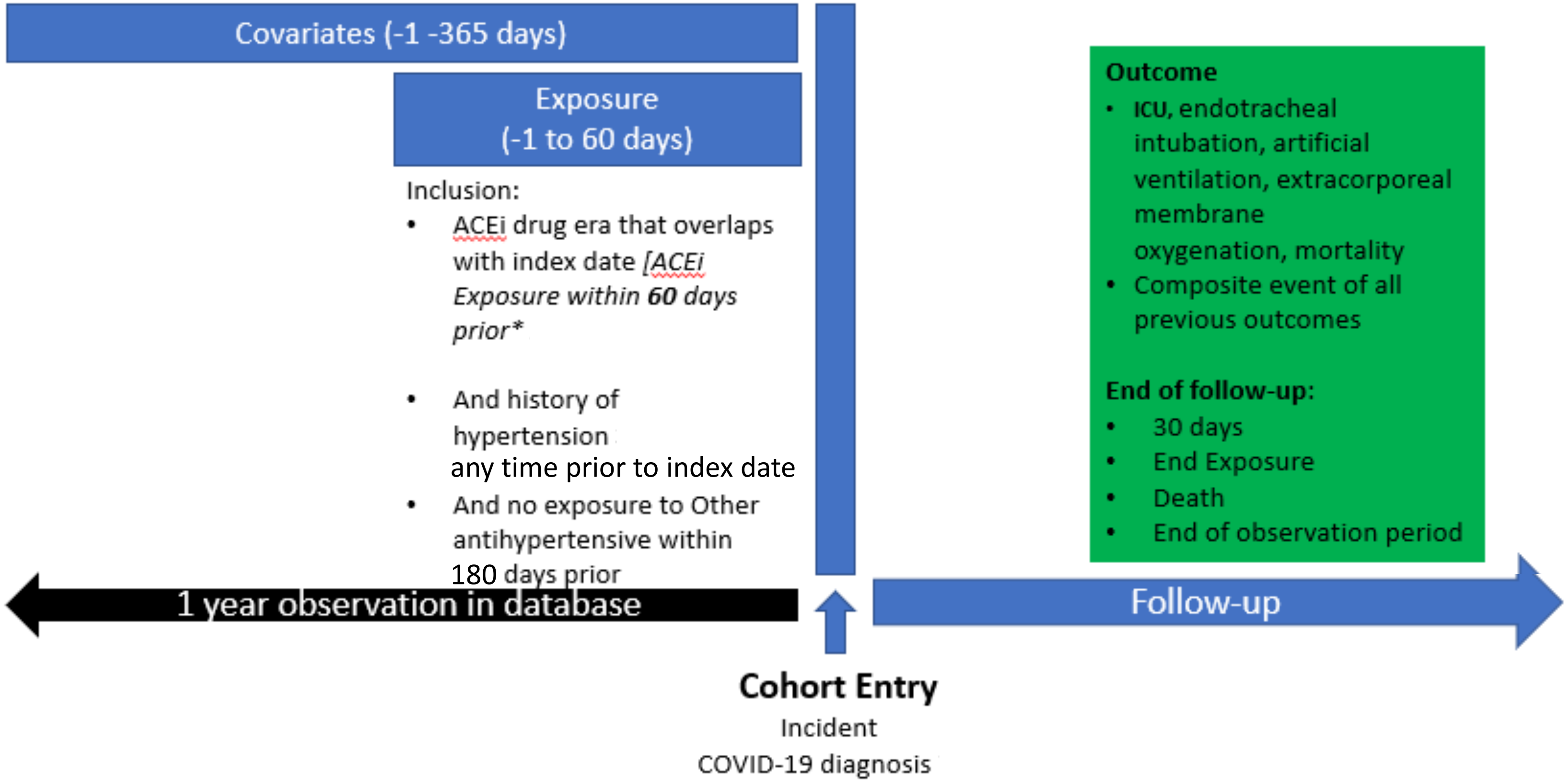
1. Prevalent ACE or ARB use is associated with a difference in risk of COVID-19 infection relative to an active comparator in hypertensive patients

