# Developing and Evaluating Intelligent Health Systems

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A Clinical System: Statistical Modeling for Prescribing Decision Support

A Population Health System: Knowledge Modeling for Public Health

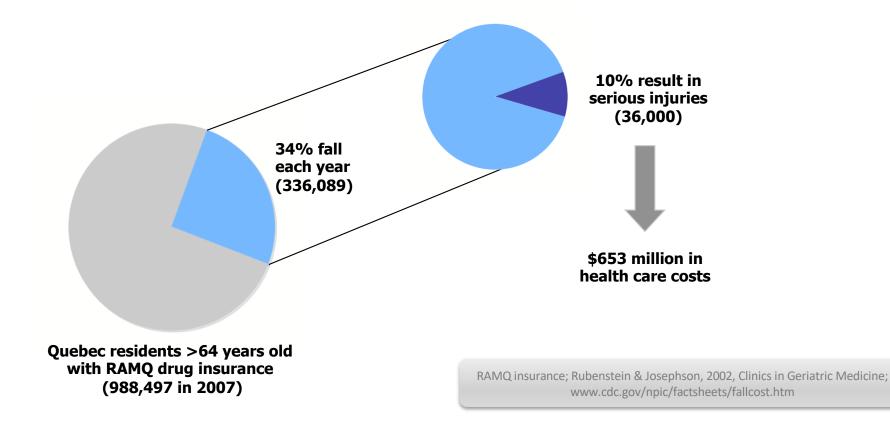
**Closing Thoughts** 

A Clinical System: Statistical Modeling for Prescribing Decision Support

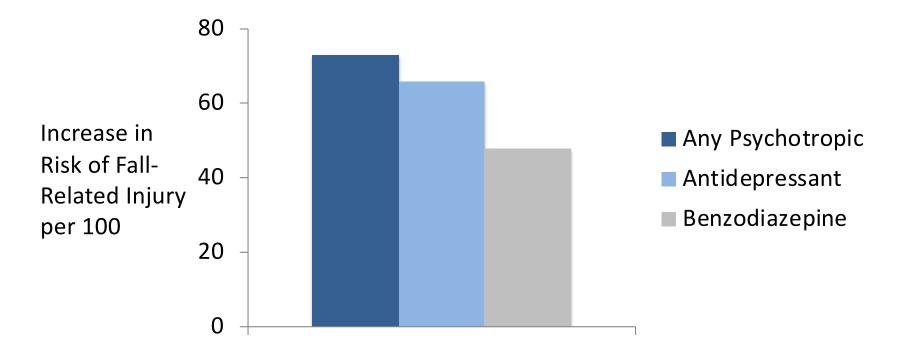
A Population Health System: Knowledge Modeling for Public Health

**Closing Thoughts** 

## Fall-Related Injuries in Older Adults are Common and Costly

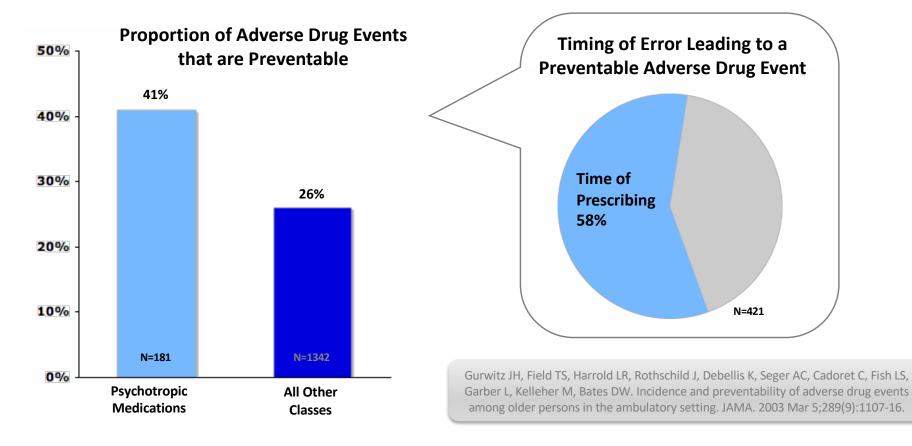


## Psychotropic Medications Cause Fall-Related Injuries



Medication as a Risk Factor for Falls: Critical Systematic Review Sirpa Hartikainen, Eija Lönnroos, Kirsti Louhivuori. The Journals of Gerontology. Oct 2007. Vol. 62A, Iss. 10; p. 1172

## Adverse Drug Events are Preventable at the Time of Prescribing



## **Current Prescribing Decision Support**

- "Top-down" knowledge engineering by expert opinion
  - Shared metabolic pathways
  - Potential (although vaguely defined) additive effects
- Encoded as large knowledge base (e.g., FDB, Vigilance)
- Many alerts (drug-drug, drug-disease, drug-age) can be generated for a single patient, graded by "importance"
- Implications of alerts for a given patient often unclear
- Clinicians ignore most (50%-90%) alerts

## Statistical Guidance by Outcome

- Identify outcome(s) of clinical interest
- Develop a {statistical | ML} model to predict outcome
  - All known individual risk factors for outcome
  - Drugs associated with the outcome
- Use the model in clinical context
  - To estimate the (modifiable) drug risk for a patient
  - To predict the change in risk if medication(s) modified
  - (To prioritize changes based on likely risk reduction)

# **Prescribing Decision Support**

- Traditional drug alerts
  - Generic
  - Clinical implications unclear
  - Ignored
- Probabilistic alerts can give clear, target message
  - Personalized alert
  - Linked to quantified risk of important outcome

