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16. Abstract

The Federal Aviation Administration (FAA) Office of Aerospace Medicine is responsible for the medical certification of pilots such that the risk of pilot acute incapacitation is below a target risk threshold. This study sought to design a repeatable method of using commercial healthcare datasets to segment pilots with existing chronic conditions into acute incapacitation risk groups for the purpose of informing medical standards and certification policy guidance. Based on availability to the researchers, Merative's Explorys electronic health record dataset, comprising 11-years of data, was used for method development. In collaboration with FAA medical officers, researchers operationalized pilot acute incapacitation as a composite outcome of 16 medical conditions and their associated diagnostic codes. These conditions were identified based on the scenario that a pilot is medically qualified to fly, conducts an adequate preflight self-assessment, and during flight experiences the acute onset of a state incompatible with active aircraft control such that orderly transfer of control to another pilot or automation is unlikely. Approaches to developing quantitative risk models for the outcome of pilot acute incapacitation were explored for four chronic conditions: diabetes, obstructive sleep apnea, chronic obstructive pulmonary disease, and atrial fibrillation. Three general approaches were explored: whole-population risk, disease severity models, and a de novo method. Using whole-population risk resulted in over- and -under estimation of pilot acute incapacitation risk for a significant portion of the population. Using existing disease severity scores produced poor risk stratification for pilot acute incapacitation. The de novo method was designed to be broadly applicable to any condition of interest. The method was comprised of the following steps: (1) define the cohort for the condition of interest; (2) use a clinical reference tool (DynaMed, UpToDate, etc.) to produce relevant clinical factors; (3) use a clinical mapping tool (e.g., Unified Medical Language System) to link clinical factors to medical codes; (4) use information gain to select risk factors (relevant to both the chronic condition of interest and the outcome) from clinical factors for inclusion in pilot acute incapacitation risk models; (5) compute stratified incidence rates for pilot acute incapacitation; and (5) compare incident rates to the target risk threshold.

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Assessing Pilot Aeromedical Risk Using Commercial Healthcare Data

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Agenda

- Study overview
- High-level explanation of risk stratification
- Case study: application of process to diabetes
- Additional case studies
- Key findings
- Suggestions for further work

Research question: Can commercial healthcare data be used to model pilot aeromedical risk?

- **Focus:** For pilots with existing chronic conditions, design a methodology for using commercial healthcare datasets to segment pilots into acute incapacitation risk groups for the purpose of policy making
- **Outcome:** A repeatable methodology to determine the incidence rate for aeromedically relevant events stratified by underlying disease severity

A method was developed using Explorys Electronic Health Record (EHR) Data*

- Merative Explorys EHR data
  - 11 terabytes
  - Covers 11 years
- Important data elements
  - Diagnosis: ICD9 / ICD10 codes
  - Observations: LOINC codes
  - Medications: RxNorm codes
- Key limitations
  - No enrollment information
  - Individuals may see a provider outset the dataset
  - Mortality data removed in the last year
  - No SNOMED codes for observations
- Refer to https://doi.org/10.21949/1528556 for an assessment of numerous datasets.