2. Prevalent ACE or ARB use in COVID-19+ patients is associated with a difference in risk of intensive outcomes relative to an active comparator in hypertensive patients

Protocol for Hypothesis 1

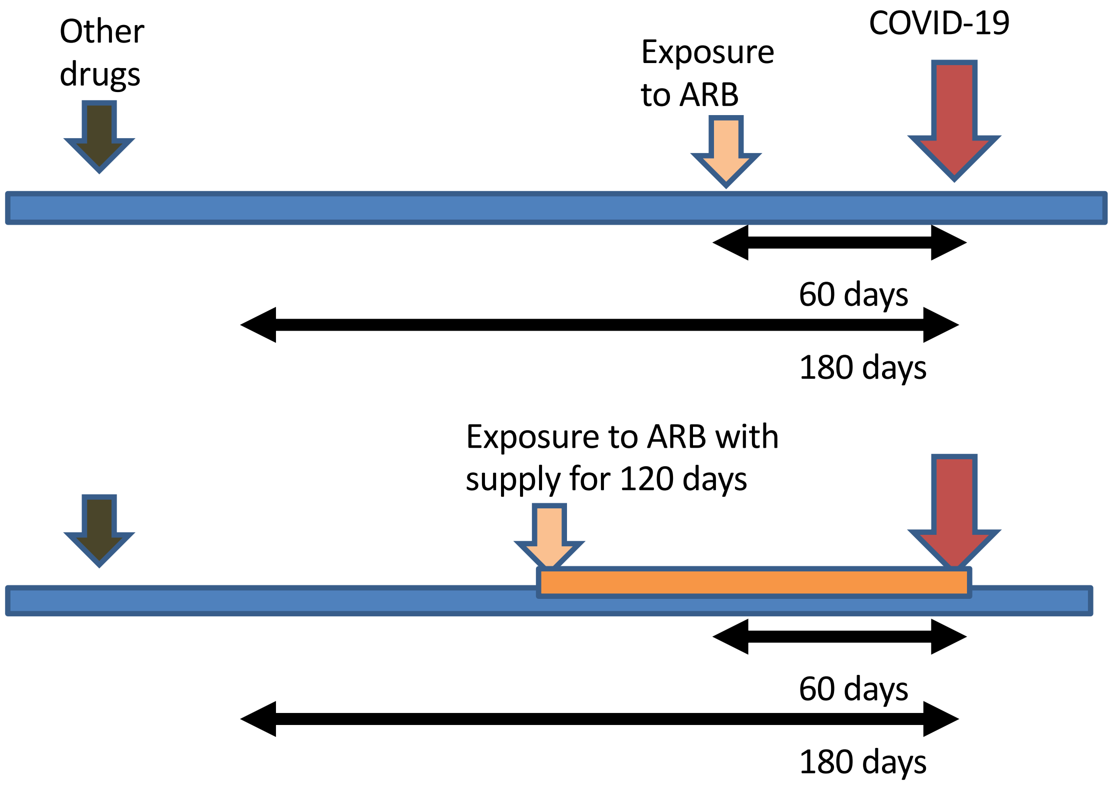


Protocol for Hypothesis 2



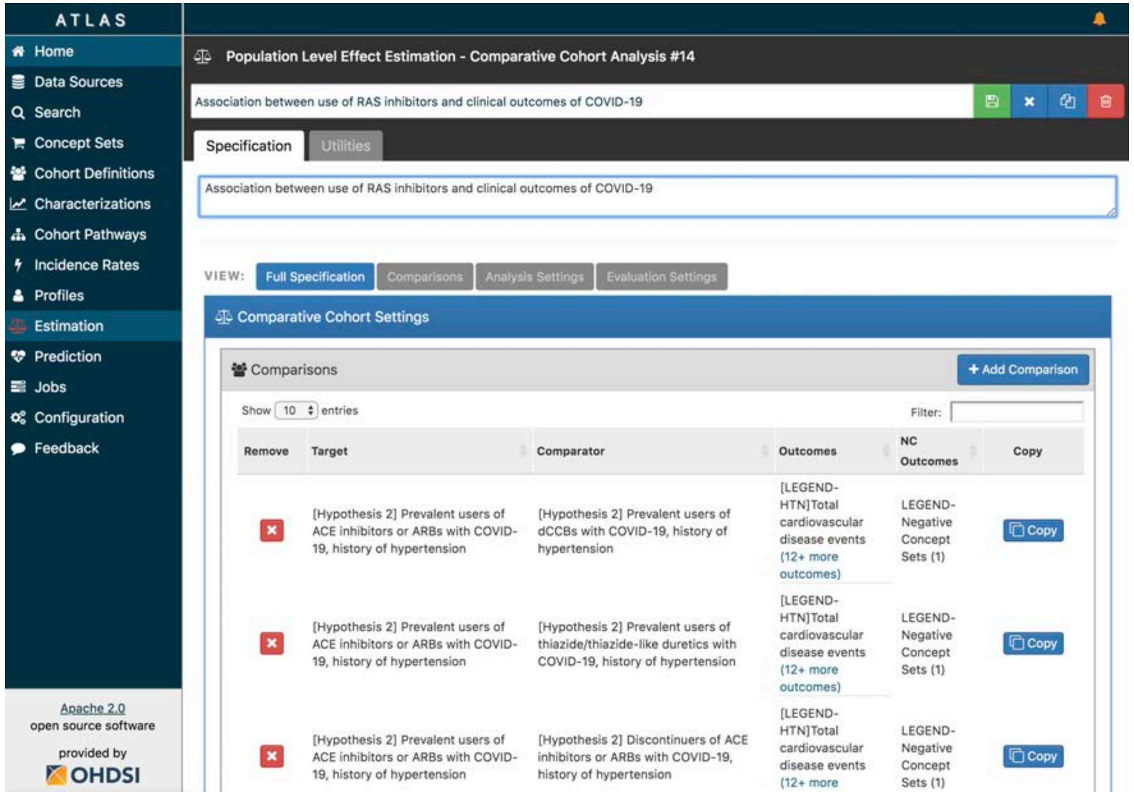
Drug Exposure Specification

Prevalent users of ARBs, with COVID-19, history of hypertension



http://atlas-covid19.ohdsi.org/#/cohortdefinition/268

Specification



Design:

- Logistic regression outcome (30/60/90 days) (cohort 2)
- PS matched / stratified (including age, gender, month)
- Potential for large-scale PS with larger cohorts

Comparisons:

- ACE vs CCB
- ACE vs THZ
- ARB vs CCB
- ARB vs THZ
- RAS vs Discontinued RAS
- ACE vs ARB
- RAS vs CCB
- RAS vs THZ

Outcomes:

- ICU Care
- Ventilation
- ECMO
- All-cause mortality

- MI, HF, Stroke, CV death
- AKI

- LEGEND negative controls

Results

- HIRA: study executes and preliminary results (coming in next presentation)
- Columbia University Medical Center/NYP
  - Successfully ran the main cohort of HTN, recent ACE, no other anti-HTN drugs, sufficient lookback => about 20 patients
  - Analysis using SQL showed we can increase patient numbers using less recent ACE (note we have 30d prescriptions with 5 refills = 180d)
  - Do not have hospital disposition yet, but have inferred ICU, for example, via medications given
  - (Do have a subpopulation on hydroxychloroquine)

Acknowledgments

Key participants:

- Kees van Bochove
- Mitchell Conover
- George Hripcsak
- Christophe Lambert
- Michael Matheny
- Daniel Morales
- Fredrik Nyberg
- Nicole Pratt
- Daniel Prieto Alhambra
- Marc Suchard
- Cynthia Sung
- Seng Chan You

Apologies if your name is not here; let Marc know – he haphazardly compiled this list

