Use of electronic health records to evaluate treatment pathways – a Common Data Model approach

Tan Hui Xing
Data Analyst
Vigilance and Compliance Branch
Health Sciences Authority, Singapore

Objectives

- Demonstrate the use of a common data model (CDM) to harmonize electronic medical records (EMR)
  - To transform data from an acute care hospital in Singapore to the CDM developed by the Observational Medical Outcomes Partnership (OMOP)
  - To apply analytical tools on the data to uncover treatment patterns of patients newly diagnosed with diabetes mellitus, hypertension or depression.

Methodology

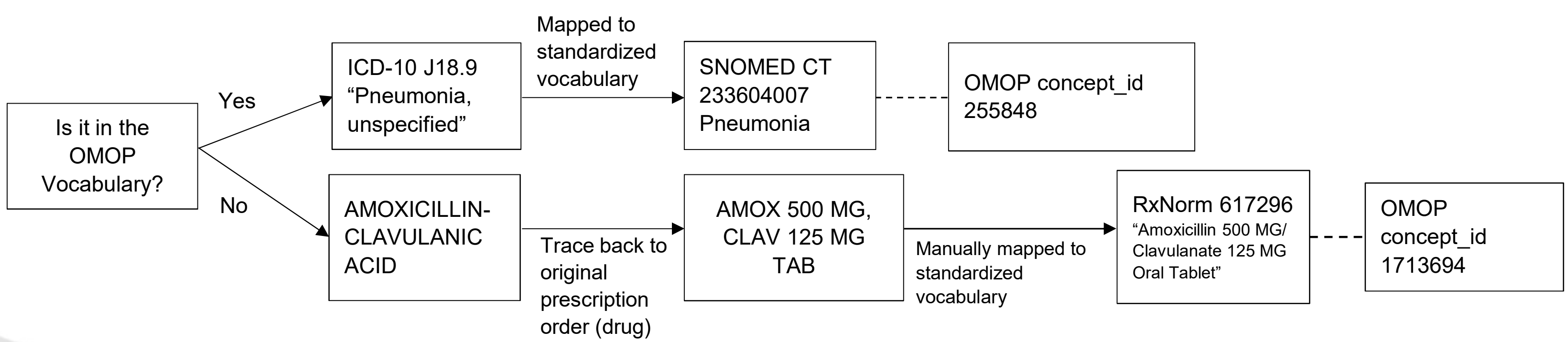
1. Conversion of source data files to the OMOP CDM
2. Modified query on the transformed data

Conversion of source data files to OMOP CDM

- Data source:
  - Approximately 250,000 patients
  - Tertiary care hospital in Singapore
  - Data from January 2013 to December 2016 comprising the following:
    - 1.1 million rows of diagnoses
    - 5.2 million rows of ordered medications
    - 15.5 million lab records

Conversion of source data files to OMOP CDM

- Data vocabularies employed:
  - Systematic Nomenclature of Medicine Clinical Terms (**SNOMED CT**) for diagnosis codes,
  - **RxNorm** Extension for drugs, and
  - Logical Observation Identifiers Names and Codes (**LOINC**) for laboratory tests and vitals measurements
- Extract, Transform, Load (ETL) process
- Mapped to OMOP table based on "Concept Name"