Electronic health record (EHR) data

merative

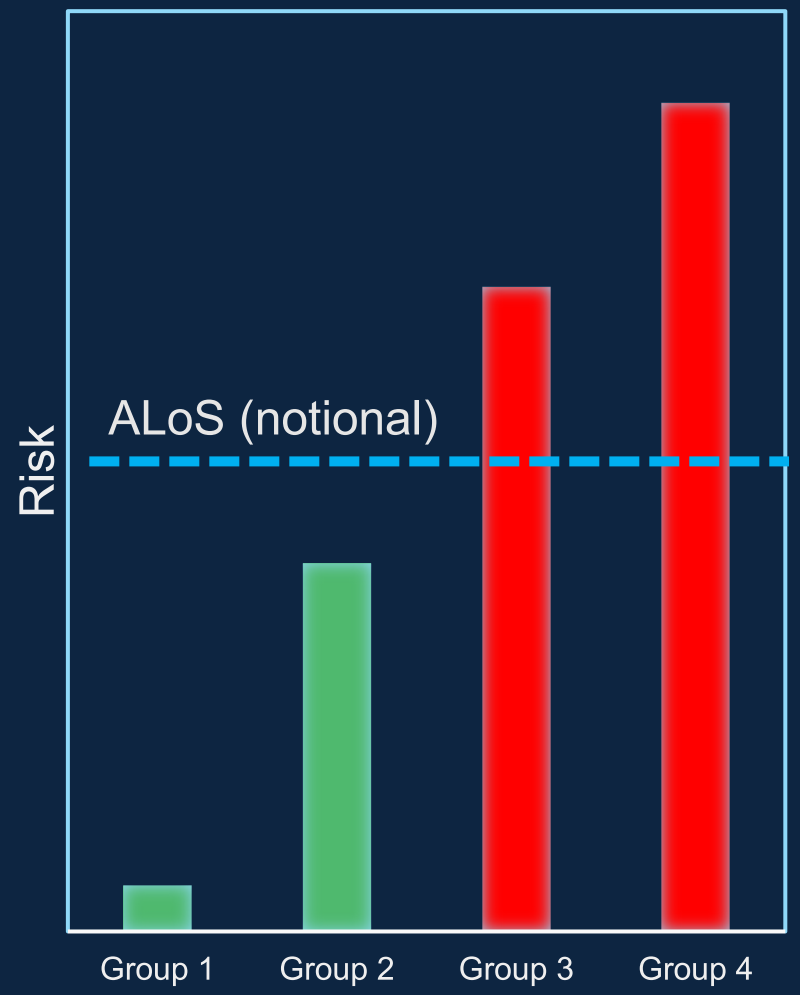
Patient-level EHR data
- Demographics
- Medical and surgical history
- Immunization history
- Social history and health maintenance
- Risk assessments and patient-reported outcomes

Encounter-level EHR data
- Encounter type (IP, OP, ED)
- Provider specialty
- Vitals and biometrics
- Clinical encounter data (diagnoses, procedures, outcomes, etc.)
- Treatments ordered / drugs prescribed and administered
- Devices used in care
- Lab data

Facility-level EHR data
- Provider specialties and demographics
- Hospital-level utilization data

Binning the population into risk groups/cohorts will support application of an acceptable level of safety (ALoS)

- Goal: Bin the population into distinct risk groups that enable risk-based policy decisions.
- Implied questions:
  - What risk are we measuring?
  - What population are we considering?
  - How should we separate the population into risk groups?



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Aeromedical risk is associated with conditions that may lead to acute incapacitation

- Defining acute incapacitation for this study:
  - Pilot qualified to fly
  - Adequate pre-flight self-assessment
  - Acute onset of a state incompatible with active control of aircraft such that it prevents orderly transfer of control to another pilot or automation
- MITRE collaborated with the Office of Aerospace Medicine to develop a list of proposed acutely incapacitating conditions and their related medical codes
- Study did not address subtle incapacitation, which follows from a pre-condition and may result in slowed reaction times
- Study did not associate encounter type with incapacitating events, so outcomes may be over-estimated

Acutely incapacitating conditions
Acute glaucoma
Acute hemorrhage
Anaphylactic shock
Aneurysms and dissections
Dissection of aorta
Cardiac conduction abnormalities
Cardiac tamponade
Headache (migraine)
Hypoglycemia
Myocardial infarction / cardiac arrest
Nephrolithiasis
Pulmonary embolism
Seizure, unspecified
Stroke
Tension pneumothorax
Vertigo

Study narrowed to four chronic conditions

- For this study we focused on:
  - Diabetes
  - Chronic obstructive pulmonary disease (COPD)
  - Obstructive sleep apnea (OSA)
  - Atrial fibrillation
- Inclusion criteria:
  - Between ages of 18 and 70 on diagnosis date
  - First visit at least one year prior to diagnosis date
  - Last visit at least one year after diagnosis date
  - No acute events prior to index date

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Problem: Whole-population aeromedical risks result in over- or under-regulation of sub-populations

