# CBK Metadata, Computable Phenotypes, Research Networks

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IMLS / Mobilizing Computable Biomedical Knowledge (MCBK) Training Online Pilot Class

January 3, 2021

# Posted Readings/Websites for Module

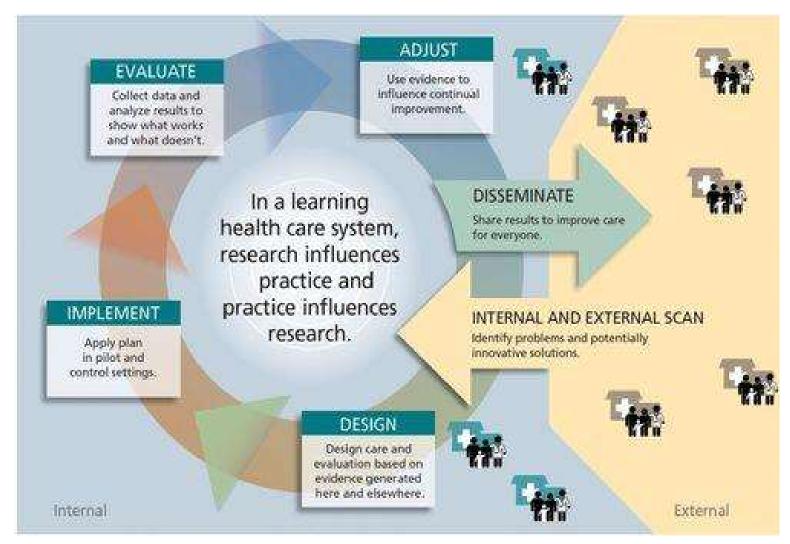
- Alper, BS, Flynn, A, Bray, BE, et al. Categorizing metadata to help mobilize computable biomedical knowledge. Learn Health Sys. 2021;e10271. <a href="https://doi-org.proxy.lib.umich.edu/10.1002/lrh2.10271">https://doi-org.proxy.lib.umich.edu/10.1002/lrh2.10271</a>
- Richesson R, Wiley LK, Gold S, Rasmussen L. Electronic Health Records—Based Phenotyping: Introduction. In: Rethinking Clinical Trials: A Living Textbook of Pragmatic Clinical Trials. Bethesda, MD: NIH Health Care Systems Research Collaboratory. Updated July 27, 2021. <a href="https://rethinkingclinicaltrials.org/chapters/conduct/electronic-health-records-based-phenotyping/electronic-health-records-based-phenotyping-introduction/">https://rethinkingclinicaltrials.org/chapters/conduct/electronic-health-records-based-phenotyping-introduction/</a>
- Chapman M, Mumtaz S, Rasmussen LV, et al. Desiderata for the development of nextgeneration electronic health record phenotype libraries. Gigascience. 2021;10(9):giab059. doi:10.1093/gigascience/giab059 <a href="https://www.ncbi.nlm.nih.gov/pmc/articles/PMC8434766/">https://www.ncbi.nlm.nih.gov/pmc/articles/PMC8434766/</a>
- OHDSI: https://www.ohdsi.org/
- MCBK: https://mobilizecbk.med.umich.edu/
- COVID-19 Knowledge Accelerator (COKA): <a href="https://gps.health/covid-19-knowledge-accelerator-coka/">https://gps.health/covid-19-knowledge-accelerator-coka/</a>; https://confluence.hl7.org/pages/viewpage.action?pageId=97468919
- PheKB: <a href="https://phekb.org/">https://phekb.org/</a>
- NLM Value Set Authority Center: https://vsac.nlm.nih.gov/

# Learning Objectives

- Describe the relevance of CBK to clinical care delivery, learning health systems, and health improvement
- List types of metadata categories that are important for managing CBK
- List 3 challenges for "mobilizing" CBK for action (in health systems)
- Describe role of research networks in developing and implementing CBK
- Describe how common data models (CDMs) and computable phenotypes support the development and application of CBK
- Identify features for libraries of CBK artifacts (e.g. computable phenotypes)
- Describe challenges for managing CBK at scale and highlight areas needing future development and research

## Outline

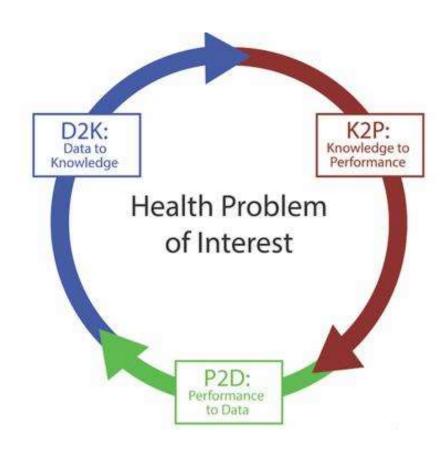
- Review CBK, LHS, FAIR
- Metadata for CBK
- Mobilizing CBK for Action
  - Research Networks
  - Common Data Models
  - Computable Phenotypes
- Example: Desiderata for computable phenotype libraries
- Outstanding Challenges and Future Directions



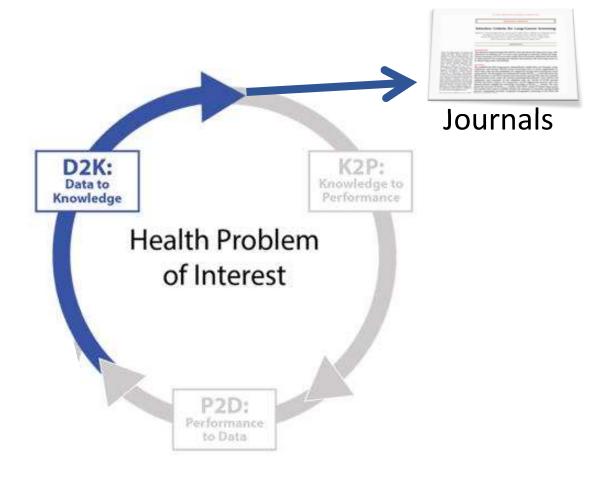


Thomas M. Maddox. Circulation. The Learning Healthcare System and Cardiovascular Care: A Scientific Statement From the American Heart Association, Volume: 135, Issue: 14, Pages: e826-e857, DOI: (10.1161/CIR.00000000000000480)

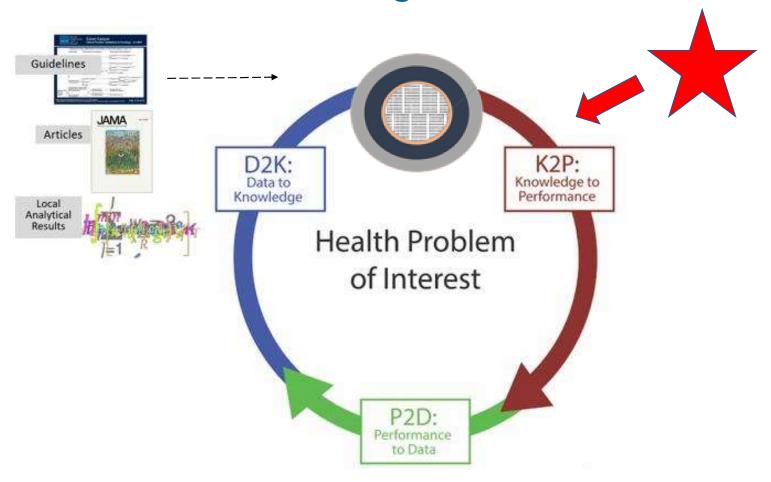
# Better Health Requires This



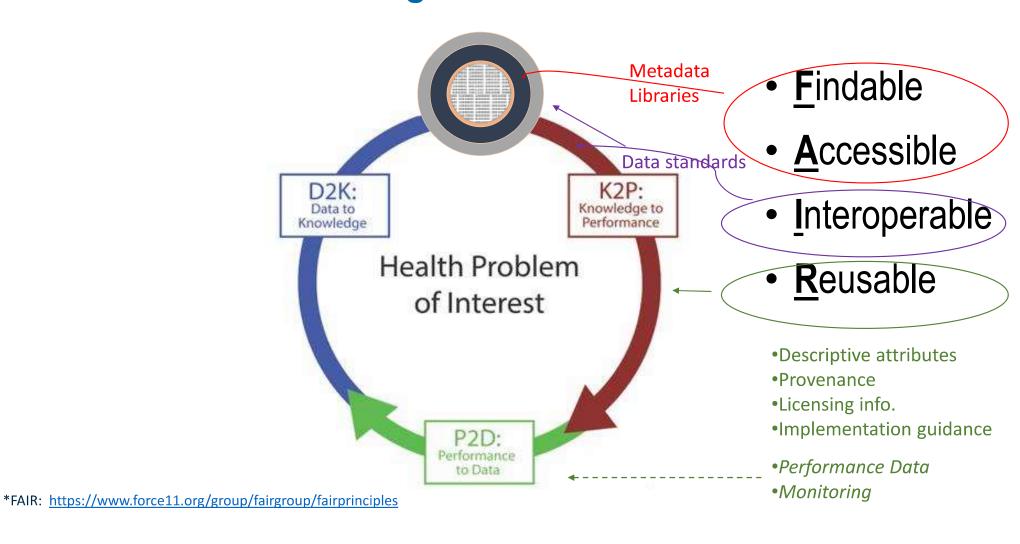
## Not Just This



# **Knowledge to Practice**



## **Knowledge should be FAIR\***



## **ACTIVITY**

- Finding, understanding, and using CBK...
- Instructions
  - Divide into 4 groups
  - Each group examine one CBK artifact, answer questions, and report back
  - Artifacts can be found here: https://drive.google.com/drive/folders/17idZFaz785807xQhHu9dfL9GR1WhFeqE?usp=sharing