Taylor & Tamblyn, 2005; Shah, et.al, 2006; Van der Sijs, et.al, 2006; Eslami, et.al, 2007

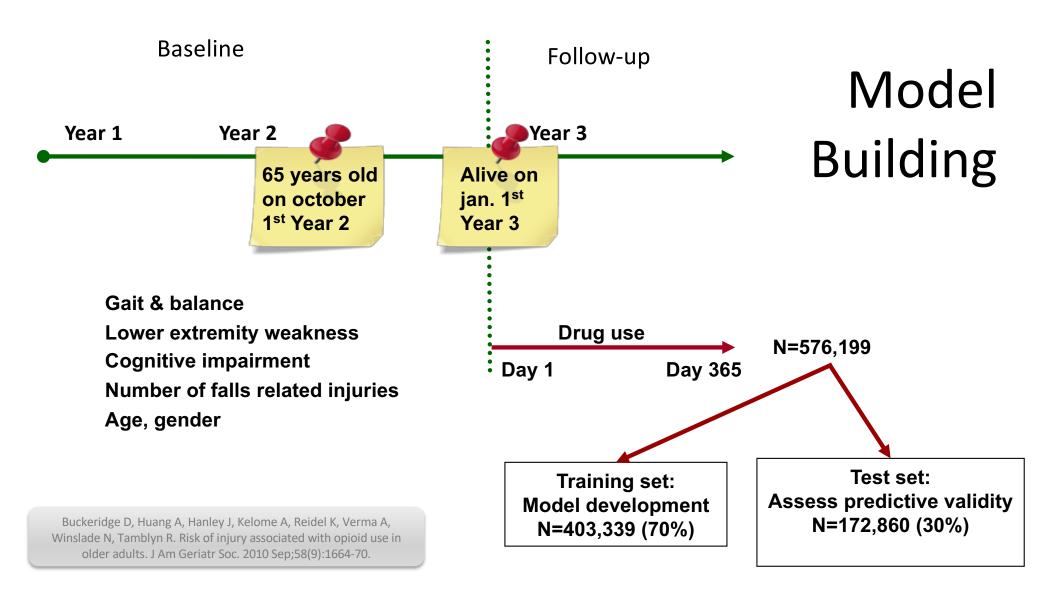


### Traditional

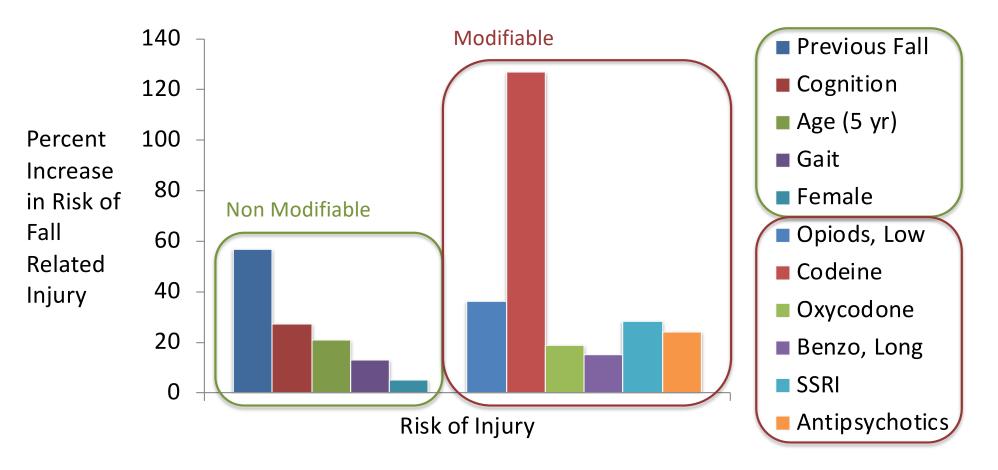
"Level 2 Alert: Age-Drug Interaction with Opiates"

### Probabilistic

"15% chance this patient will fall on current dose of codeine"



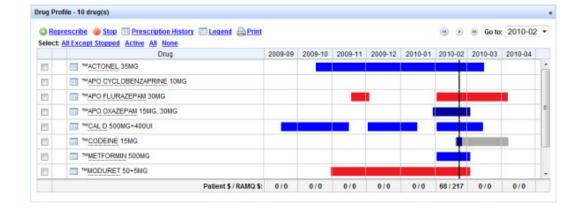
## Adjusted Risk Factors for Fall Related Injury





# Embedding Model in EMR

- The MOXXI EMR
- User-centered design of risk communication
  - Focus groups with MD
  - Key concepts:
    absolute vs relative
    risk, modifiable risk