- Diabetes example:
  - 302,638 individuals
  - 49,723 first acute events
  - 872,816 person-years prior to first acute event
  - 0.057 acute events per person-year
- Solution: Use risk factors to stratify population into groups with similar risks amenable to acceptability decisions

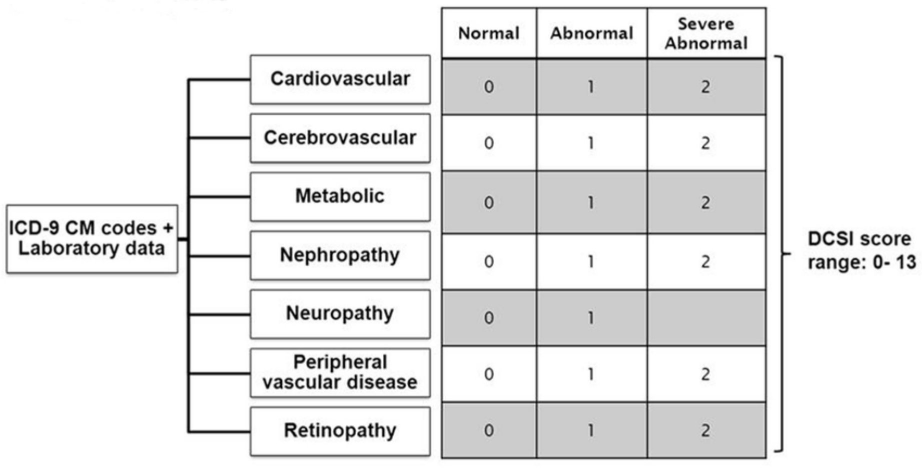
$$Incidence\ rate = \frac{\#\ of\ acute\ events}{time}$$

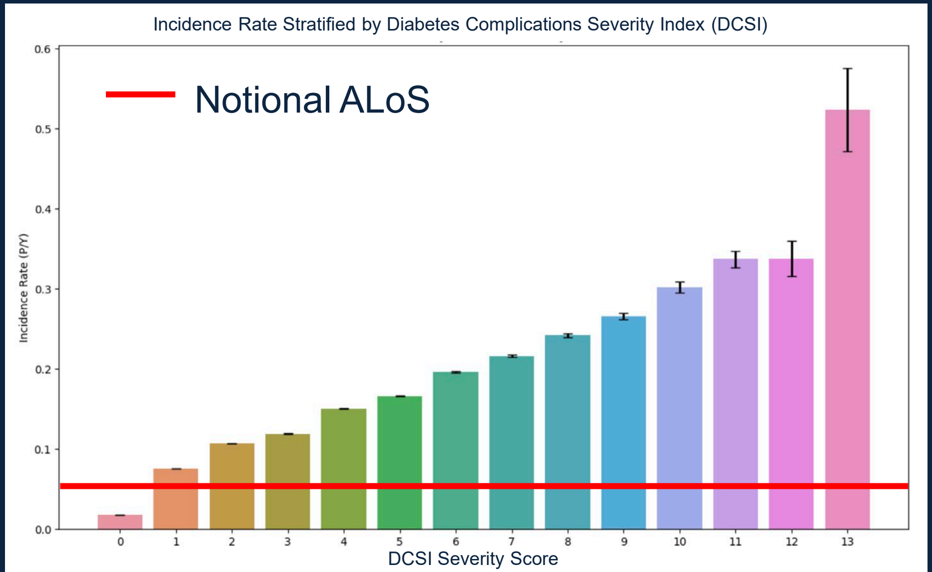
$$= \frac{49{,}723\ acute\ events}{872{,}816\ person - years}$$

$$= 0.057\,\frac{acute\ events}{person - year}$$

A repeatable approach cannot depend on existing severity scores

- Existing severity scores produce poor risk stratification for acutely incapacitating events
- *Example:* Diabetes has an existing severity score called the Diabetes Complications Severity Index (DCSI) that can be used to construct a risk stratification
- Issues / complications:
  - "Severe abnormal cardiovascular" includes individuals who have had a heart attack – an acutely incapacitating event!
  - Limited stratification: ALoS would correspond to diabetes and any other condition
  - Most conditions do not have an existing severity score
- Answer: Develop a more general repeatable approach that does not require severity scores