Credit and appreciation to Dr. Allen Flynn, PhD, PharmD, UM Dept of LHS
 https://medicine.umich.edu/dept/lhs/allen-flynn-phd-pharmd

#### **BACKGROUND**

An increasing quantity of biomedical knowledge is being expressed in computer-readable and computer-executable formats. An early example is MYCIN, which used about 600 computer-executable rules to guide the diagnosis and treatment of blood infections. In addition to more advanced <u>rule-based systems</u>, there are recent examples of computer-executable machine-learning models being developed and tested for accuracy in detecting and diagnosing disease in <u>images</u> or identifying <u>treatment problems</u>.

#### **OVERALL TOPIC**

As more biomedical knowledge used in laboratories, clinics, and homes comes in computer-readable and computer-executable formats, how are knowledge infrastructures changing? In other words, how are libraries, publishers, authors, and knowledge users adapting their tools and processes to handle *computable biomedical knowledge*?

#### **GROUP TASK**

Carefully examine the computable biomedical knowledge artifact at the link given and then answer the following questions.

# QUESTIONS for each knowledge artifact:

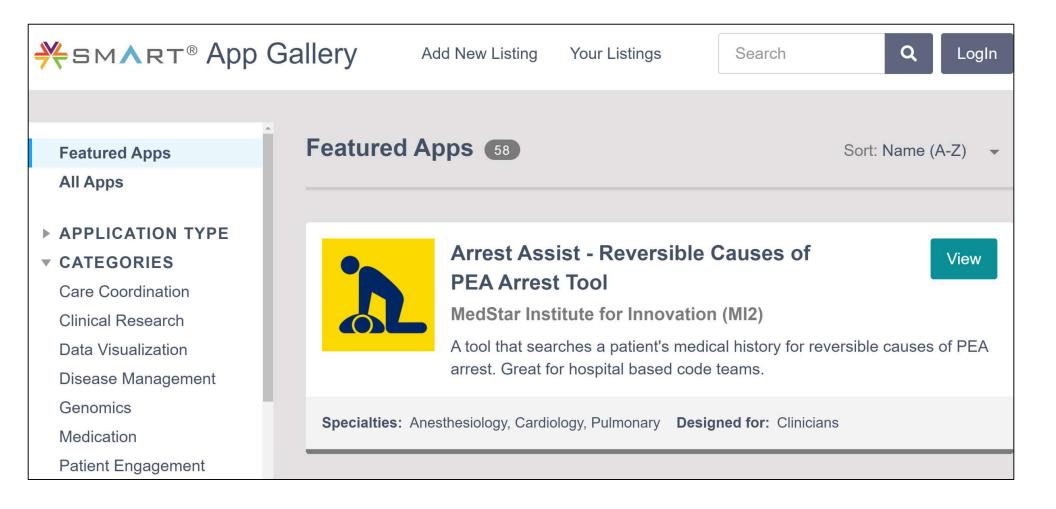
- 1. Which organization(s) is/are providing this computable biomedical knowledge (CBK) artifact online?
- 2. What is the purpose of the CBK artifact (ML model)? What is it for? What does it do?
- 3. What formats or programming languages are used to encode the CBK artifact? Can you tell?
- 4. Can you find instructions for deploying and using the CBK artifact? How does a person create it or run it or execute it? Can you tell?
- 5. What are your overall impressions about the knowledge infrastructure involved as users of this CBK artifact web page?

Grp 1: Statin Use for the Primary Prevention of CVD in Adults: Clinician-Facing CDS Intervention

Grp 2: <u>Tammemagi</u>, 6 year Lung <u>Cancer Risk Prediction Model for Screening</u>

Grp 3: <u>Deep EHR: Chronic Disease</u> <u>Prediction Using Medical Notes</u>

Grp 4: <u>Supervised Classification on</u> liver-disorders – Run 8891972



https://apps.smarthealthit.org/apps/featured

#### METADATA

What types of metadata are needed to describe CBK artifacts sufficiently to make them findable, accessible, interoperable, and re-usable (F.A.I.R.)?



Alper, BS, Flynn, A, Bray, BE, et al. Categorizing metadata to help mobilize computable biomedical knowledge. *Learn Health Sys.* 2021;e10271. <a href="https://doi-org.proxy.lib.umich.edu/10.1002/lrh2.10271">https://doi-org.proxy.lib.umich.edu/10.1002/lrh2.10271</a>

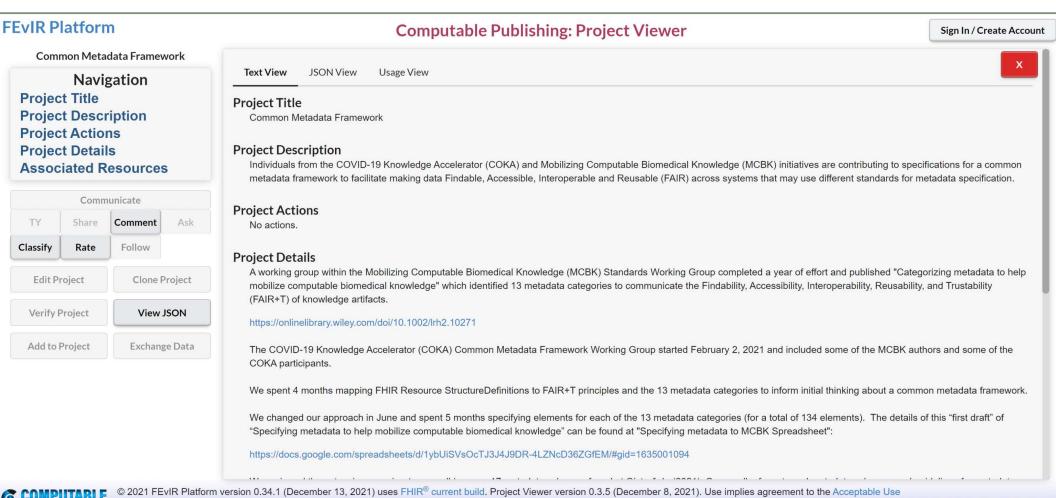
 TABLE 1
 List of metadata categories related to making CBKs and FAIR+T

Metadata category	Metadata elements in this category	Example predicates	Main principle supported	From
1. Type	Elements that classify CBKs by describing the nature of CBKs in some general way	[CBK] is_a {type}	FINDABLE	49,50
2. Domain	Elements relating CBKs to the <b>biomedical domains or topics</b> to which they belong	[CBK] is_about {domain}	FINDABLE	51,52
3. Purpose	Elements describing the <b>purposes</b> or circumscribing and limiting the <b>intended uses</b> of CBKs	[CBK] has_purpose_of [CBK] is_intended_to [CBK] is_not_intended_to	FINDABLE	53
4. Identification	Elements indicating persistent identifiers or persistent unique identifiers and versions assigned to CBKs	[CBK] has_identifier [CBK] has_name [CBK] has_version	FINDABLE	49,50
5. Location	Elements indicating the <b>physical or virtual locations</b> where CBKs can be accessed	[CBK] has_location {ADDRESS} [CBK] is_located_at {URL}	ACCESSIBLE	49,50
6. CBK-to-CBK relationships	Elements describing a relationship between one CBK and some other CBK	[CBK] is_modification_of [CBK] [CBK] is_predecessor_of [CBK] [CBK] is_successor_of [CBK] [CBK] is_used_with [CBK]	INTEROPERABLE	49,50
7. Technical	Elements to describe a wide array of <b>technical characteristics</b> of CBKs that need to be known to deploy, integrate, operate, and use them	[CBK] has_file_type [CBK] has_file_size [CBK] has dependency [CBK] can be executed using [CBK] has input [CBK] has output	INTEROPERABLE	54,55
8. Authorization and rights management	Elements describing <b>rights and responsibilities</b> pertaining to CBKs	[CBK] is_available_to [person] [CBK] has_license [license] [CBK] copyright_held_by [agent] [CBK] has_disclaimer [disclaimer]	REUSABLE	56