Partial funding provided through NIH U19 AI135995 and R01 LM006910

#OpenData4COVID

Seng Chan You, Ajou University
Yeunsook Rho, HIRA

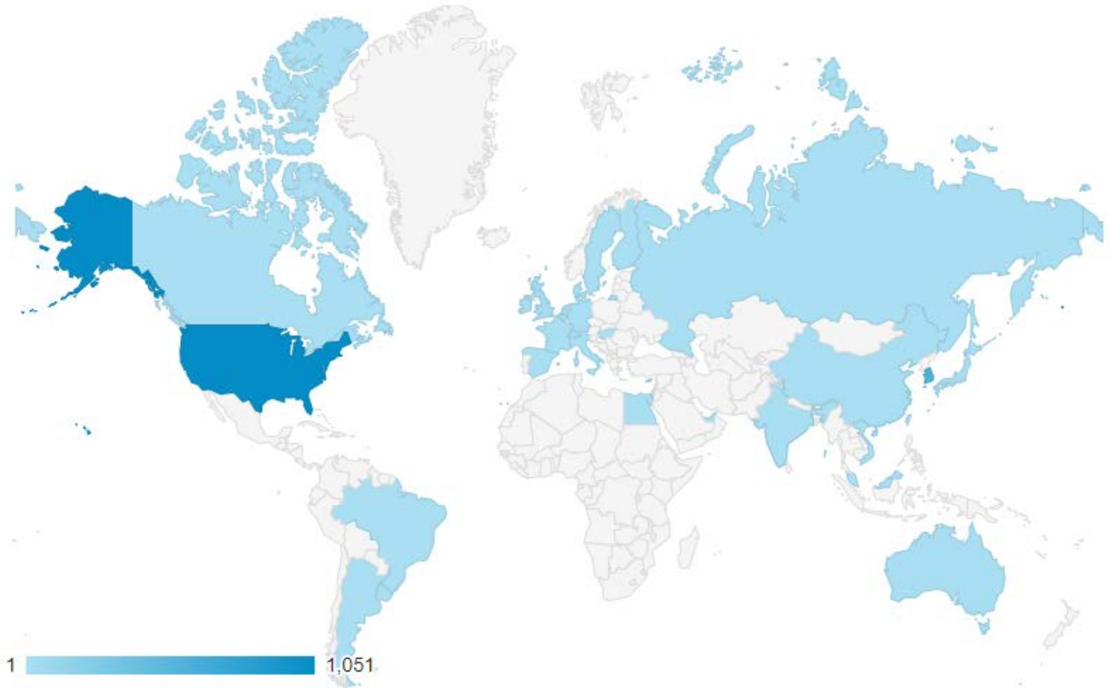
Summary of
COVID-19 Study w/ HIRA Data

March 29/30, 2020

SUMMARY OF "OPENDATA4COVID19" PROJECT W/ HIRA DATA

WE'VE GOT 1,772 VISITORS FROM 32 COUNTRIES FOR 3 DAYS

- More than 160 individual researchers have registered from 15 countries
- Nearly, 30 research projects are submitted for analysis
  (disease characterization, relationship b/w baseline condition and death, relationship baseline drug intake and death, patient-level prediction using machine learning program, etc.)
- Ongoing project



국가		획득		
		사용자	신규 방문자	세션
		1,772 전체 대비 비율 (%): 100.00% (1,772)	**1,772** 전체 대비 비율 (%): 100.00% (1,772)	**1,988** 전체 대비 비율 (%): 100.00% (1,988)
1.	United States	**1,051 (59.31%)**	1,051 (59.31%)	1,083 (54.48%)
2.	South Korea	**575 (32.45%)**	575 (32.45%)	734 (36.92%)
3.	United Kingdom	**24 (1.35%)**	24 (1.35%)	27 (1.36%)