Conversion of source data files to OMOP CDM

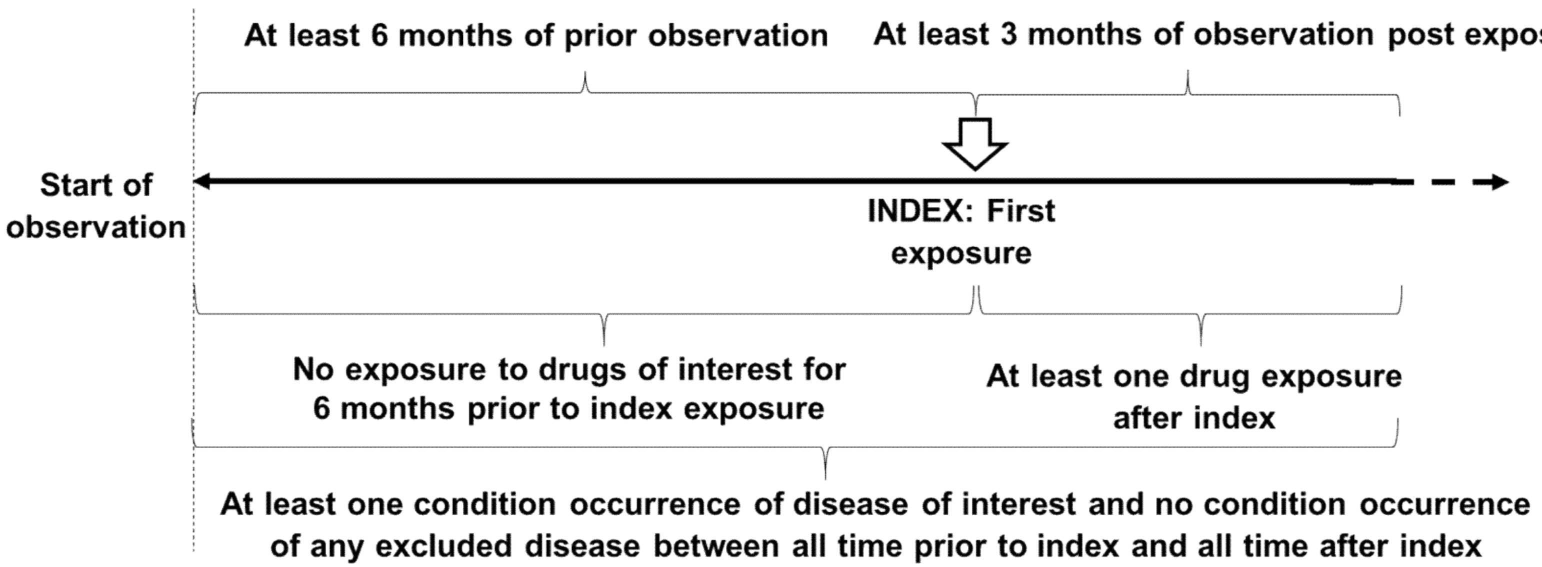
- Percentage of records converted:

OMOP CDM Tables		Source Tables		
Table name	Number of rows of records	Table name	Number of rows of records	Proportion migrated
person	245,561	t_demographics	258,038	95.2%
condition_occurrence	Primary: 210,830	t_primary_diagnosis	222,554	94.7%
	Secondary: 799,169	t_secondary_diagnosis	839,265	95.2%
measurement	14,116,544	t_lab_result	15,523,576	90.9%
visit_occurrence	1,041,587	t_encounter	1,057,263	98.5%
drug_exposure	4,378,657	t_eprescription_dispensing*	2,147,505	84.8%
		t_inpatient_med_order†	3,015,159	

*Refers to outpatient pharmacy orders and inpatient discharge prescriptions
†Refers to medications used during inpatient ward stay

Modified query on the transformed data

- Selection criteria of diabetes, hypertension and depression cohorts



Modified query on the transformed data

- Diseases of interest, excluded diseases and drugs used in each cohort

Cohort	Disease of interest	Excluded disease	Drug classes included
Diabetes	Diabetes mellitus	Findings related to pregnancy	Insulins, biguanides, sulfonylureas, DPP4 inhibitors*, alpha-glucosidase inhibitors, SGLT2 inhibitors^
Hypertension	Hypertensive disorder	Findings related to pregnancy	Antihypertensives, diuretics, peripheral vasodilators, beta blockers, calcium channel blockers, agents acting on the renin-angiotensin-aldosterone system
Depression	Depressive disorder	Findings related to pregnancy, bipolar I disorder, schizophrenia	Antidepressants

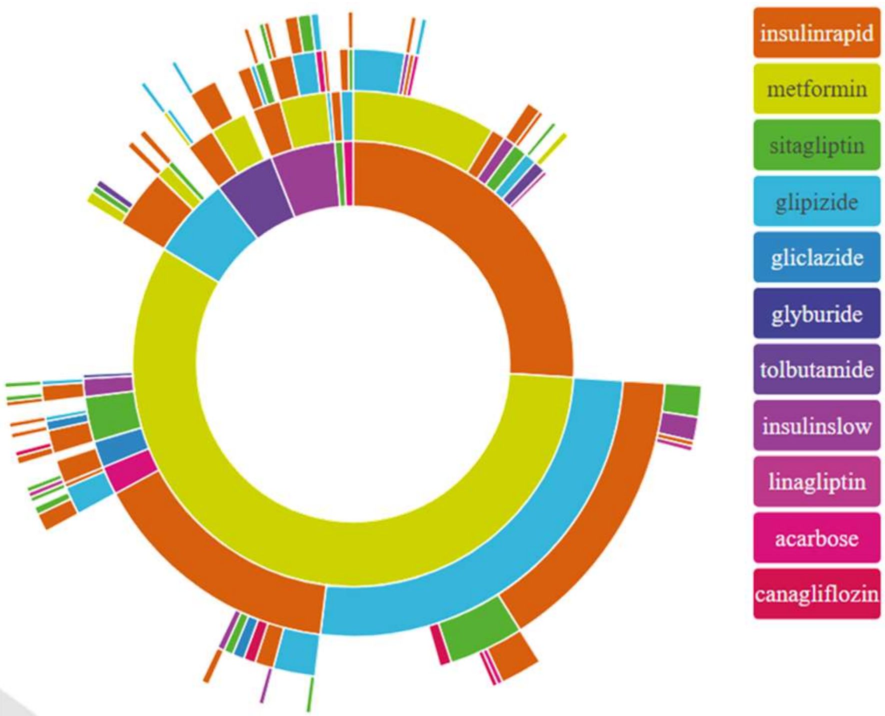
*dipeptidyl peptidase 4 inhibitors
^sodium-glucose transport protein 2 inhibitors