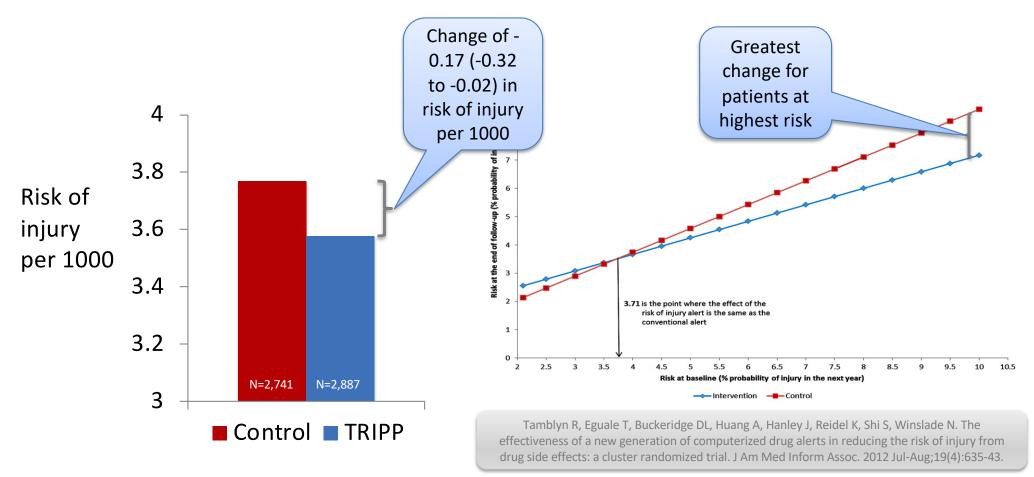


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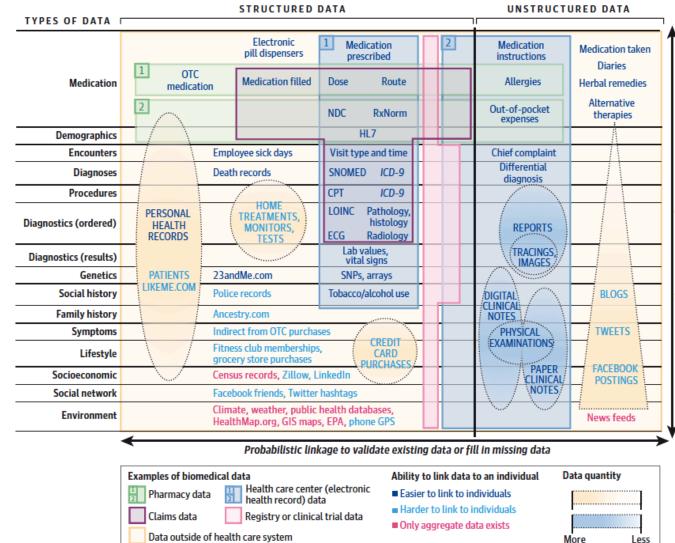
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**Closing Thoughts** 

# Lots of Relevant Data

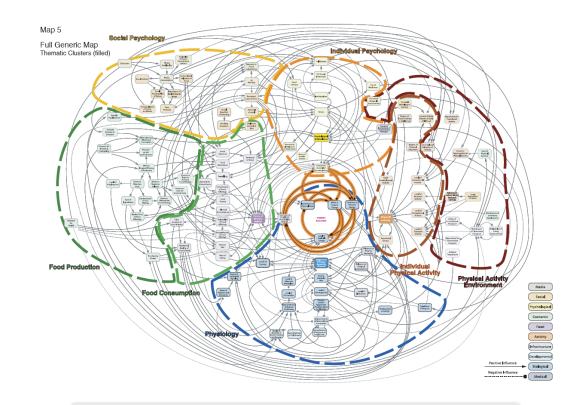
Weber GM, Mandl KD, Kohane IS. Finding the Missing Link for Big Biomedical Data. JAMA. 2014;311(24):2479 -2480.



Probabilistic linkage to obtain new types of data

## Complex Web of Knowledge

- Many diseases have complex causality
- Analysis requires longitudinal, linked data from multiple sectors
- Resulting indicators must be presented in interpretable manner



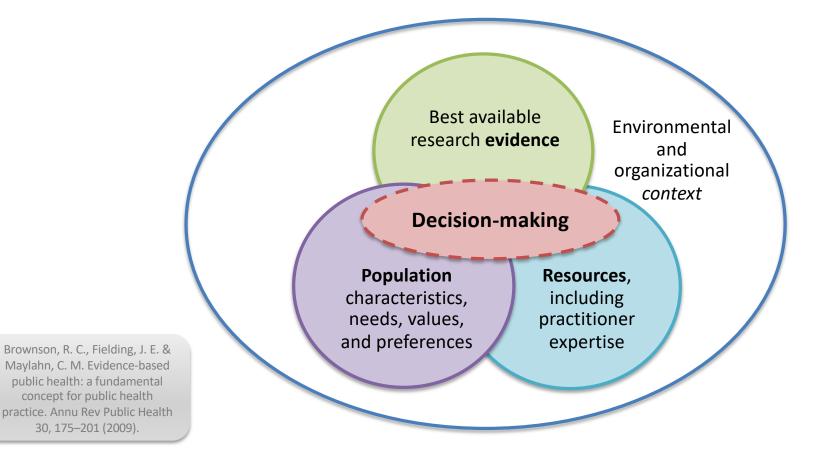
http://www.foresight.gov.uk/OurWork/ActiveProjects/Obesity/

## Defining a Population Health Record

- Representative information for a defined population
- Evidence about population health and health systems
- Explicit population health framework used to organize information and evidence
- Facilitates population health decision making
  - Integrated data on determinants, outcomes, healthcare
  - Alignment of information and evidence regarding population health and health system interventions

Friedman DJ, Parrish RG. The population health record: concepts, definition, design, and implementation. JAMIA 2010;17:359-366.

