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

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Outline

• Drug safety surveillance system in Singapore
  – Spontaneous reporting system
  – Using Electronic Medical Records (EMR)

• Study: “Use of electronic health records to evaluate treatment pathways – a Common Data Model approach”
Traditional Drug Safety Surveillance

• Spontaneous, voluntary reports to drug regulatory authority
• 2006: Critical Medical Information Store (CMIS)
  – Real time drug safety reports from public hospitals and polyclinics
• 20,000 reports annually
Limitations of Spontaneous Reporting Systems

• Under-reporting, stimulated reporting

• Captures only basic information
  – Often missing data on drug dosages, concomitant medications
  – Missing information on patient history, co-morbidities etc.

• Lack of data on drug usage – unable to calculate incidence
Enhancement with Electronic Medical Records

Passive ADR reporting program ➔ Active Surveillance System
Use of electronic health records to evaluate treatment pathways – a Common Data Model approach

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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. Federated query on the transformed data
Conversion of source data files to OMOP CDM

- Data source:
  - Approximately 250,000 patients
  - Tertiary care hospital in Singapore
    - 795-bed general and acute care, with A&E services
    - Serves a wide range of medical specialties from cardiology to general surgery to renal medicine, across multiple age groups and demographics of patients
    - Get referral from primary care providers e.g. general practitioners, government clinics for management of diabetes, hypertension
  - 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”

```
Is it in the OMOP Vocabulary?

Yes

ICD-10 J18.9 “Pneumonia, unspecified”

SNOMED CT
233604007
Pneumonia

OMOP concept_id
255848

AMOXICILLIN-CLAVULANIC ACID

AMOX 500 MG, CLAV 125 MG TAB

OMOP concept_id
1713694

No

Mapped to standardized vocabulary

RxNorm 617296
“Amoxicillin 500 MG Clavulanate 125 MG Oral Tablet”

OMOP concept_id
1713694

Trace back to original prescription order (drug)

Manually mapped to standardized vocabulary
```
Federated query on the transformed data

Selection criteria of diabetes, hypertension and depression cohorts

- At least 6 months of prior observation
- At least 3 months of observation post exposure

INDEX: First exposure

- No exposure to drugs of interest for 6 months prior to index exposure
- At least one drug exposure after index

- At least one condition occurrence of disease of interest and no condition occurrence of any excluded disease between all time prior to index and all time after index
Federated query on the transformed data

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

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

* dipeptidyl peptidase 4 inhibitors  
^ sodium-glucose transport protein 2 inhibitors
### Results and Discussion

#### Percentage of records converted:

<table>
<thead>
<tr>
<th>OMOP CDM Tables</th>
<th>Source Tables</th>
<th>Table name</th>
<th>Number of rows of records</th>
<th>Number of rows of records</th>
<th>Proportion migrated</th>
</tr>
</thead>
<tbody>
<tr>
<td>person</td>
<td></td>
<td>t_demographics</td>
<td>245,561</td>
<td>258,038</td>
<td>95.2%</td>
</tr>
<tr>
<td>condition_occurrence</td>
<td></td>
<td>t_primary_diagnosis</td>
<td>210,830</td>
<td>222,554</td>
<td>94.7%</td>
</tr>
<tr>
<td></td>
<td></td>
<td>t_secondary_diagnosis</td>
<td>799,169</td>
<td>839,265</td>
<td>95.2%</td>
</tr>
<tr>
<td>visit_occurrence</td>
<td></td>
<td>t_encounter</td>
<td>1,041,587</td>
<td>1,057,263</td>
<td>98.5%</td>
</tr>
<tr>
<td>drug_exposure</td>
<td></td>
<td>t_eprescription_dispensing*</td>
<td>4,378,657</td>
<td>2,147,505</td>
<td>84.8%</td>
</tr>
<tr>
<td></td>
<td></td>
<td>t_inpatient_med_order†</td>
<td></td>
<td>3,015,159</td>
<td></td>
</tr>
</tbody>
</table>

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

Diabetes Mellitus

Period of Data: Jan 2013 to Dec 2016
Results and Discussion

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.

Hypertension
Period of Data: Jan 2013 to Dec 2016
Observations

• PNAS treatment pathways study (published 2016): most prevalent drugs were hydrochlorothiazide, lisinopril, amlodipine

• Our study: 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

Any Questions?