SUMMARY OF “OPENDATA4COVID19” PROJECT W/ HIRA DATA

FUTURE CONSIDERATIONS

- Wonderful experience
- Data update issues
- Further opportunities

CHARACTERIZATION OF PATIENTS WITH COVID-19

Covariate Name	HIRA Proportion
Age group	
15-19	1.9%
20-24	10.9%
25-29	13.9%
30-34	10.5%
35-39	11.6%
40-44	9.4%
45-49	7.2%
50-54	5.7%
55-59	6.5%
60-64	5.7%
65-69	3.9%
70-74	3.3%
75-79	4.1%
80-84	3.2%
85-89	1.8%
90-94	0.5%
Gender: female	51.9%
Race	
race = Korean	100.0%

Cohort	HIRA	
	Entries	Subjects
COVID ID1 v1	4,123	4,123

Medical history: General	
Chronic liver disease	5.5%
Chronic obstructive lung disease	3.8%
Crohn's disease	<0.2%
Dementia	4.5%
Depressive disorder	11.7%
Diabetes mellitus	16.0%
Gastroesophageal reflux disease	29.8%
Gastrointestinal hemorrhage	2.7%
Human immunodeficiency virus infection	<0.2%
Hyperlipidemia	29.9%
Hypertensive disorder	21.7%
Lesion of liver	4.7%
Obesity	0.3%
Osteoarthritis	13.6%
Pneumonia	13.8%
Psoriasis	1.4%
Renal impairment	3.9%
Rheumatoid arthritis	3.3%
Schizophrenia	1.4%

Medication use	
Agents acting on the renin-angiotensin system	13.8%
Antibacterials for systemic use	74.4%
Antidepressants	12.5%
Antiepileptics	11.8%
Antiinflammatory and antirheumatic products	63.2%
Antineoplastic agents	3.2%
Antipsoriatics	0.8%
Antithrombotic agents	36.7%
Beta blocking agents	10.6%
Calcium channel blockers	14.0%
Diuretics	10.4%
Drugs for acid related disorders	66.5%
Drugs for obstructive airway diseases	24.9%
Drugs used in diabetes	9.7%
Immunosuppressants	2.9%
Lipid modifying agents	16.8%
Opioids	65.8%
Psycholeptics	29.7%
Psychostimulants, agents used for adhd and nootropics	8.2%

Led by Edward Burn (Oxford Univesity, UK)

COMPARISON OF CLINICAL OUTCOME BETWEEN ANTI-HYPERTENSIVE MEDICATIONS

Evidence Explorer

Target

Prevalent ARB user as monotherapy for HTN within 30 days before COVID-19 diagnosis ▾

Comparator

Prevalent dCCB user as monotherapy for HTN within 30 days before COVID-19 diagnosis ▾