10. Integrity [CBK] has\_hash [hash function output] REUSABLE 58 Elements conveying outputs from cryptographic functions that allow CBK [CBK] uses\_hash\_function\_type [type] users to confirm CBK has not been tampered with 11. Provenance Elements indicating changes in ownership, [CBK] is\_owned\_by [agent] **TRUSTABLE** 59 custody, and status during CBK lifecycles [CBK] ownership\_changed\_on [date] [CBK] has status [status] [CBK] status\_changed\_on [date] [CBK] is\_authored\_by [author] [CBK] is\_reviewed\_by [reviewer] [CBK] is endorsed by [endorser] Two evidence categories 12. Evidential Elements describing the data upon which the [CBK] is\_based\_on\_data\_about \_\_\_\_ **TRUSTABLE** 2,60-62 basis claims in CBKs are based, the methods of [CBK] is\_based\_on\_data\_colleted\_at [place] obtaining and analyzing those data, and the [CBK] is\_based\_on\_data\_collected\_by [agent] strength of the evidential basis of CBKs. [CBK] is\_based\_on\_data\_collected\_on [date] [CBK] is\_based\_on\_data\_collected\_for \_\_\_\_ [CBK] is\_based\_on\_data\_analysis\_method\_of [CBK] is\_based\_on\_data\_analysis\_results\_of [CBK] has\_certainty\_of\_evidence \_\_\_\_ 13. Evidence Elements describing data arising from CBK use, CBK] use\_is\_evaluated\_in \_\_\_\_ **TRUSTABLE** 61-63 the methods of obtaining and analyzing from use [CBK] use\_is\_associated\_with \_\_\_\_ those data, and the strength of evidence [CBK] use causes \_\_\_\_ about CBK use [CBK] use\_evidence\_has\_certainty\_of \_\_\_\_

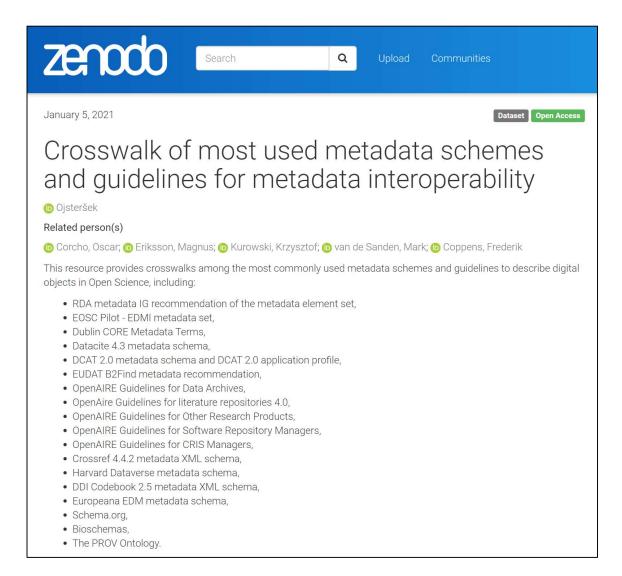
 TABLE 3
 Research agenda for further CBK metadata exploration and analysis

Research agenda item	Brief description of research agenda item	Related metadata category	
CBK typologies	A variety of different approaches have been taken to define the types and subtypes of CBKs. More work is needed to synthesize these efforts into coherent CBK typologies to support standards for CBK types.	Туре	
Schema for purpose metadata	There is an apparent need to formalize CBK purpose metadata. As complex artificial artifacts, all CBKs emerge from some human design process. It may be possible to create schema to convey the motivations and intents of CBK designers and of CBK users and others coherently and usefully.	Purpose	
Schema for CBK-to-CBK relationships metadata	The many ways in which CBKs relate to one another are not clear.  Work is needed to examine potential relationships between types of CBKs and actual relationships between existing CBKs.	CBK-to-CBK relationships	
CBK lifecycles	The lifecycles of CBKs need to be better understood. Since CBK lifecycles may vary by CBK type, interactions between Provenance Metadata and Type Metadata need to be explored.	Provenance, Type, Preservation	
CBK use outcomes	It is not clear which outcomes from using CBKs are of most interest to users. Studies of CBK user needs for evidence arising from use of CBKs are needed to better understand outcomes of interest.	Evidence from Use	
Relationships between CBK metadata and the FAIR and trustability principles	Studies to test the hypotheses surfaced here that metadata from 13 categories can uphold the findability, accessibility, interoperability, reusability, and trustability of CBKs are needed.	All	



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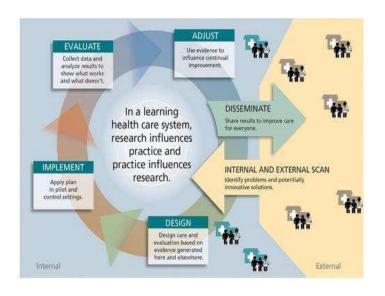
https://fevir.net/resources/Project/29201



https://zenodo.org/record/4420116#.YbjDJGDMJPY

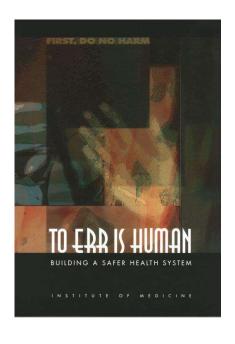
#### **Question:**

## What are challenges for mobilizing CBK (for Action)?

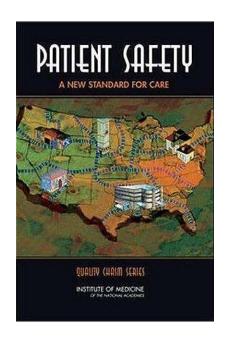


## Next topics

- Mobilizing CBK for Action
  - EHR Data
  - Research Networks
  - Common Data Models
  - Computable Phenotypes
- Example: Desiderata for computable phenotype libraries
- Outstanding Challenges and Future Directions

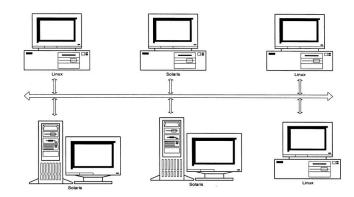






"Interoperability must be addressed now, or else widespread adoption of stand-alone EHRs will be a fait accomplis."

David Brailer, MD, PhD, National Coordinator for Health Information Technology; Remarks at HIMSS 2005 Annual Conference, Feb 17, 2005



## **Types of EHR data**

- Diagnoses
- •Problems
- Procedures
- Tests
- •Lab results/values

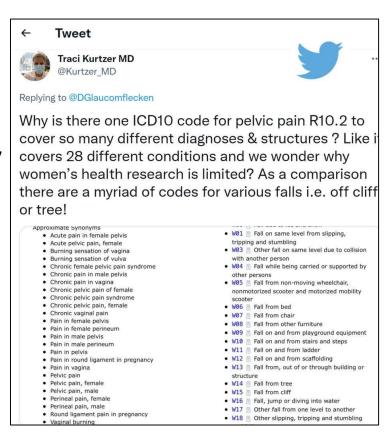
- •Family History
- Allergies
- •Immunization
- Utilization
- Reports
- Notes



### **Types of EHR data**

- Diagnoses
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- Lab results/values

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- Allergies
- Immunization
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- Reports
- Notes



#### What types of data are needed for patient-centered care and are missing here?

### **Types of EHR data**

Diagnoses

Family History

•Problems

Allergies

Procedures

•Immunization

Tests

- Utilization
- Lab results/values
- Reports
- Notes
- Nursing; PT / OT / Diet / otherFunctioning and QOL
- Preferences
- •SDOH
- Demographics