Results and Discussion

- Number of patients identified per cohort
  - Diabetes mellitus (n = 1,006)
  - Hypertension (n = 3,175)
  - Depression (n = 251)

- Sequence of drug exposures in these patients were tracked, and plotted on sunburst diagrams

Results and Discussion



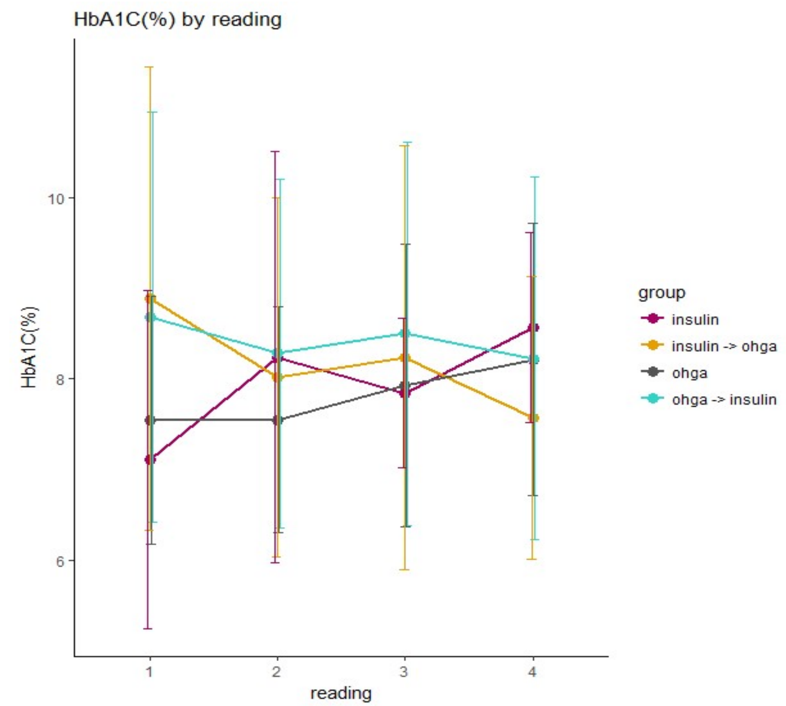
Diabetes Mellitus
Period of Data: Jan 2013 to Dec 2016

Diabetes Mellitus (n=1,006)

- Metformin most often prescribed as the first medication (53.5%).
- Sulfonylureas (SU) were the most common second line agent used in diabetes.
- Among SU, glipizide was the most common (43.3%), followed by tolbutamide (7.1%).
- Newer generation alternatives such as gliclazide and glimepiride were used less frequently, at 5.5 and 0.6%, respectively.