Outcome

All-cause mortality ▾

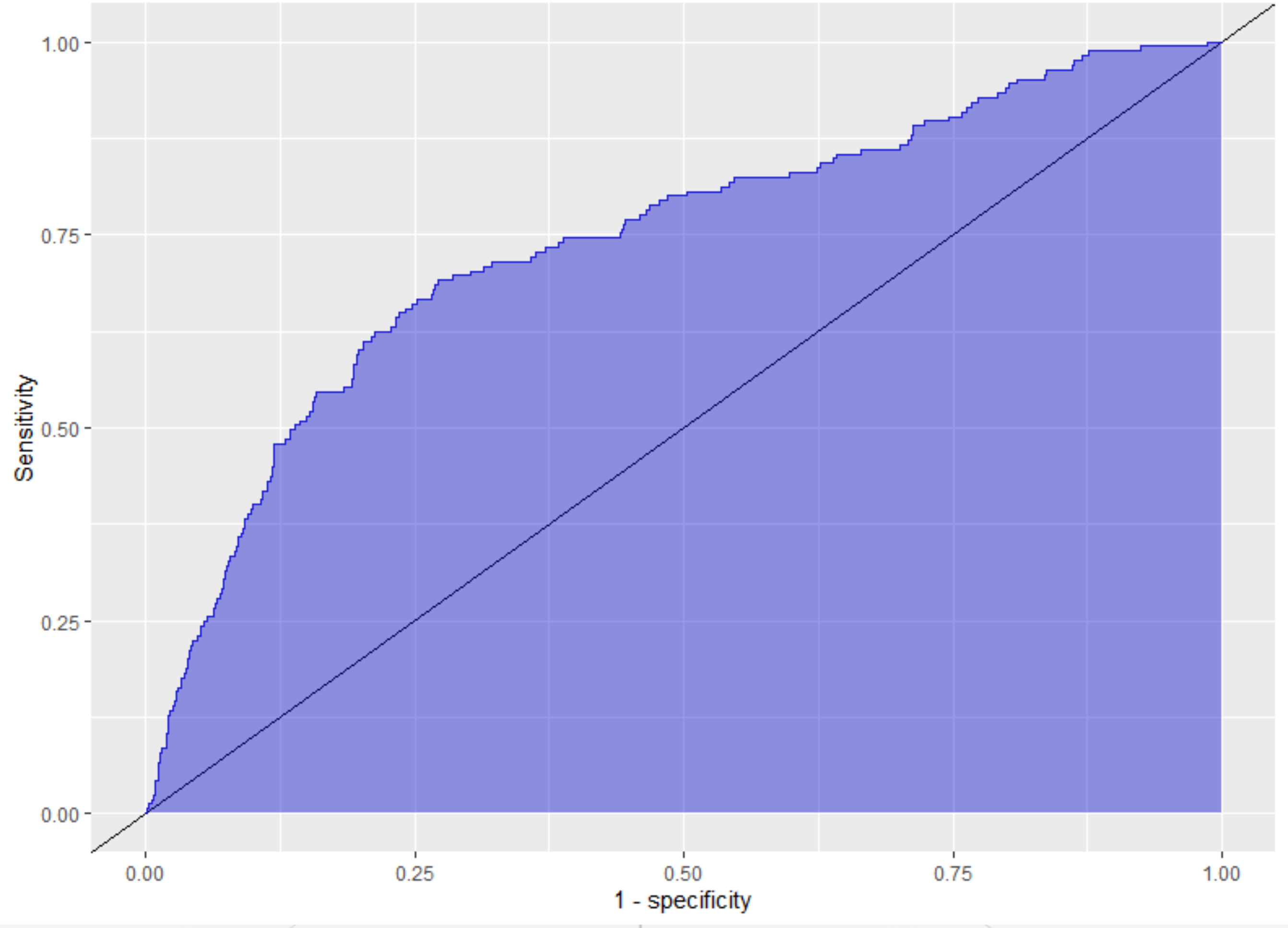
Show 15 ▾ entries

Analysis	Data source	HR	LB	UB	P
Without PS adjustment-Logistic (age/gender/year/month)	HIRA	1.21	0.14	10.32	0.86
Without PS adjustment-Cox (age/gender/year/month)	HIRA	1.21	0.15	10.07	0.86
Minimum PS stratification -Cox	HIRA	1.21	0.15	10.07	0.86
Minimum PS stratification -Logistic	HIRA	1.21	0.14	10.05	0.86
Full PS stratification -Cox	HIRA	1.21	0.15	10.07	0.86
Full PS stratification -Logistic	HIRA	1.21	0.14	10.05	0.86
Unadjusted with all demographic covariates (+14 / logistic)	HIRA	2.42	0.23	52.80	0.52

Showing 1 to 7 of 7 entries

Led by Seng Chan You (Ajou University, Korea)

PREDICTION OF HOSPITALIZATION AMONG PATIENTS SYMPTOMS RELATED WITH VIRAL INFECTION OR DIAGNOSIS OF COVID-19



Led by Peter Rijnbeek (Erasmus University, Netherland)

Thank you!

The journey ahead

Patrick Ryan
Janssen Research and Development
Columbia University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ohdsi.org/covid-19-updates
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Yiliang Zhu
Oleg Zhuk
Jason Zucker
(other names not fully entered in registration)
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/company/ohdsi
#JoinTheJourney

Thank you literature review team!

Thank you phenotype team!