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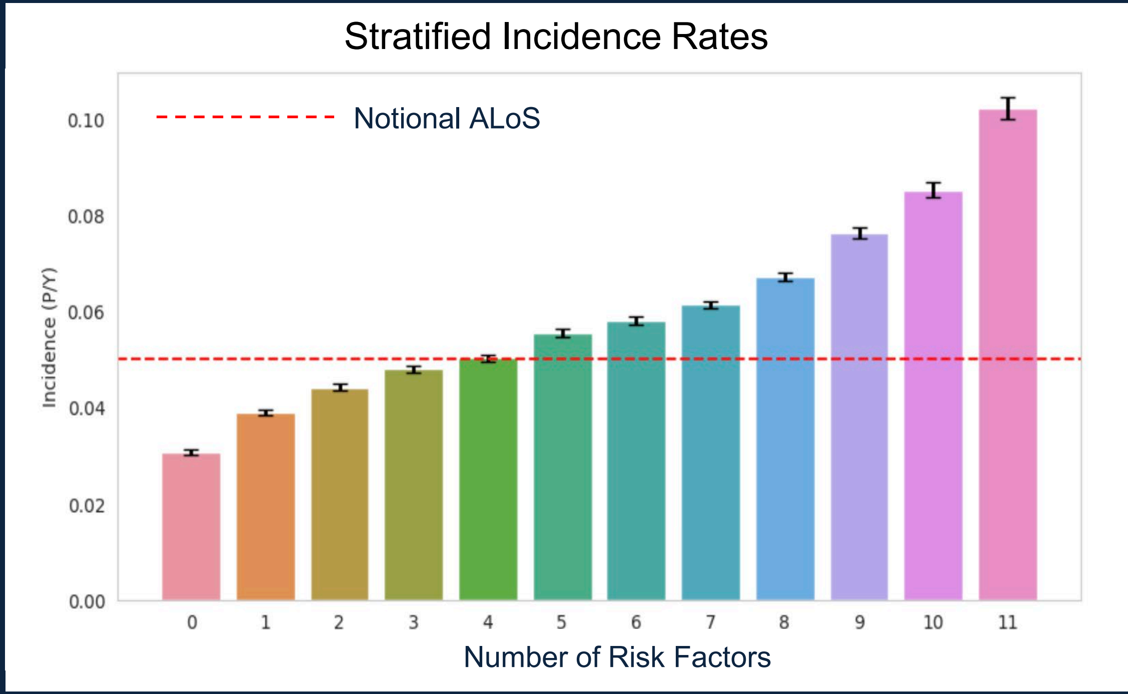
A repeatable risk analysis process is broadly applicable to any condition of interest

Define cohort for condition of interest → Use clinical reference tool to produce relevant clinical factors → Use clinical mapping tool to map clinical factors to medical codes → Use models to select risk factors from from clinical factors → Compute stratified incidence rates → Compare incidence rates against ALoS

Example application: Diabetes



Subset of relevant clinical factors for diabetes

Body mass index
Hemoglobin A1c
Triglyceride level (fasting)
High density lipoprotein cholesterol (fasting)
Alanine aminotransferase level (fasting)
Obesity
Depression
Antiretroviral therapy
Statin use
Serum biomarkers associated with diabetes
HS C-reactive protein
Elevated liver enzymes
Low potassium levels
Obstructive sleep apnea

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A repeatable approach starts with identifying relevant clinical factors and mapping to medical codes

1 — DynaMed’ s data-driven research

DynaMed' s content is based on comprehensive reviews of diseases, conditions, and abnormal findings to highly focused topics on evaluation, differential diagnosis, and management. Drug and laboratory monographs developed and maintained by IBM Micromedex are also included.