## Evidence-Based Public Health



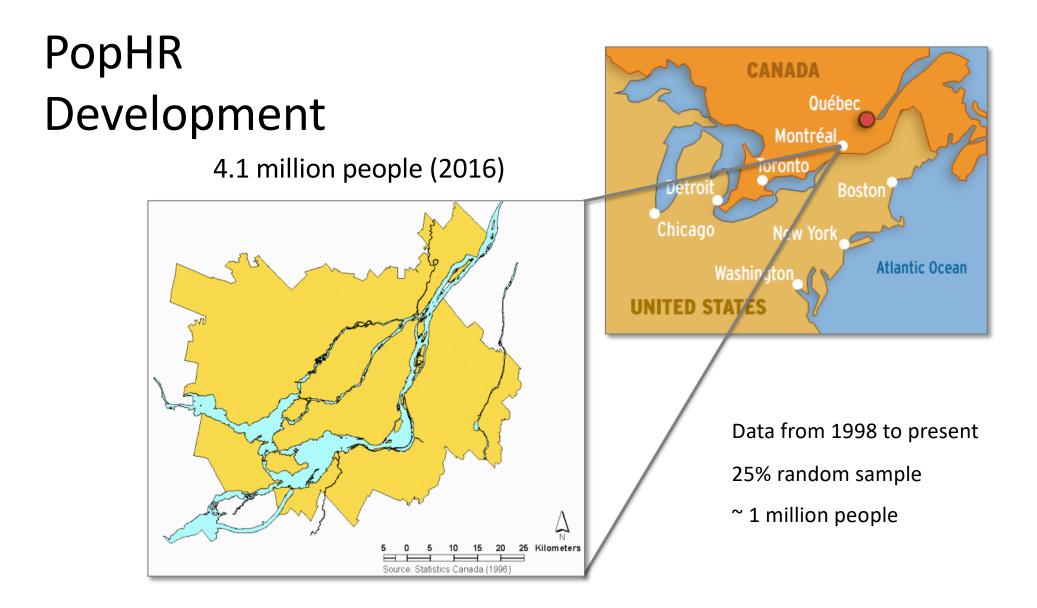
## Types of Scientific Evidence

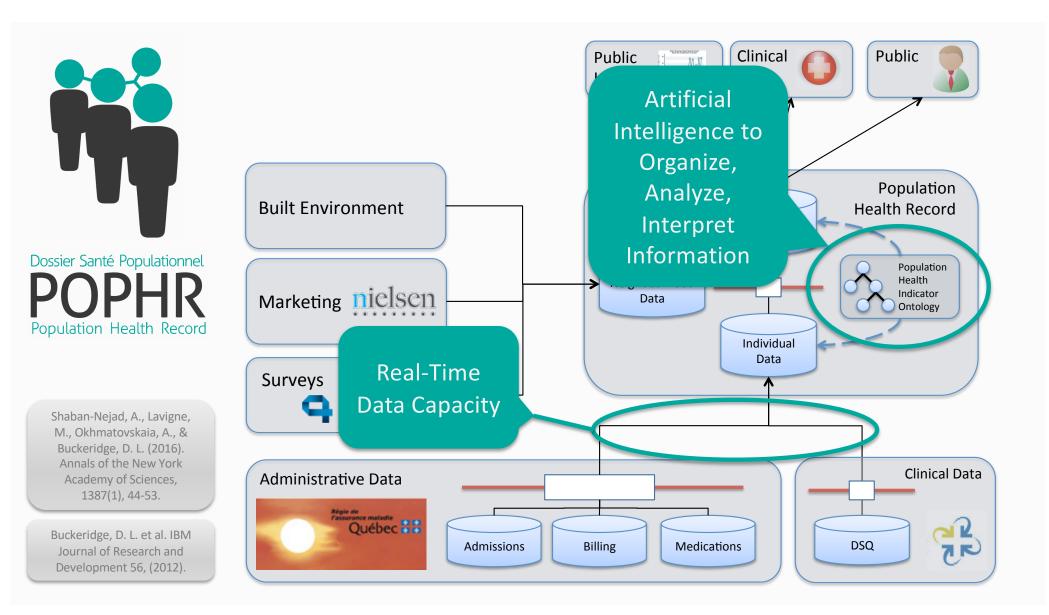
Characteristic	Type One	Туре Тwo	Type Three
Typical data/	Size and strength of preventable	Relative effectiveness of public	Information on the adaptation and
relationship	risk—disease relationship (measures	health intervention	translation of an effective
	of burden, etiologic research)		intervention
Common	Clinic or controlled community	Socially intact groups or	Socially intact groups or
setting	setting	community wide	community wide
Example	Smoking causes lung cancer	Price increases with a targeted	Understanding the political
		media campaign reduce smoking	challenges of price increases or
		rates	targeting media messages to
			particular audience segments
Quantity	More	Less	Less
Action	Something should be done	This particular intervention	How an intervention should be
		should be implemented	implemented

Brownson, R. C., Fielding, J. E. & Maylahn, C. M. Evidence-based public health: a fundamental concept for public health practice. Annu Rev Public Health 30, 175–201 (2009).