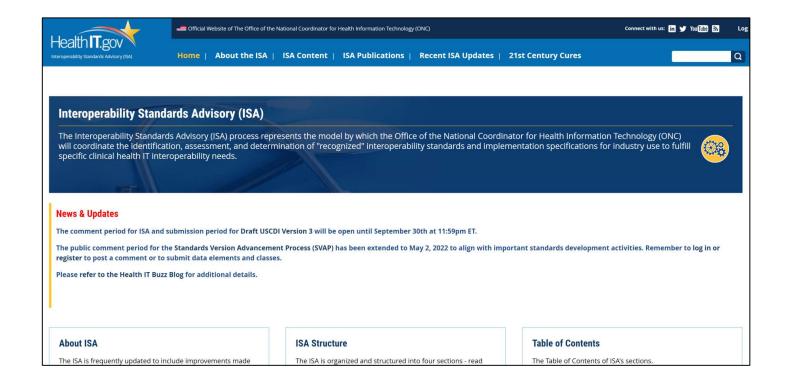




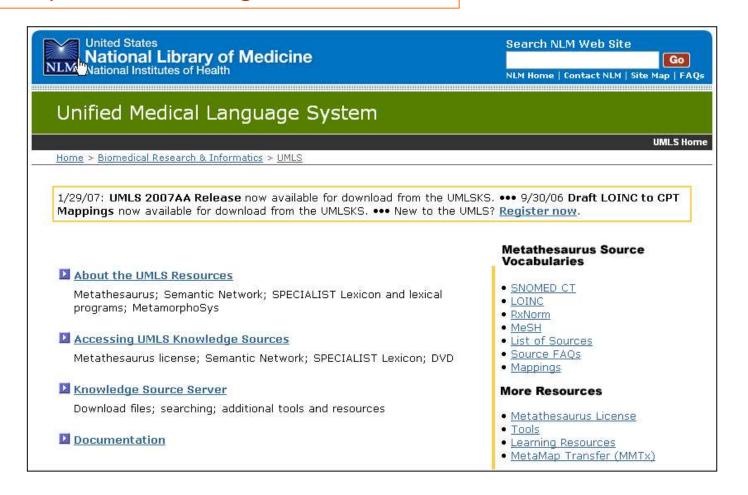
#### Newsroom

#### http://www.healthit.gov/newsroom/about-onc



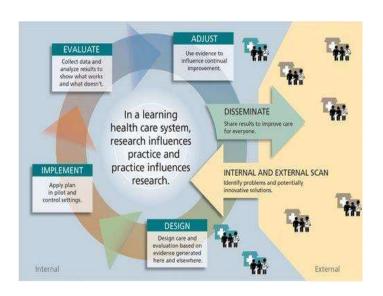


#### http://www.nlm.nih.gov/research/umls/



#### **Question:**

# What is the role of research / healthcare networks in building and implementing CBK (at scale)?



# Networked Research and Common Data Models



# PCORnet, the National Patient-Centered Clinical Research Network

PCORnet, the National Patient-Centered Clinical Research Network, is an innovative initiative of the Patient-Centered Outcomes Research Institute (PCORI). PCORnet will transform clinical research by engaging patients, care providers and health systems in collaborative partnerships that leverage health data to advance medical knowledge and improve health care. PCORnet will bring together health research and healthcare delivery, which have been largely separate endeavors. By doing so, this national health data network will allow us to explore the questions about conditions, care and outcomes that matter most to patients and their families.

PCORnet represents a unique opportunity to make a real difference in the lives of patients and their families. Until now, we have been unable to answer many most important questions affecting health and healthcare. But by combining the knowledge and insights of patients, caregivers, and researchers in a revolutionary network with carefully controlled access to rich sources of health data, we will be able to respond to patients' priorities and speed the creation of new knowledge to guide treatment on a national scale.



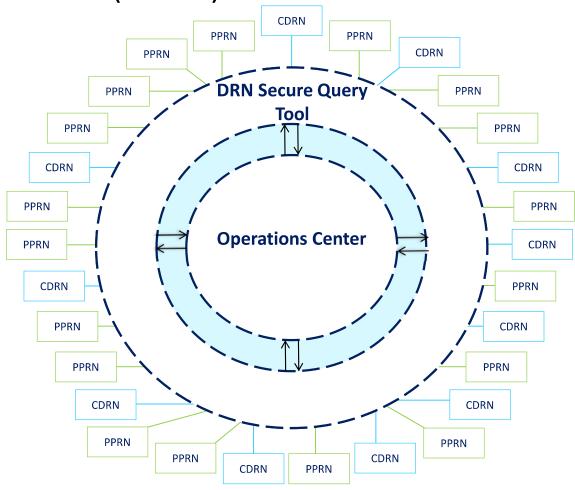
http://pcornet.org/

# 11 Clinical Data Research Networks and 18 Patient Powered Research Networks

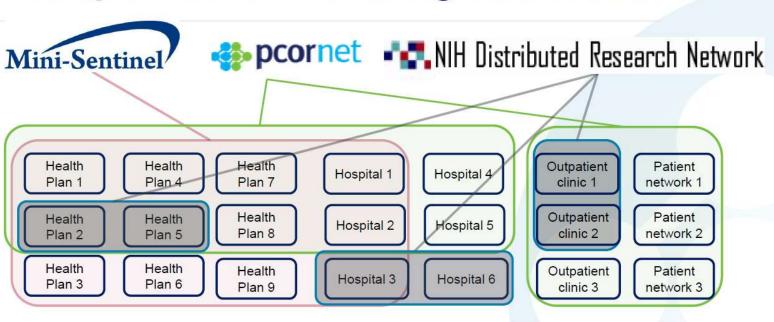




PCORnet Distributed Research Network (DRN)



## **Multiple Networks Sharing Infrastructure**





Who We Are Who We Serve Data Standardization Software Tools Resources Join the Journey Events

#### Welcome to OHDSI!

The Observational Health Data Sciences and Informatics (or OHDSI, pronounced "Odyssey") program is a multi-stakeholder, interdisciplinary collaborative to bring out the value of health data through large-scale analytics. All our solutions are open-source.

OHDSI has established an international network of researchers and observational health databases with a central coordinating center housed at Columbia University.

Read more about us, about our goals, and how you can help support the OHDSI community.

Join the Journey

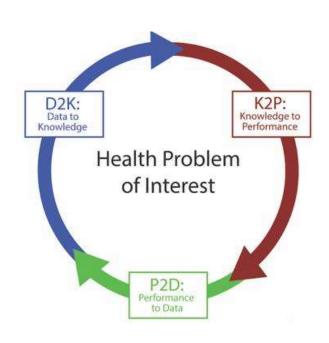


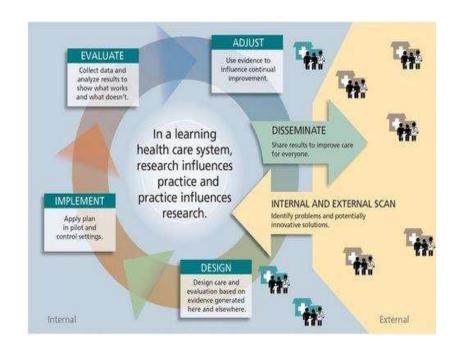
### Other networks

- NIH Collaboratory Distributed Research Network (DRN)
- the High Value Healthcare Collaborative (HVHC)
- the Health Care Systems Research Network
- the Observational Health Data Sciences and Informatics (OHDSI) program

### Re-cap:

# Describe role of research networks in developing and implementing CBK.

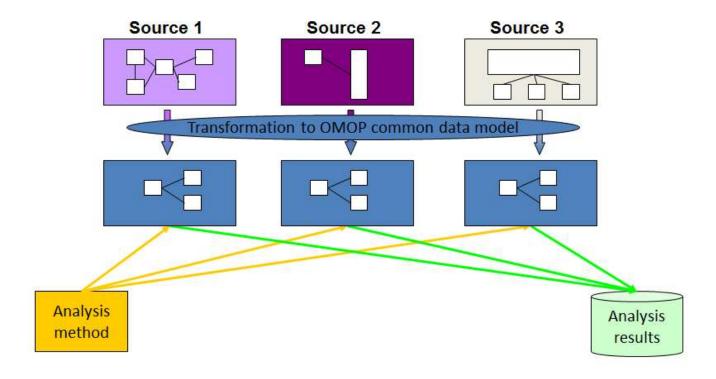




# Common Data Models (CDM)

- Allows for the systematic analysis of disparate observational databases.
- Approach is to transform data from disparate databases into a common format (data model), and then perform systematic analyses using a library of standard analytic routines, based on the common format.
- Why do we need a CDM?
- Observational databases differ in both purpose and design.
- Have different logical organization and physical formats, and the terminologies used vary.

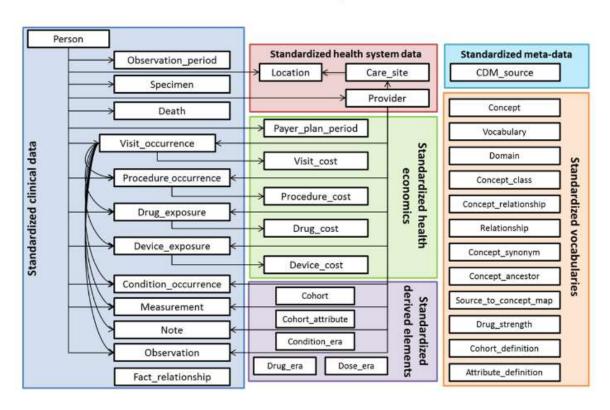
### **OMOP Common Data Model**



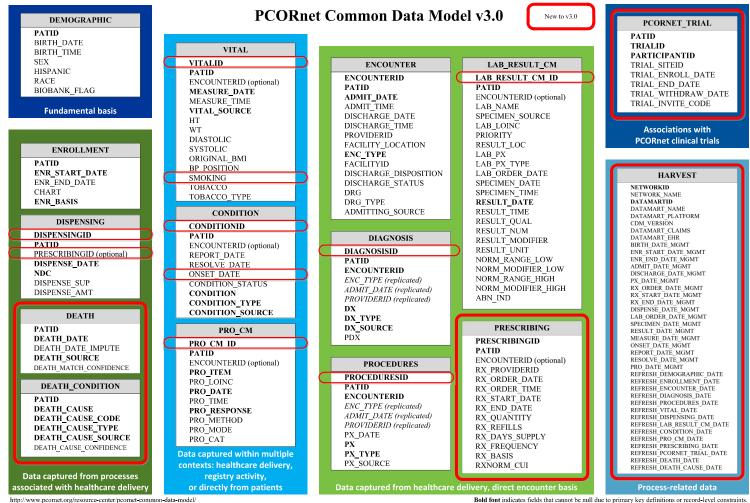
OMOP = The Observational Medical Outcomes Partnership