2 — Key findings

Text descriptions of relevant conditions, comorbidities, and sequalae

3 — Human assessment

Clinician validation conditions, comorbidities, and sequalae

4 — Conversion of text to code

Converting text descriptions of conditions into ICD-9, ICD-10, LOINC, and SNOMED codes

5

Use ICD-9, ICD-10, LOINC, and SNOMED codes as the basis for querying Explorys to mine data for risk modeling

The Unified Medical Language System (UMLS) simplifies the medical code mapping process

Subset of relevant clinical factors for diabetes
Body mass index
Hemoglobin A1c
Triglyceride level (fasting)
High density lipoprotein cholesterol (fasting)
Alanine aminotransferase level (fasting)
Obesity
Depression
Antiretroviral therapy
Statin use
Serum biomarkers associated with diabetes
HS C-reactive protein
Elevated liver enzymes
Low potassium levels
Obstructive sleep apnea

Subset of relevant clinical factors for diabetes	LOINC	ICD-10	ICD-9
Body mass index	39156-5		
Hemoglobin A1c	4548-4	R73.09	790.29
Triglyceride level (fasting)	2571-8	R73.09	790.29
High density lipoprotein cholesterol (fasting)	2085-9	R73.09	790.29
Alanine aminotransferase level (fasting)	1742-6	R79.0	790.6
Obesity		E66, E66.9	278
Depression		F32.9	296.2
Antiretroviral therapy	81248-5	Z79.899	V08
Statin use	81259-2	Z79.899	V58.83
Serum biomarkers associated with diabetes	49765-1	R79.89	1580.6
HS C-reactive protein	1988-5, 30522-7	R79.82	1580.2
Elevated liver enzymes	1742-6	R94.5	1580.8
Low potassium levels	2823-3	E87.6	553.6
Obstructive sleep apnea		G47.33	

The UMLS is a set of files and software developed by the National Library of Medicine that brings together many health and biomedical vocabularies and standards to enable interoperability between computer systems

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Risk factors should be relevant to both the chronic disease and acutely incapacitating events

- Clinical reference tools (e.g., Dynamed, UpToDate, etc.) provide clinical factors relevant to the chronic disease
- We want clinical factors relevant to both the chronic disease and acutely incapacitating events
- Approach:
  - Use commercial EHR data to cross-reference clinical factors relevant to the chronic disease with the risk of acutely incapacitating events
  - Construct prediction dataset
    - Factors:
      - Normal / abnormal last observation prior to interval
      - Yes / no diagnosis code prior to interval
    - Outcome: Acute event within one year of diagnosis
- Multiple approaches to determine importance of each factor

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We can use Information Gain to select risk factors

- Information Gain quantifies each risk factor's reduction in uncertainty about the occurrence of an acutely incapacitating event
- Information Gain can be used to select risk factors via a weighting scheme
- Current approach:
  - Choose a minimum threshold for risk factor inclusion.
  - Assign all features above threshold a weight of one
  - Utilize weights to perform the risk stratification
- Future work: Compare and contrast methods to select risk factors

Feature	Information Gain	weights
Hemoglobin A1c	0.087519	1
High density lipoprotein cholesterol (fasting)	0.071484	1
Low potassium levels	0.060763	1
Triglyceride level (fasting)	0.052075	1
Statin use	0.051041	1
Elevated liver enzymes (gamma-glutamyltransfer...	0.050403	1
Body Mass Index	0.047031	1
Alanine aminotransferase level (fasting)	0.044715	1
Antiretroviral therapy	0.044296	1
Obesity	0.031610	1
Depression	0.015083	1
Sleep disorders	0.013988	1
Obstructive Sleep Apnea	0.012455	1
Serum biomarkers associated with diabetes	0.010002	1
HS C-reactive protein	0.007993	1
Thiazide diuretics and beta-blockers	0.005351	1
Total Iron-Binding Capacity (TIBC)	0.005034	1
Low serum vitamin C levels	0.004963	0
Kidney stones	0.004247	0