## PopHR Project Timeline







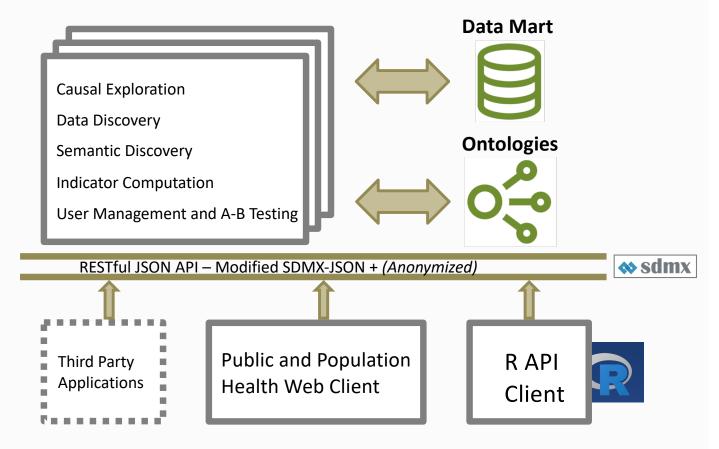


## **Knowledge-Based Architecture**

Requests made to server via RESTful JSON API

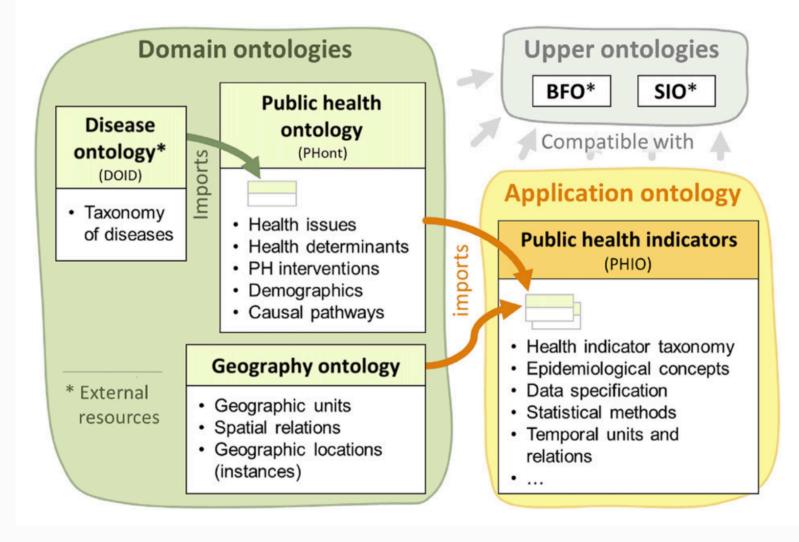
Data packages returned in modified sdmx datacube format

R package pophr allows requests within R session



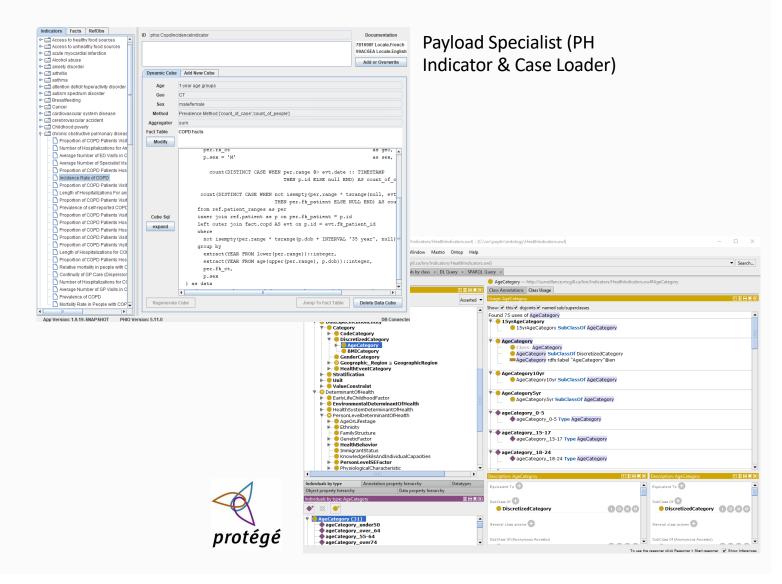


## Ontologies





## Loading and Annotating Data





## Downloaded Dataset

Query Parameters Stratification Dimensions Filtering Dimensions Standardization Dimensions Missing Data Strategy Indicator and Concept	Indicator Details Associated PH Concept Units (as stored) and (for visualization) Provenance (work in progress)
Data Cube -> Cube Specification -> Column 1   Dimension   Ref   1 -> Column 2   Measure   Ref   1	
->	



### Metadata in Ontology

### Indicators

#### Type:

- several classification frameworks {CIHI, PHAC, ICD chapters}
- statistical {count, rate, etc.}

#### **Properties:**

- indicator of {disease, RF, etc.}
- burn-in period
- excluded age groups
- default age standardization groups
- unit, internal
- unit displayed
- highest geo resolution
- defined by {organization}
- data source {admin., survey, etc.}

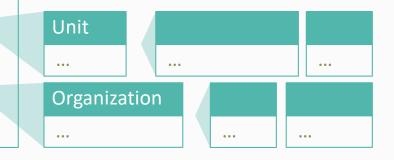
### Health issues & determinants

#### Type:

- established classifications of diseases, functioning issues, determinants of health, etc.
- property of individual, population, or environment (region)

#### **Properties:**

 has positive/negative effect on {health issue or determinant}





# Uses of Metadata

### Current (mainly internal)

- To inform data visualization
- To guide users in navigating with data
- To guide analysts in creating and maintaining public health indicators and case definitions
- To enable intelligent filtering and aggregation of dimension categories

### Future (interoperability, transparency)

- Generation of methodology documents
- Shared annotation / aligned PH algorithms
- Extending causal annotations
- Adding supporting evidence
- References to know interventions
- Annotation of natural experiments

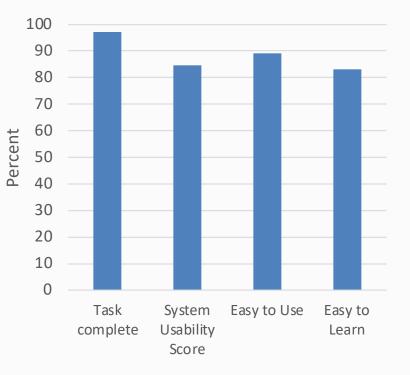


## User Workshops

- Three interactive workshops using PopHR with 23 public health practitioners in Montreal and Quebec
- Obtained qualitative and quantitative feedback on application and suggestions for how to improve PopHR

"L'avantage c'est que c'est très visuel, en terme de la chronologie par exemple, pour stratifier par sexe, tout est là."