### OMOP Common Data Model Specifications Version 5.0

October 14, 2014

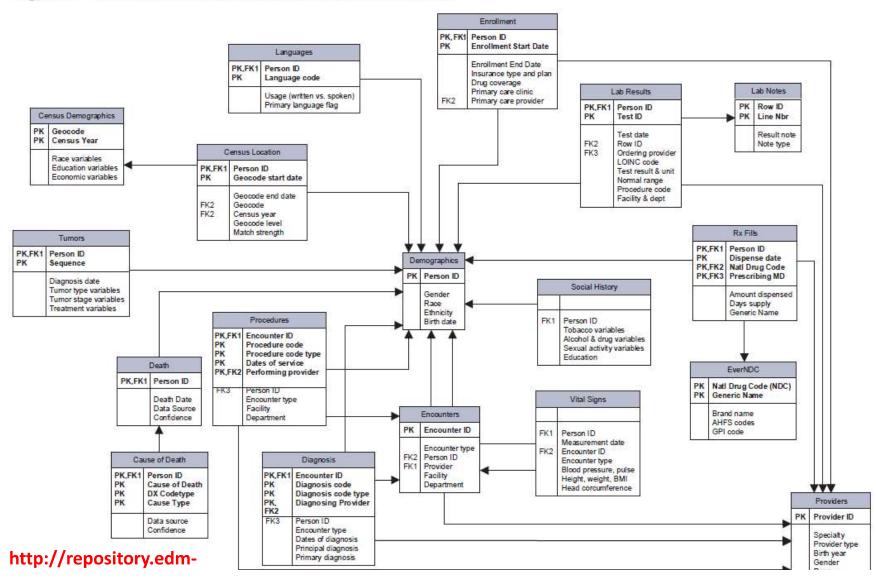


https://github.com/OHDSI/CommonDataModel/blob/master/OMOP%20CDM%20v5.pdf; http://www.ohdsi.org/web/wiki/doku.php?id=documentation:cdm:details\_of\_the\_model



http://www.pcornet.org/resource-center/pcornet-common-data-model/

Figure 3 – The HMORN Virtual Data Warehouse Data Model





"best slide ever" – from AMIA CRI Summit, 2015-03-27 Panel, Parsa Mirhaji; Shawn N. Murphy; Christian G. Reich; Keith Marsolo. "Tug of Ontologies: How Many Information Models Does It Take to Weave a Nationwide Clinical Date Research Network?"

## Comparisons of OMOP vs PCORnet

- http://forums.ohdsi.org/t/omop-data-model-alternatives/406 (several posters listed and good / recent discussion)
- https://www.ncbi.nlm.nih.gov/pmc/articles/PMC3900207/
- https://www.ncbi.nlm.nih.gov/pubmed/23774519
- https://www.ncbi.nlm.nih.gov/pmc/articles/PMC3824370/

#### Pragmatic Data Domain Selection for a National Distributed Research Network: The PCORnet Common Data Model Strategy

Shelley A. Rusincovitch<sup>1</sup>, Abel N. Kho, MD, MS<sup>2</sup>, Jon E. Puro, MPA:HA<sup>3</sup>, Daniella Meeker, PhD<sup>4</sup>, Pedro Rivera, MSCS<sup>3</sup>, Aaron A. Sorensen, MA<sup>5</sup>, Jeffrey S. Brown, PhD<sup>6</sup>, and Lesley H. Curtis, PhD<sup>7</sup>

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OR; <sup>4</sup>Department of Health, RAND Corporation, Santa Monica, CA; <sup>5</sup>Temple University
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Medical School and Harvard Pilgrim Health Care Institute, Boston, MA; <sup>7</sup>Duke University
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#### Abstract

The PCORnet Common Data Model (CDM) is the foundation for the PCORI national distributed research network. We describe our experiences in assessing potential data domains and making decisions for inclusion in the CDM, including modeling attributes, dimensions of assessment, and lessons learned.

#### Introduction and Background

The PCORnet Common Data Model (CDM) specifies the data foundation for the national distributed research network under development by the Patient-Centered Outcomes Research Institute (PCORI). The PCORnet CDM is developed with a phase-based approach, with each phase incorporating new concepts and data tables to support distributed clinical research (observational and interventional). The first version of the CDM established six tables reflecting key patient-level data captured routinely within healthcare delivery and billing systems. In order to establish priorities for subsequent CDM development, it was necessary to establish a method of assessing new concepts and making decisions for inclusion to serve the functional, pragmatic focus of the initiative.

#### Methods

The assessment was organized by data domains; i.e., the high-level concepts of data organization based upon existing data sources, workflows, and processes. Our assessment included best practices established by existing data models and advice from external experts for specific topics. We chose four dimensions for assessment: Effort to acquire data; analytic value of data; ability to standardize data; and availability of data. Each of these dimensions was classified using a

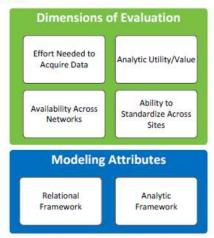


Figure 1. Overview of the data domain evaluation and modeling elements.

simple high, moderate, or low ranking. The CDM Working Group (CDM WG), initially convened in 3 meetings during the summer of 2014 to evaluate and prioritize new data domains for the CDM.

#### Results

During devalorment and modeling of domains we noid alone attention to DCOP not according consistent or only as

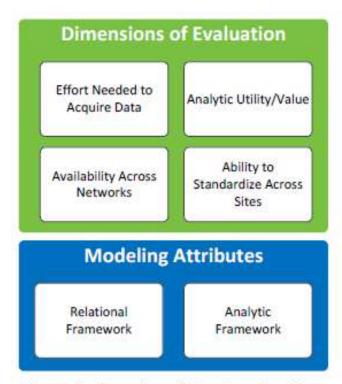


Figure 1. Overview of the data domain evaluation and modeling elements.

## **Key Points**

- Research networks and collaborations have formed and have potential to generate evidence.
- Common data models are being used.
- These data models developed from with data that is widely available in EHRs; many gaps exist.
- Future full of opportunities to leverage and expand these networks and (data, models) to facilitate evidence and discovery on a national scale.

# Computable Phenotype Definition

- Specifications for identifying patients or populations with a given characteristic or condition of interest from EHRs using data that are routinely collected in EHRs or ancillary data sources.
- EHR-based condition definition

# Example

### Diabetes defined as<sup>1</sup>:

ICD-9 codes

 one inpatient discharge diagnosis (ICD-9-CM 250.x, 357.2, 366.41, 362.01-362.07)

or any combination of <u>two</u> of the following events occurring within 24 months of each other:

- A1C ≥ 6.5% (48 mmol/mol)
- fasting plasma glucose ≥ 126 mg/df (7.0 mmol/L)
- random plasma glucose > 200 mg/dl (11.1 mmol/L)
- 2-h 75-g OGTT ≥ 200 mg/dl
- outpatient diagnosis code (same codes as inpatient)
- anti-hyperglycemic medication dispense (see details below)
- NDC in associated list
- ...etc., etc...



1. Nichols GA, Desai J, Elston Lafata J, et al. Construction of a Multisite DataLink Using Electronic Health Records for the Identification, Surveillance, Prevention, and Management of Diabetes Mellitus: The SUPREME-DM Project. Prev Chronic Dis. 2012;9:110311.

#### Research and applications

### A comparison of phenotype definitions for diabetes mellitus

Rachel L Richesson, <sup>1</sup> Shelley A Rusincovitch, <sup>2</sup> Douglas Wixted, <sup>3</sup> Bryan C Batch, <sup>4</sup> Mark N Feinglos, <sup>4</sup> Marie Lynn Miranda, <sup>5</sup> W Ed Hammond, <sup>2,6</sup> Robert M Califf, <sup>3,7</sup> Susan E Spratt<sup>4</sup>

 Additional material is published online only. To view please visit the journal online (http://dx.doi.org/10.1136/ amiaini-2013-001952).

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Received 19 April 2013 Revised 30 July 2013 Accepted 20 August 2013 Published Online First

To cite: Richesson RL, Rusincovitch SA, Wixted D, et al. I Am Med Inform

### ABSTRACT Objective This study compares the yield and characteristics of diabetes cohorts identified using

heterogeneous phenotype definitions.