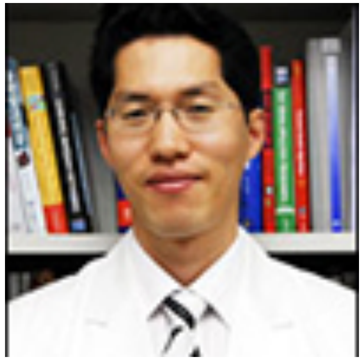
Thank you network execution team!



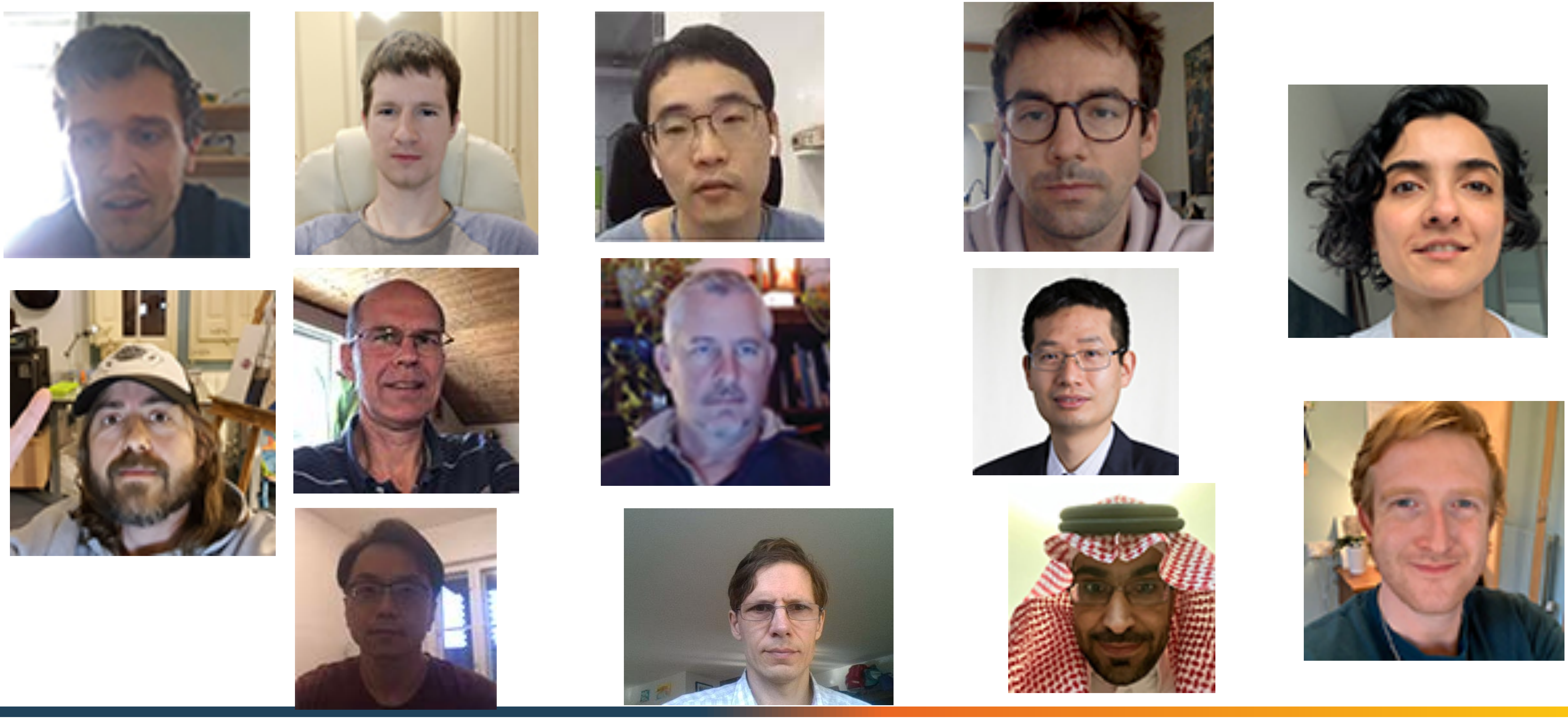








Thank you characterization team!