" C'est un avantage d'avoir les schémas qui présentent les facteurs de risqué, avec les indicateur et ses conséquences sur la santé, c'est une belle organisation. "

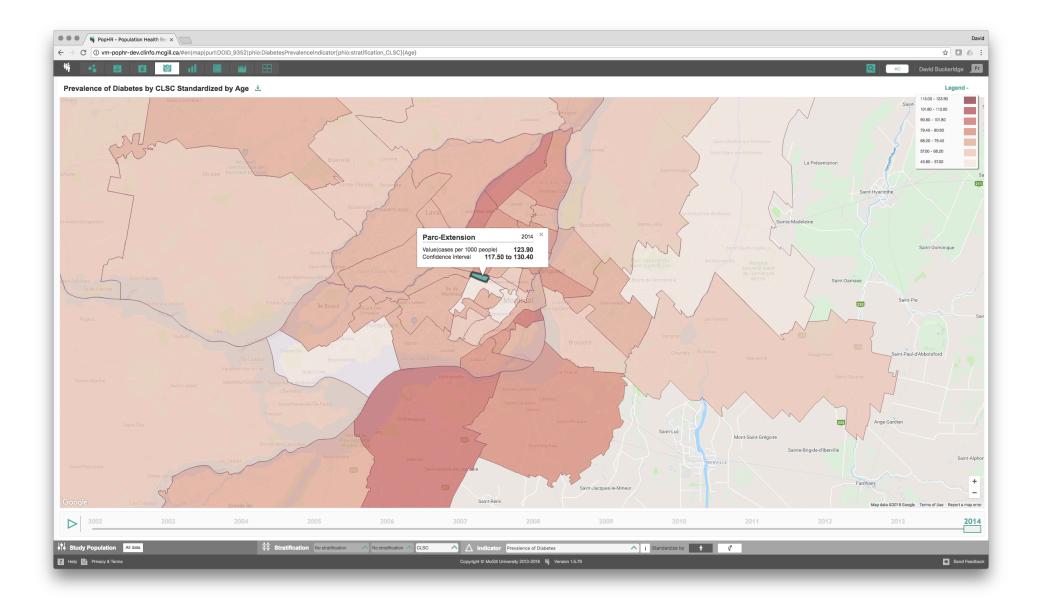


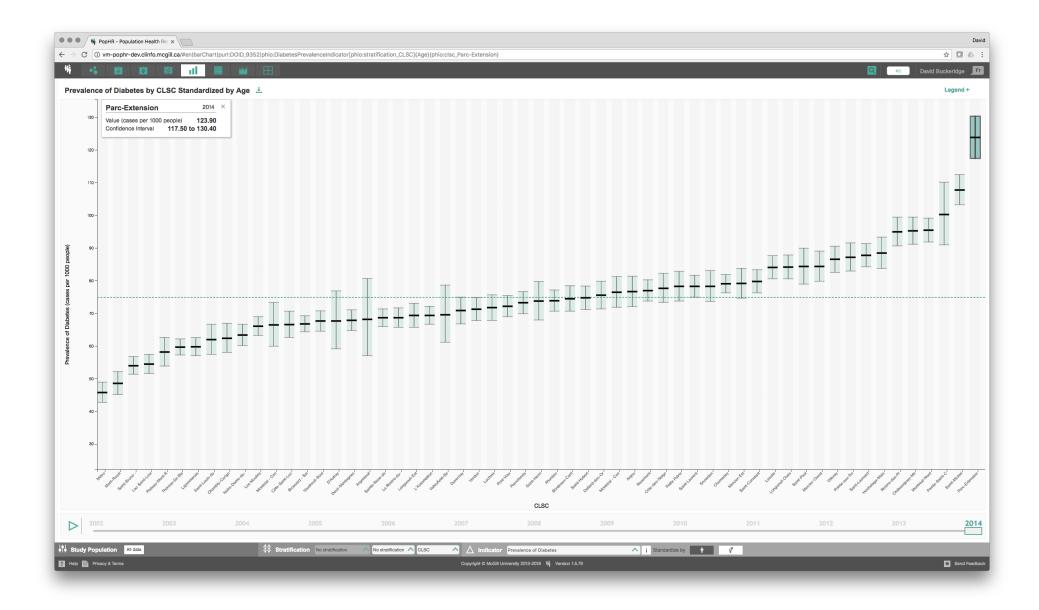


The Population Health Record brings together information and knowledge to help people understand and improve population health.