Diabetes risk factor weighting

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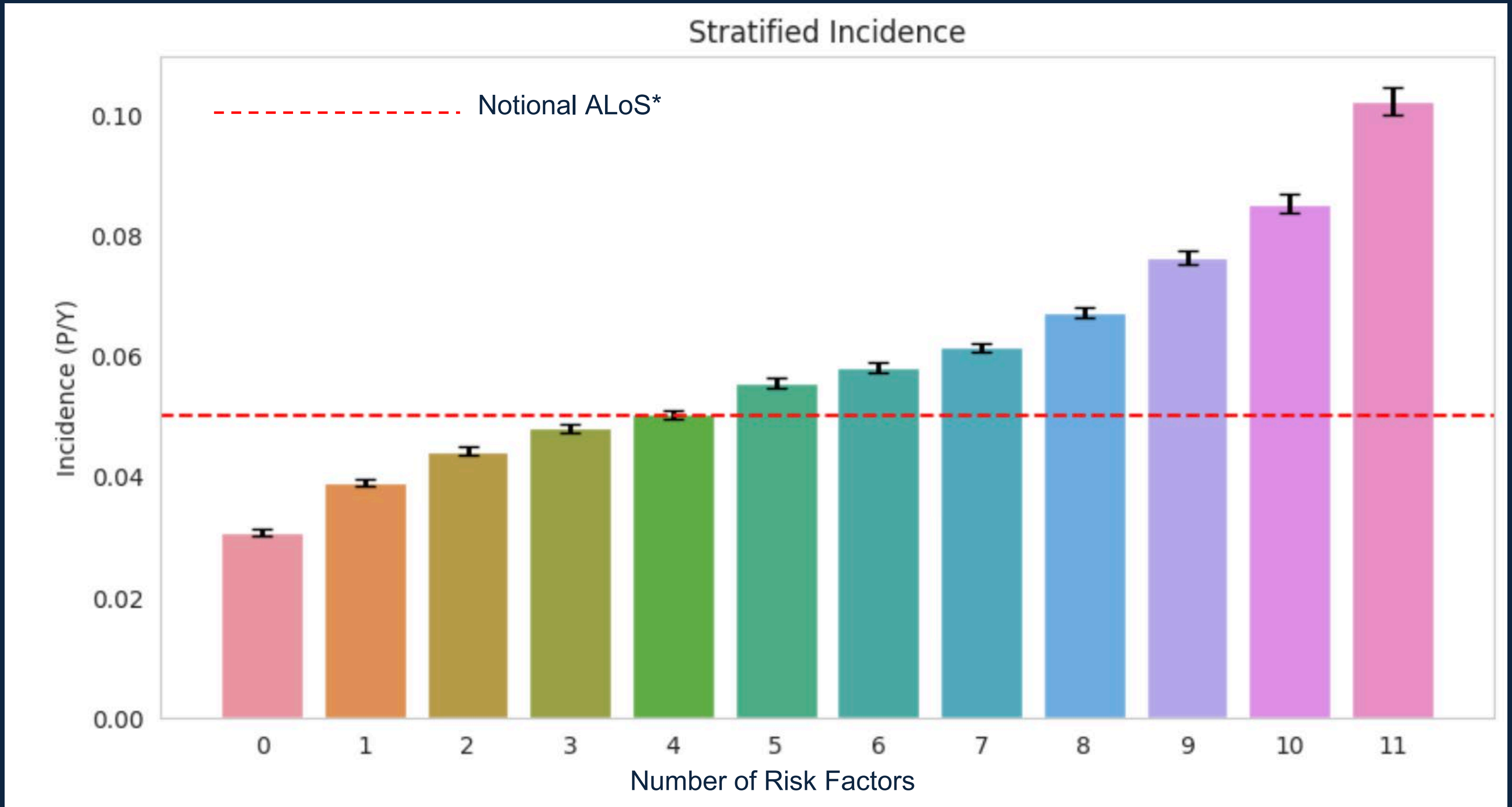
Risk factors enable risk stratification for conditions such as diabetes

- Risk factors:
  - True / false for ICD codes
  - Normal / abnormal for measurements
- 302,638 individuals
- 872,994 person-years (prior to an acute event)
- 48,964 acute events