Thank you prediction team!

Thank you estimation teams!





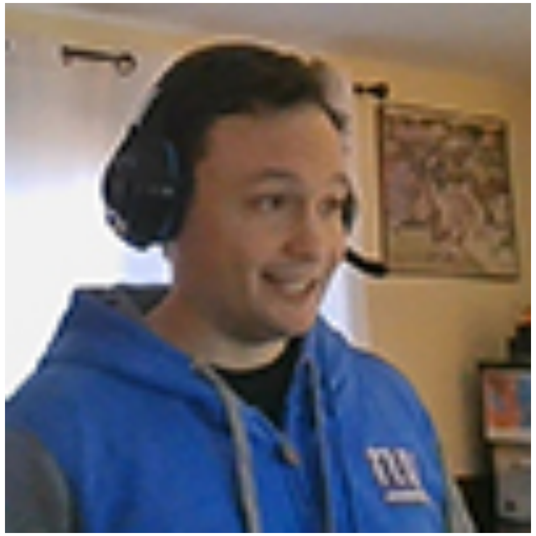








Thank you infrastructure support teams!



The journey ahead

- Study-a-thon may be finishing today, but this is only the START of our journey today
  - Thanks to Erasmus MC, The MSTeams collaboration platform will continue to be available to support OHDSI collaborations
  - ATLAS-COVID19.ohdsi.org will remain available for collaborative development of analyses
  - Each study team needs to determine their own strategy for dissemination
    - Data.ohdsi.org to make results publicly available as soon as possible
    - Publications to be drafted by the community will be open access

Many more important questions need answering…

Name	Question
Alan Goldhammer	Correlation between universal BCG vaccination policy and reduced morbidity and mortality for COVID-19
Jeff Hammerbacher	Blood groups of stratified subpopulations of interest
Geert Byttebier	Potential impact of statin use
Rimma Belenkaya	Specific patterns in the lungs as markers of the disease as it develops over the course of a week and a half
Michael_Shamberger	Does evidence support that taking anti inflammatories can cause adverse outcome?
Sajan Khosla	Length of Stay or 30 Day mortality in patients hospitalized with viral pneumonia to understand patterns of antiviral use and potential differences in endpoints?
Chiara Attanasio	Clinical use cases on cancer patients in relation with COVID-19
Annalisa Trama	Treatment choices for cancer patients planned for surgery and those on cytotoxic chemotherapy or immunotherapy?
Jenny Lane	Compare epidemiological characteristics of the Chinese infections to other countries
Evan Minty	Risk of cardiac injuries (e.g. myocarditis) in COVID-19
Vojtech_Huser	Chronic medication stockpiling (preparing for pandemic) by patients
Jason 10033	The role of steroids in COVID-19 ARDS and ventilation management for patients
Sara Dempster	COVID-19 mortality in different countries
Ru Cheng	Studying pregnancy and lactation: rate of infection in pregnancy, complication rates for pregnant infected women, transmission to newborn (especially c-section vs vaginal) and through milk, premature birth rates, fetal loss
Michael Kallfelz	Role of coinfection with Varicella Zoster or Epstein Barr

Our ask of all of you:

- Keep asking good questions….
  - post your thoughts on the OHDSI forums
- ….and continue to collaborate with each other to help:
  - translate those questions into analysis designs…
  - implement those designs into study packages….
  - execute those packages to generate results….
  - share results across the community to synthesis reliable real-world evidence

OHDSI

OBSERVATIONAL HEALTH DATA SCIENCES AND INFORMATICS

THANK YOU

We like to thank the large group of community members that worked extremely hard to make these four days possible.

We like to thank the Data Partners that have participated in this effort, and those who will join the journey shortly.

We like to thank you for your active participation in these four days.

Questions & Answers

Start of a Journey

- This disease isn't stopping yet, and neither will we
- We will remain committed to generating reliable real-world evidence to meet the needs of public health
- Thank you for continuing on the journey with us