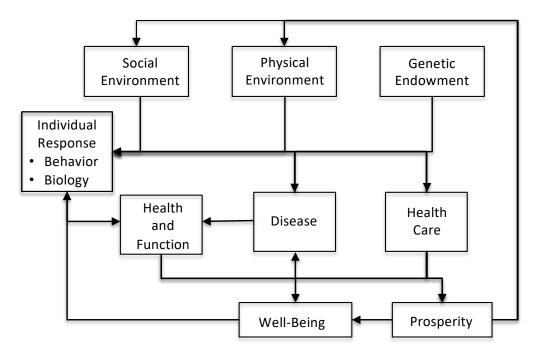
lence of Diabetes by years, CLSC 👎





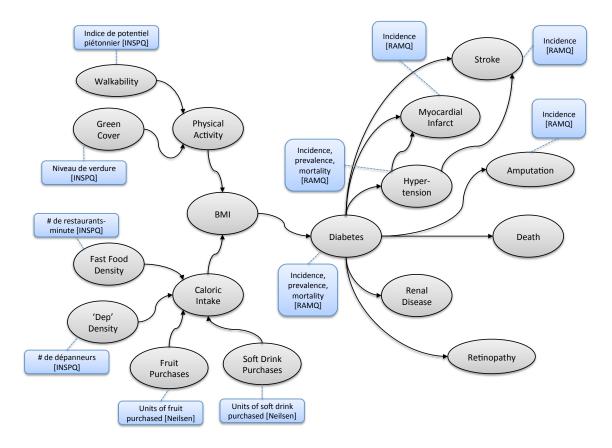


## Template for Population Health

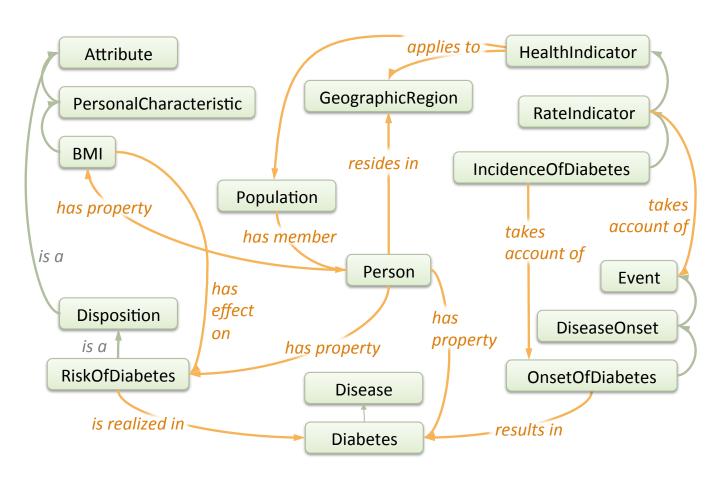


Evans R, Stoddart G. Producing Health, Consuming Health Care. Canadian Institutes for Advanced Research. Program in Population Health. Working Paper No. 6, p 51. Toronto, April 1990.

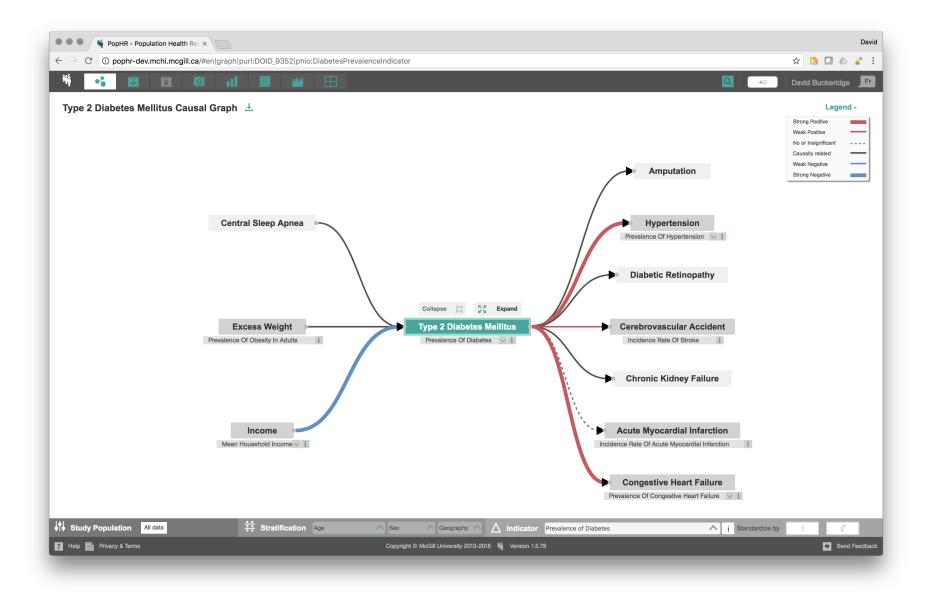
## Informal Model

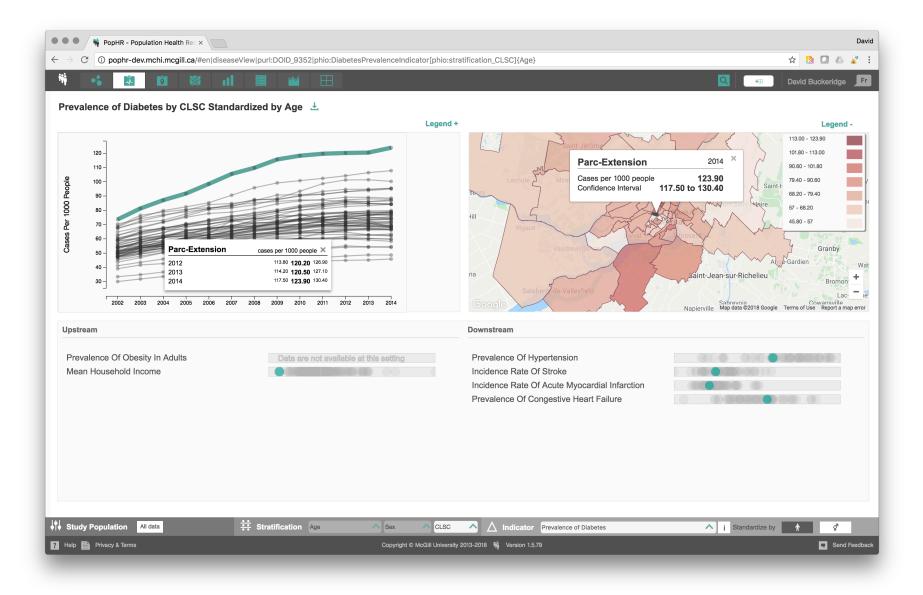


### Formal Model



Shaban-Nejad, A. et al. PHIO: a knowledge base for interpretation and calculation of public health indicators. Stud Health Technol Inform 192, 1207 (2013).