*ALoS threshold on the graph is notional

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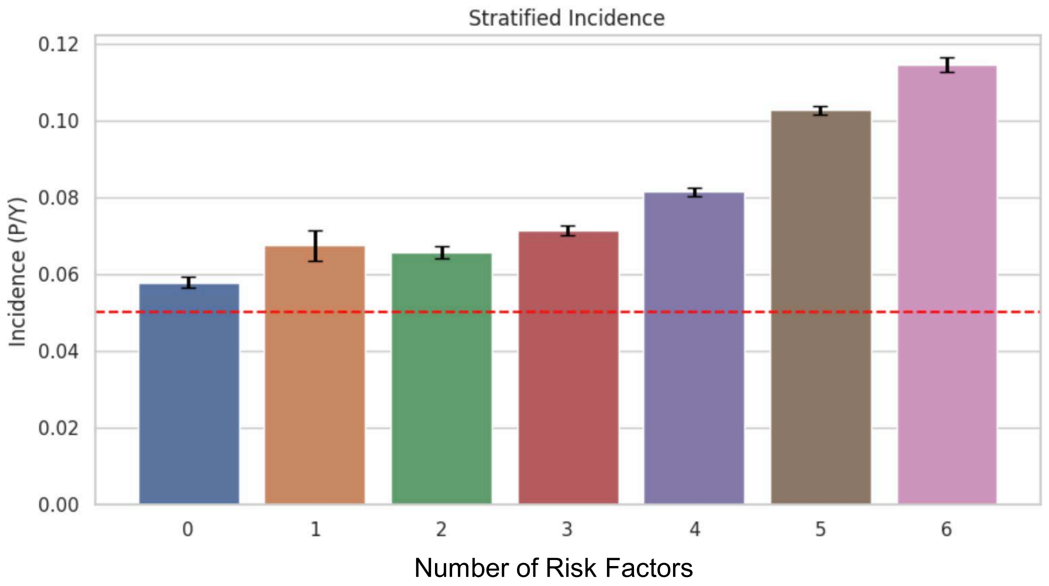
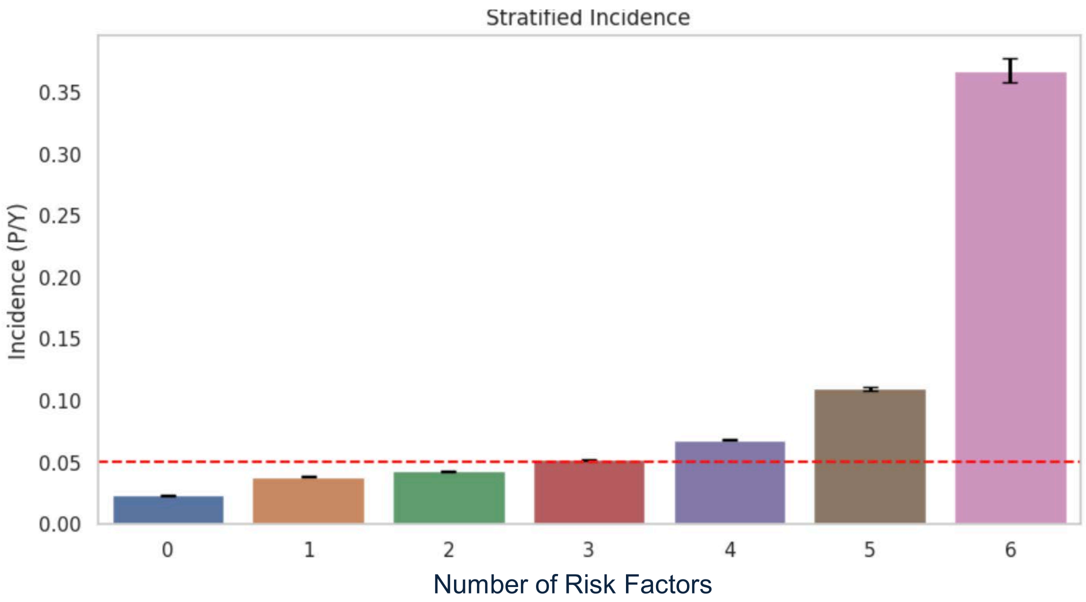
The risk analysis process is repeatable for other chronic conditions

Define cohort for condition of interest → Use clinical reference tool to produce relevant clinical factors → Use clinical mapping tool to map clinical factors to medical codes → Use models to select risk factors from from clinical factors → Compute stratified incidence rates → Compare incidence rates against ALoS