Materials and methods Inclusion criteria from seven diabetes phenotype definitions were translated into query algorithms and applied to a population (n=173 503) of adult patients from Duke University Health System. The numbers of patients meeting criteria for each definition and component (diagnosis, diabetes-associated medications, and laboratory results) were commaned.

Results Three phenotype definitions based heavily on ICD-9-CM codes identified 9-11% of the nationt population. A broad definition for the Durham Diabetes Coalition included additional criteria and identified 13%. The electronic medical records and genomics, NYC A1c Registry, and diabetes-associated medications definitions which have restricted or no ICD-9-CM criteria, identified the smallest proportions of patients (7%). The demographic characteristics for all seven phenotype definitions were similar (56-57% women, mean age range 56-57 years). The NYC A1c Registry definition had higher average patient encounters (54) than the other definitions (range 44-48) and the reference population (20) over the 5-year observation period. The concordance between populations returned by different phenotype definitions ranged from 50 to 86%. Overall, more patients met ICD-9-CM and laboratory criteria than medication criteria, but the number of patients that met abnormal laboratory criteria exclusively was greater than the numbers meeting diagnostic or medication data exclusively.

Discussion Differences across phenotype definitions can potentially affect their application in healthcare organizations and the subsequent interpretation of data. Conclusions Further research focused on defining the clinical characteristics of standard diabetes cohorts is important to identify appropriate phenotype definitions for health, policy, and research.

#### INTRODUCTION

The ability to identify people with diabetes across healthcare organizations by using a common definition has value for clinical quality, health improvement, and research. Registries have been shown to improve care in diabetes, and are the cornerstone of the chronic disease care model.<sup>1 2</sup> Standard phenotype definitions can enable direct comparison of population characteristics, risk factors, and complications, allowing decision makers to identify and target patients for interventions demonstrated in similar

populations. Furthermore, standard phenotype definitions can streamline the development of patient registries from healthcare data, and enable consistent inclusion criteria to support regional surveillance and the identification of rare disease complications. An understanding of the populations generated from various phenotype definitions will inform standard methods for identifying diabetes cohorts, facilitate the rapid generation of patient registries and research datasets with uniform sampling criteria, and enable comparative and aggregate analysis. This descriptive study presents and compares the size and characteristics of patient populations retrieved using different phenotype definitions adopted from prominent diabetes registries and research networks, a large community intervention program in our county, and federal reporting standards.

#### BACKGROUND AND SIGNIFICANCE

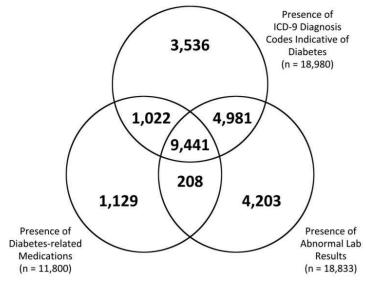
Diabetes diagnosis and management

Diabetes is a complex disease with multiple subtypes associated with different etiologies, diagnostic indicators, and clinical management strategies. Type 2 diabetes mellitus (T2DM) is the most common (95%) type of diabetes in the USA and can be treated with diet and exercise, oral medication, or insulin. Type 1 diabetes mellitus (T1DM) is less common and requires treatment with insulin. Rare types of diabetes result from drug interactions, genetic defects of beta cell or insulin action function, pancreatic disorders, and inherited endocrine disorders. All types of diabetes manifest in high blood glucose, and laboratory values are the primary means for diagnosis and management.<sup>3</sup>

#### Diabetes-relevant data available for electronic health record-based phenotyping

Data from three domains (International Classification of Disease, revision 9, clinical modification (ICD-9-CM) coded diagnoses, laboratory test results, and medication data) in varying combinations and thresholds constitute most phenotype definitions used for diabetes cohort identification. The ICD-9-CM coding system has more than 20 broad codes (and scores of higher precision codes) suggestive or indicative of diabetes (presented in the diabetes phenotype definition shared on Phenotype KnowledgeBase), and is a critical component of most queries and phenotypes. However, ICD-9-CM has been shown to be insufficient for capturing etiology, subtypes, or all cases of diabetes. 3-10.

Diabetes-related medications are often included in phenotype definitions because medication data



**Figure 1** Overlap of diabetes cohorts identified from different categories of phenotype eligibility criteria; n=24 520 patients identified by criteria from any of the three categories.

Richesson RL, Rusincovitch SA, Wixted D, et al. A comparison of phenotype definitions for diabetes mellitus. *J Am Med Inform Assoc*. 2013;20(e2):e319-e326. doi:10.1136/amiajnl-2013-001952

Data domain criteria used in selected phenotype definitions Table 1 Data domain criteria **Expanded ICD-9-CM** ICD-9-CM 250.x0 and Phenotype 250.x2 (excludes type 1 Codes (249.xx, 357.2, Diabetes-associated ICD-9-CM Fasting Random Abnormal definitions: specific codes) 362.0x, 366.41) HbA1c glucose glucose OGTT medications\* 250.xx ICD-9-CM 250.xx CMS CCW **A**\*\\ **A**\*\\ NYC A1c Registry Diabetes-associated medications DDC SUPREME-DM **\* eMERGE**†

=Sole criteria.

▲ =Optional criteria, one of many.

CMS CCW, Centers for Medicare and Medicaid Services Chronic Condition Data Warehouse; DDC, Durham Diabetes Coalition; eMERGE, electronic medical records and genomics; HbA1c, hemoglobin A1c; ICD-9-CM, International Classification of Disease, revision 9, clinical modification; NYC, New York City; OGTT, oral glucose tolerance test; SUPREME-DM, Surveillance, Prevention, and Management of Diabetes Mellitus.

<sup>\*</sup>Medications vary by phenotype definition and are listed for each in the supplementary appendix (available online only).

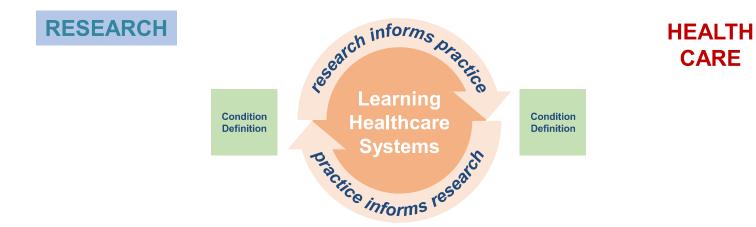
<sup>†</sup>The eMERGE phenotype definition consists of five case scenarios with varying combinations of criteria. Any instance of type 1 specific codes (ie, 250.x1, 250.x3) results in the exclusion of the patient.

<sup>=</sup>Distinction made between inpatient and outpatient context.

<sup>\ =</sup> Distinction made for multiple instances and/or time points.

# Benefits from Standard Phenotypes...

- Development and conduct of new multi-site studies (interventional and observational)
  - Efficiencies of re-using executable phenotype code
  - Comparability of EHR-derived data sets
- Comparison of study results and aggregation of evidence
- Reporting of data sets or results (e.g., ClinicalTrials.gov, NIH)
- Description of research populations in medical journals



- Ideally, research and clinical definitions should be semantically equivalent.
  - i.e., they should identify equivalent populations.

### **ORIGINAL ARTICLE**

### Multicenter Study Comparing Case Definitions Used to Identify Patients with Chronic Obstructive Pulmonary Disease

Valentin Prieto-Centurion<sup>1</sup>, Andrew J. Rolle<sup>1</sup>, David H. Au<sup>2</sup>, Shannon S. Carson<sup>3</sup>, Ashley G. Henderson<sup>3</sup>, Todd A. Lee<sup>4</sup>, Peter K. Lindenauer<sup>5,6</sup>, Mary A. McBurnie<sup>7</sup>, Richard A. Mularski<sup>7</sup>, Edward T. Naureckas<sup>8</sup>, William M. Vollmer<sup>7</sup>, Binoy J. Joese<sup>9</sup>, and Jerry A. Krishnan<sup>1,9</sup>; on behalf of the CONCERT Consortium

<sup>1</sup>Division of Pulmonary, Critical Care, Sleep and Allergy and <sup>4</sup>Department of Pharmacy Systems, Outcomes and Policy, University of Illinois at Chicago, Chicago, Illinois; <sup>2</sup>University of Washington/VA Puget Sound, Seattle, Washington; <sup>3</sup>Division of Pulmonary and Critical Care Medicine, University of North Carolina at Chapel Hill, Chapel Hill, North Carolina; <sup>5</sup>Department of Medicine and Center for Quality of Care Research, Baystate Medical Center, Springfield, Massachusetts; <sup>6</sup>Tufts University School of Medicine, Boston, Massachusetts; <sup>7</sup>The Center for Health Research, Kaiser Permanente, Portland, Oregon; <sup>8</sup>Section of Pulmonary and Critical Care, University of Chicago Medicine, Chicago, Illinois; and <sup>9</sup>Population Health Sciences Program, University of Illinois Hospital and Health Sciences System, Chicago, Illinois

Am J Respir Crit Care Med. 2014 Nov 1;190(9):989-95. doi: 10.1164/rccm.201406-1166OC.