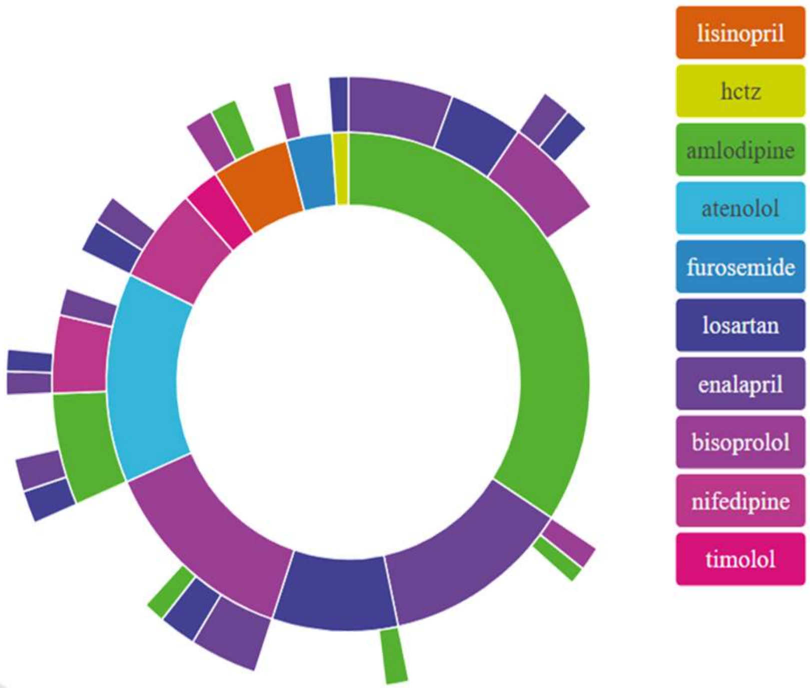
Observations

- Fair proportion of patients using insulin as first-line medication
- Patients could have obtained medication from other healthcare providers.
- No observable difference in Hba1c levels between patients given insulin vs patients given other agents as first line medication over 4 readings
- Converting EHR to CDM provides opportunities for such analysis to be carried out efficiently



Error bars showing mean $\pm$ 1 s.d. of first 4 HbA1C readings by treatment group
Average duration between readings: 3.2 months

Results and Discussion



Hypertension
Period of Data: Jan 2013 to Dec 2016

Hypertension (n=3,175)

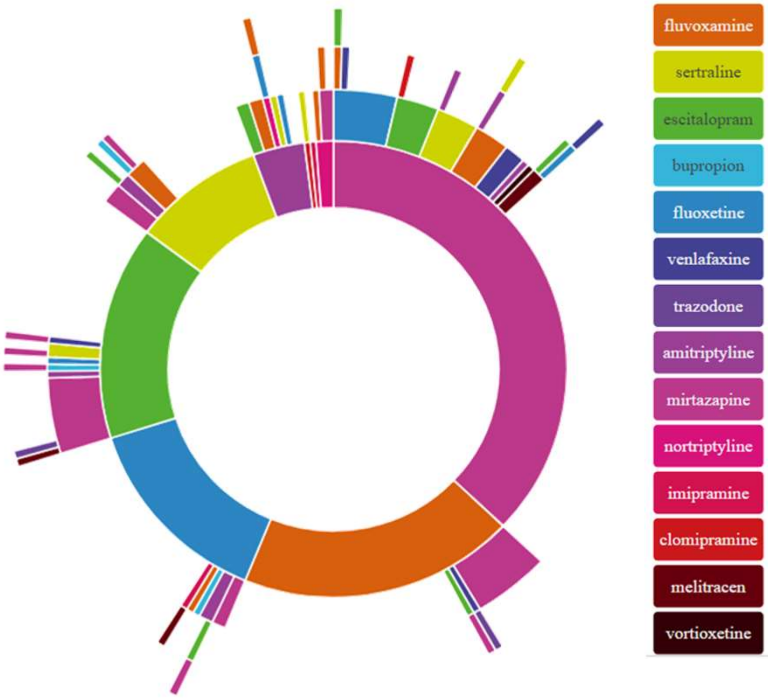
- Amlodipine (22.1%) was the most commonly used first line medication for hypertension.
- Considerable heterogeneity for first-line treatment for hypertension.
- However, for second-line options, most common drugs used were enalapril, losartan, nifedipine and amlodipine.

Observations

- In PNAS treatment pathway study (published in 2015), the most prevalent drugs were hydrochlorothiazide, lisinopril, amlodipine

- In our KTPH study, the most prevalent were amlodipine, losartan, enalapril (very few diuretics)
  - Data were from Jan 2013 to Dec 2016
  - Clinicians likely adopted a newer version of the treatment guidelines i.e. JNC-8

Results and Discussion



Depression
Period of Data: Jan 2013 to Dec 2016

Depression (n=251)

- Mirtazapine (37.1%) and fluvoxamine (19.1%) were the most commonly used first line medications for depression.
- Overall, a large variety of drug choices across all levels of treatment. Little consensus on prescribing patterns.

Limitations with Sunburst Diagrams

- Dosages and dosing frequency of different treatments not compared
- Unable to identify whether treatment was stopped or switched

Conclusion

- Considerable heterogeneity in treatment patterns for hypertension and depression, whereas for diabetes, metformin was the most common first-line agent (53.5%)
- Use of CDM and federated query[1] were feasible for the data source
- These models provide drug regulators valuable insights on real world drug utilization patterns and adherence to recommended treatment guidelines

1. Hripcsak, G., et al. Observational Health Data Sciences and Informatics (OHDSI): Characterising treatment pathways at scale using the OHDSI network. Proc Natl Acad Sci U.S.A, 2016. 113(27):7329-36.

Any Questions?