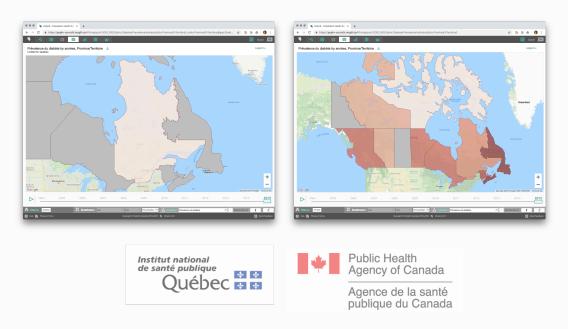




# System Implementations

#### Quebec

- Outcomes computed from individual claims data
- High geographical resolution (Local health region)
- Adoption workshops in Fall 2019 in Montreal, Quebec with public health partners
- Roll-out to entire province in 2020



#### Canada

- All indicators precomputed
- Low geographical resolution (Province, health area)
- Initial presentation to funding agency in Summer 2019
- Plans for extension to US indicators and interoperability project

### Knoweldge in PopHR System

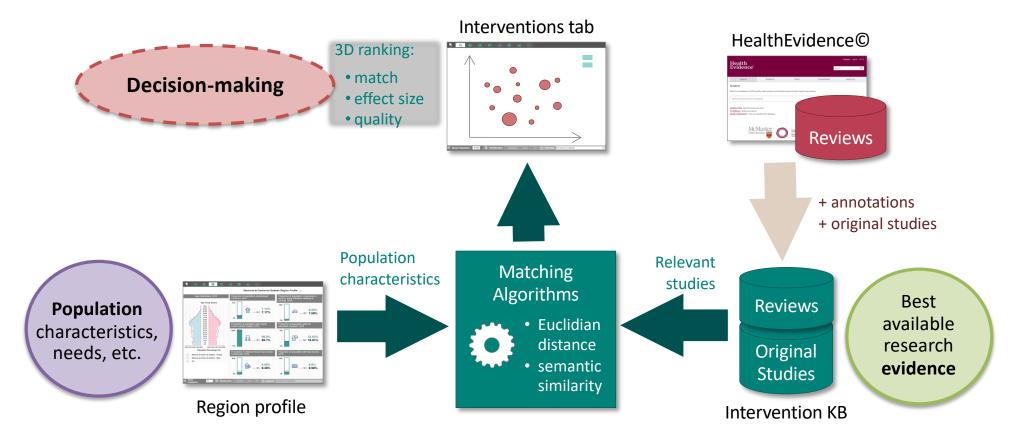
Type I Causal relationships between health indicators	Type 2 Effectivenss of public health interventions	Type 3 Adaptation and translation of effective interventions	EBPH Types of Evidence
Interpret indicators using existing knowledge	Identify interventions suited to a population	Document implemented interventions	PopHR Function
			Display

### Precision Public Health

"Stratify populations to improve prioritization of health status and selection of interventions."



### Precision Public Health: Using AI to Match Interventions to Populations



# Inputs to Precision Public Health

- Information about defined population
  - Indicators often created from big (e.g., grocery retailing, remote sensing) or large (e.g., administrative claims) data
  - Many indicators may be needed to classify the population
- Evidence about possible interventions
  - Currently extracted mainly manually, but automation (i.e., NLP) necessary to scale efficiently
- Mechanism to determine 'match' or even estimate effect of intervention
  - Ontology defined criteria for classification
  - Matching can be semantic (logical similarity) or quantitative







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**Closing Thoughts** 

## Challenges, Opportunities for Intelligent Systems in Health

- 1. Management of 'Knowledge'
  - Probabilistic approaches
    - model and parameters
    - (re) training, transferring, equity
  - Logical approaches
    - ontologies
    - scope, reuse, alignment, extension and maintenance

## Challenges, Opportunities for Intelligent Systems in Health

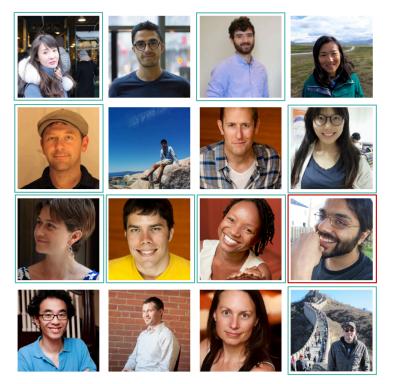
- 2. Mixing Probabilistic and Logical Approaches
  - Clinical setting
    - A logical framework to prioritize, integrate multiple alerts
    - Maintenance and provenance of predictive models
  - Population health setting
    - Causal knowledge as a prior for statistical learning
    - Prioritization, evaluation of 'natural experiments'

## Challenges, Opportunities for Intelligent Systems in Health

- 3. Evaluation in Real-world Settings
  - Clinical settings
    - Challenges: to insert into clinical workflow, to work with commercial software vendors
    - Opportunities: interest in 'precision medicine' has heightened awareness of potential, accuracy of predictions improving
  - Population health settings
    - Challenges: research with resource-constrained partners, limited foundational infrastructure
    - Opportunities: interest in 'learning health systems', growing desire for 'open' data at population level

## McGill Clinical and Health Informatics

#### Surveillance Lab



#### **Clinical Decision Support Lab**





















#### surveillance.mcgill.ca



#### pophr.mchi.mcgill.ca