Table 2. Clinical Characteristics of Patients Who Met and Did Not Meet the Clinical Trial Reference Standard

		Clinical Trial Reference Standard		
Characteristic	Total Sample (n = 998)	Yes* (n = 560)	No <sup>†</sup> (n = 438)	P Value
Comorbid conditions, %				
Cardiovascular disease	76	74	78	0.15
Hypertension	66	63	69	0.03
Heart failure	18	16	22	0.01
Coronary artery disease	23	22	24	0.66
Myocardial infarction	19	18	20	0.43
Stroke	15	14	15	0.95
Depression	42	36	50	< 0.0001
Arthritis	36	33	41	0.006
Diabetes	28	22	34	< 0.0001
Cancer history	23	26	19	0.02
Anemia	28	26	30	0.17
Kidney disease	20	18	21	0.30
Dementia	2	2	3	0.15
Dyspnea at rest (Borg), %				
0, no dyspnea	52	54	50	0.02
0.5-2, slight	38	38	37	
≥3, moderate to very severe	10	7	13	
Spirometry, post-bronchodilator, %				
FEV <sub>1</sub> /FVC <70%	61	100	11	< 0.0001
FEV <sub>1</sub> <80% predicted	72	86	55	< 0.0001
6-minute-walk distance, %				
Distance walked <350 m	53	52	54	0.67

Patients who met the trial reference standard are more likely to have airflow obstruction by spirometry but report being less dyspneic. Patients who met the reference standard also have different prevalence of comorbidities. For example, they are more likely to have hypertension, heart failure, and depression. Data for 6-minute-walk distance missing in 9% patients (9% and 10%) and dyspnea scores missing in 8% patients (8% and 9%) in those who met and did not meet the clinical trial reference standard, respectively.  ${}^*(A + D + E + G)$  and  ${}^{\dagger}(B + C + F)$  in Figure 2.

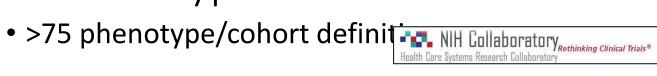
Table 3. Characteristics Associated with Meeting the Clinical Trial Reference Standard

Characteristics	Odds Ratio (95% CI)
Race (vs. white)	
Black	0.37 (0.26-0.53)*
Other	0.52 (0.27-1.00)
Education (vs. high school or less)	(/
College/professional degree	0.38 (0.26-0.56)*
Some college	0.68 (1.06-2.03)*
BMI, kg/m <sup>2</sup> (vs. normal)	,
<18.5 (underweight)	4.00 (1.27-12.50)*
25-29.99 (overweight)	0.87 (0.58-1.30)
≥30 (obese)	0.51 (0.35-0.75)*
Depression (yes vs. no)	0.53 (0.40-0.71)*
Diabetes (yes vs. no)	0.67 (0.48-0.93)*
Cancer (yes vs. no)	1.47 (1.05-2.08)*

Definition of abbreviations: BMI = body mass index; CI = confidence interval. Clinical trial reference standard (A + D + E + G) versus others (B + C + F) in Figure 2. Multivariable logistic regression model that included characteristics listed in Tables 1 and 2 (characteristics significantly associated with meeting the trial reference standard). Results indicate that patients who are black (vs. white), with college or higher (vs. high school or less) education, obese (vs. normal weight), with depression, or diabetes are less likely to meet the trial reference standard. Patients with a history of cancer and underweight patients (vs. normal weight) are more likely to meet the trial reference standard. Hosmer-Lemeshow goodness-of-fit test (P value = 0.17) demonstrates adequate model fit.

 $^*P < 0.05$ .

# Lots of Phenotypes



~40 public (92 private)

• 19 in PCORnet



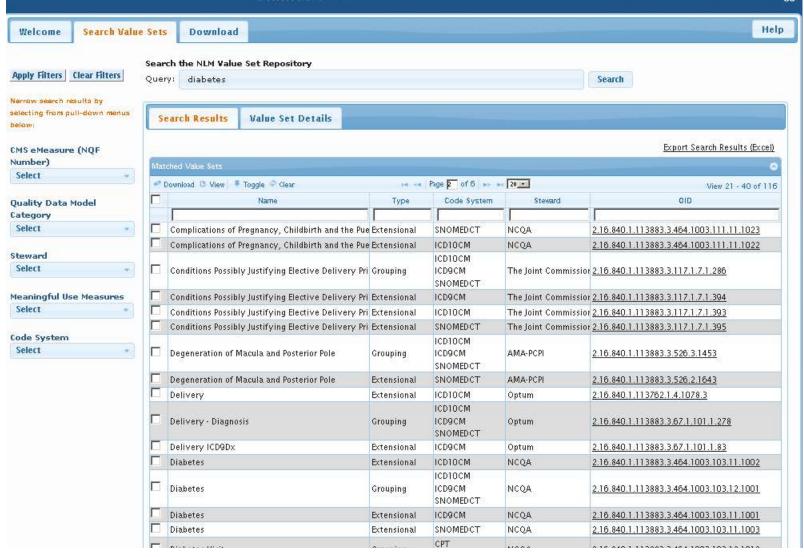




# Other Sources for Phenotypes

- Clinical Classifications Software, "AHRQ Bundles"
- CMS Chronic Conditions Warehouse
- Quality Net (CMS and Joint Commission)
- Mini-Sentinel (FDA)
- SHARPn
- .....
- Multi-site registries
- Research networks





a knowledgebase for discovering phenotypes from electronic medical records

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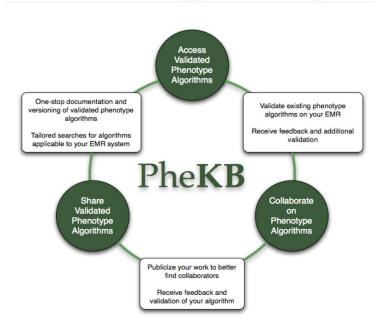
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### What is the Phenotype KnowledgeBase?



Health Data is becoming an increasing important source for clinical and genomic research. Researchers create and iteratively refine algorithms using structured and unstructured data to better identify cohorts of subjects within the health data.

The Phenotype Knowledgebase website, PheKB, is a collaborative environment to building and validating electronic algorithms to identify characteristics of patients within health data. PheKB was functionally designed to enable such a workflow and has

purposefully integrated tools and standards that guide the user in efficiently navigating each of these stages from early stage development to public sharing and reuse. PheKB

#### Most Recent Phenotypes

B HIV

Functional seizures

RxNorm RxCUI codes for Cancer Therapies

Type 1 Diabetes

Body Mass Index (BMI)

https://phekb.org/

# Activity – explore PheKB



GigaScience, 10, 2021, 1-13

https://doi.org/10.1093/gigascience/giab059 Review

#### REVIEW

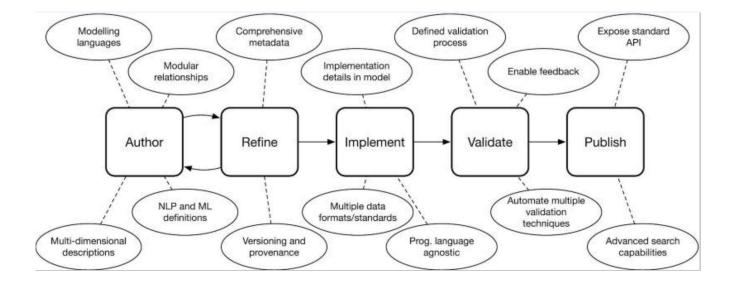
# Desiderata for the development of next-generation electronic health record phenotype libraries

Martin Chapman <sup>1,\*</sup>, Shahzad Mumtaz <sup>2</sup>, Luke V. Rasmussen <sup>3</sup>, Andreas Karwath <sup>4</sup>, Georgios V. Gkoutos <sup>4</sup>, Chuang Gao <sup>2</sup>, Dan Thayer <sup>5</sup>, Jennifer A. Pacheco <sup>3</sup>, Helen Parkinson <sup>6</sup>, Rachel L. Richesson <sup>7</sup>, Emily Jefferson <sup>2</sup>, Spiros Denaxas <sup>8</sup> and Vasa Curcin <sup>1</sup>

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https://pubmed.ncbi.nlm.nih.gov/34508578/



**Table 1:**Phenotype definition formats

Format	Description	Example	Category
Code list	A set of codes that must exist in a patient's health record in order to include them within a phenotype cohort	COVID-19 ICD-10 code "U07.1"	Rule-based
Simple data elements	Formalizing the relationship between code-based data elements using logical connectives	COVID-19 ICD-10 code "U07.1" AND ICD-11 code "RA01.0"	Rule-based
Complex data elements	Formalizing the relationship between complex data elements, such as those derived via NLP	Patient's blood pressure reading >140 OR patient notes contain "high BP"	Rule-based
Temporal	Prefix rules with temporal qualifiers	Albumin levels increased by 25% over 6 hours, high blood pressure reading has to occur during hospitalization	Rule-based
Trained classifier	Use rule-based definitions as the basis for constructing a classifier for future (or additional) cohorts	A <i>k</i> -fold cross-validated classifier capable of identifying patients with COVID-19	Probabilistic

**Table 2:**Phenotype validation mechanisms

Mechanism	Description	Example
Disease registries	Compare the phenotype cohort with those present in the registry	Comparison of a diabetes phenotype cohort with those patients present in a diabetes registry (e.g., T1D exchange)
Chart review	Compare the phenotype cohort with the patients identified by manual review of medical records	Comparison with a diabetes gold standard, produced by double manual review of patient medical records
Cross-EHR concordance	Compare percentage of cases identified by a phenotype across different sources, and identify any overlap	Comparison of the percentage of patients identified by a diabetes phenotype in primary and secondary care EHRs, and the identification of any case overlap
Risk factors	Compare the magnitude of the phenotype cohort with standard risk calculations	Comparison with the output of a Cox hazards model
Prognosis	Compare the magnitude of the phenotype cohort with external prognosis models	Comparison with a survival analysis
Genetic associations	Compare whether the presence of a patient in a phenotype cohort is consistent with their genetic profile	A patient is more likely to be a valid member of a diabetes cohort if they have the HLA-DR3 gene

## Desiderata (14)

- Support modelling languages
- Support NLP—based and machine learning—based definitions
- Support multi-dimensional descriptions
- Support versioning and data provenance
- Support modular relationships between phenotypes
- Communicate implementation information in the model
- Support tooling that provides multiple programming language implementations
- Support tooling that provides connectivity with multiple data standards

- Support a defined validation process
- Automate multiple validation techniques
- Enable feedback
- Expose a standard API
- Offer advanced search capabilities
- Include comprehensive metadata

Sections: modelling, logging, implementation, validation, and sharing and warehousing

### **Real-World Evidence**



### Real-world data (RWD) and real-world evidence (RWE) are playing an increasing role in health care decisions.

- FDA uses RWD and RWE to monitor postmarket safety and adverse events and to make regulatory decisions.
- The health care community is using these data to support coverage decisions and to develop guidelines and decision support tools for use in clinical practice.
- Medical product developers are using RWD and RWE to support clinical trial designs (e.g., large simple trials, pragmatic clinical trials) and observational studies to generate innovative, new treatment approaches.

The 21st Century Cures Act, passed in 2016, places additional focus on the use of these types of data to support regulatory decision making, including approval of new indications for approved drugs. Congress defined RWE as data regarding the usage, or the potential benefits or risks, of a drug derived from sources other than traditional clinical trials. FDA has expanded on this definition as discussed below.

#### Why is this happening now?

The use of computers, mobile devices, wearables and other biosensors to gather and store huge amounts of health-related data has been rapidly accelerating. This data holds potential to allow us to better design and conduct clinical trials and studies in the health care setting to answer questions previously though infeasible. In addition, with the development of sophisticated, new analytical capabilities, we are better able to analyze these data and apply the results of our analyses to medical product development and approval.

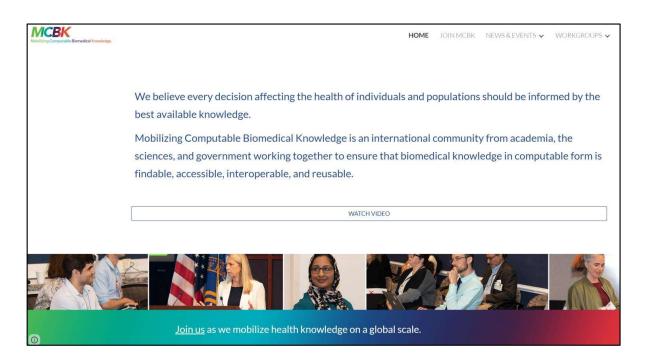
https://www.fda.gov/science-research/science-and-research-special-topics/real-world-evidence

### Conclusions

- CBK is complex and dynamic (life cycle)
- CBK representation not standardized
- CBK will interact with \*data\* hence data standards are relevant
- Interaction with data can differ across settings and time
- Context is important to represent and challenging
- Computable phenotypes are one example of CBK
- Phenotype metadata and libraries will continue to evolve



# A multi-stakeholder movement to mobilize computable knowledge



#MobilizeCBK Mobilizecbk.org

### Mobilizing Computable Biomedical Knowledge (CBK): A Manifesto

#### Preamble

Knowledge has the potential to improve health care, the health of individuals, and the health of populations. Every decision affecting health should be informed by the best available knowledge. For moral and ethical reasons, it is imperative that each and every member of society has access to what is known at the time they are making health-related choices and decisions.

It is no longer sufficient to represent knowledge in the form of printed words and static pictures. The increasingly rapid rate of scientific discovery needs knowledge representations that are more agile and amenable to scalability and mass action. This in turn can enable the continuous cycles of discovery and improvement envisioned as Learning Health Systems.

Contemporary digital technology enables knowledge to be represented in computable forms expressed in machine-executable code. Computable knowledge unleashes the potential of information technology to generate and deliver useful information—and particularly, decision-specific advice—to individuals and organizations with great speed on a world-wide scale. It is essential to take full advantage of these capabilities, while continuing established practices that validate knowledge, preserve it, and ensure that it can be trusted.

There is work to do to mobilize best available health knowledge for the greater good. To begin, biomedical knowledge in computable form must be made interoperable using open standards, and widely available so that it can be used to immediately impact health.

It is time for action on a global scale.

#### Computable Biomedical Knowledge

Computable Biomedical Knowledge is the result of an analytic and/or deliberative process about human health, or affecting human health, that is explicit, and therefore can be represented and reasoned upon using logic, formal standards, and mathematical approaches.

#### Vision

We are dedicated to:

Mobilizing biomedical knowledge that can support action toward improving human health. This should be done using computable formats that can be shared and integrated into health information systems and applications.

Efficiently and equitably serving the learning and knowledge needs of all participants, as well as the public good. This will work to significantly reduce health disparities.

### MCBK Manifesto

Ensuring that the knowledge properly reflects the best and most current evidence and science. This will ensure that knowledge can be trusted for use to improve health and health care.

Achieving this through evolution of an open Computable Biomedical Knowledge ecosystem dedicated to achieving the FAIR principles: making Computable Biomedical Knowledge easily findable, universally accessible, highly interoperable, and readily reusable." The current interest in making data "FAIR" should be matched by equally intense interest in making knowledge "FAIR"

#### Mechanisms of Activity

We believe that all of the following are important:

- . The CBK Concent
  - Sustain the Computable Biomedical Knowledge ecosystem through publicprivate partnerships.
  - Establish broadly-based participatory governance of the ecosystem.
  - Make the ecosystem diverse and inclusive.
  - Explore the sciences of Computable Biomedical Knowledge collaboratively.
  - Be agile to reflect the increasingly rapid changes in knowledge.
- The CBK Technical System
  - o Enable the ecosystem with open standards.
  - Build and uphold trust in Computable Biomedical Knowledge through the ecosystem.
  - Ensure robust and unbiased methods to support transparency and expose the currency, validity and provenance of Computable Biomedical Knowledge.
  - o Implement the highest standards of privacy and security for all stakeholders.
  - Enable a pipeline that transitions knowledge from human-readable to fully computable through successive stages.
- . The CBK Use/User System
  - Ensure the safe and effective use of Computable Biomedical Knowledge through the ecosystem.
  - Generate value for the creators of the knowledge, the users of the knowledge, and the general public.
  - Engender equity in health and in knowledge accessibility
- \*- Wilkinson MD, Dumontier M, Aalbersberg JJ, Appleton G, Axton M, Baak A, Blomberg N, Boiten JW, da Silva Santos LB, Bourne PE, Bouwman J. The FAIR Guiding Principles for scientific data management and stewardship. Scientific data. 2016;3.

### www.MobilizeCBK.org

# Workgroups & Co-Chairs

 Standards & Infrastructure

Bruce Bray Jamie McCusker

 Sustainability for Mobilization & Inclusion Jerry Perry Terrie Wheeler

 Policy & Coordination to Ensure Quality & Trust Jodyn Platt Blackford Middleton

# Questions? Follow-up?

Rachel Richesson

richessr@med.umich.edu

# Learning Objectives

- Describe the relevance of CBK to clinical care delivery, learning health systems, and health improvement
- List types of metadata categories that are important for managing CBK
- List 3 challenges for "mobilizing" CBK for action (in health systems)
- Describe role of research networks in developing and implementing CBK
- Describe how common data models (CDMs) and computable phenotypes support the development and application of CBK
- Identify features for libraries of CBK artifacts (e.g. computable phenotypes)
- Describe challenges for managing CBK at scale and highlight areas needing future development and research