Chronic obstructive pulmonary disease



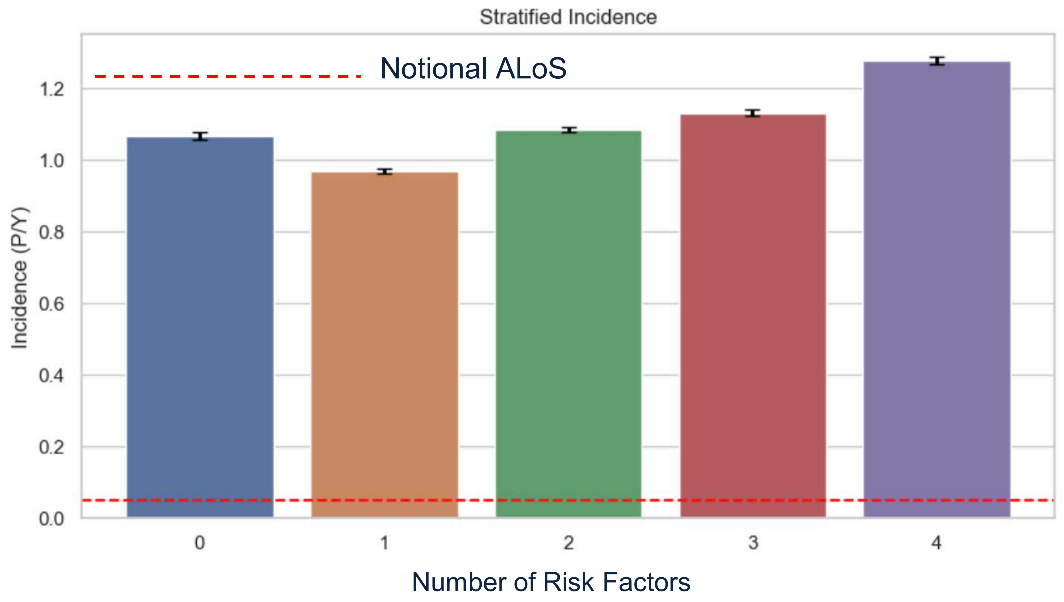
Obstructive sleep apnea

The risk analysis process is repeatable for individuals who have had an acute event such as atrial fibrillation

- With the current definition of master acute incapacitating events, any diagnosis of atrial fibrillation is an incapacitating event
- The risk analysis process can be used to evaluate the risk of a second acute event

Subset of relevant clinical factors for atrial fibrillation

Body mass index
Systolic blood pressure
Diastolic blood pressure
Cholesterol – HDL
Cholesterol – LDL
Cholesterol – LDL/HDL
Continue
C-reactive protein – high sensitivity
CBC with all components
Red blood cell distribution width
Computed tomograph calcium score



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Key findings

- Commercial health care data can be used to construct risk stratification for pilots with chronic conditions to understand the stratified incidence rate of aeromedically relevant events
- Clinical reference tools (e.g., Dynamed, UpToDate, etc.) and UMLS used together allow for a repeatable methodology to define risk factors for chronic diseases and semi-automatically create mappings to medical codes
- Merative's Explorys dataset is sufficient for conducting research and developing an analytics pipeline
- Future work should compare results from this dataset to other potentially higher quality datasets

Recommendations for future work

- Cohort and condition definitions:
  - Align inclusion criteria with the pilot population
  - Include additional information (e.g., visit type) in identifying acute events in commercial claims data
- Risk stratification:
  - Formalize the process for identifying relevant clinical factors from sources such as Dynamed
  - Determine how best to move from binary (normal / abnormal) to continuous risk factors
  - Determine best approach to selecting and weighting risk factors relevant to both the chronic condition and acutely incapacitating events
- Risk forecasting:
  - Assess the utility of commercial claims data to forecast the likelihood of health state changes
  - Determine how best to use individualized probability of health state changes
  - Compare machine learning models, statistical state change models, and large language model (LLM)-based medical code prediction models (i.e., MedBERT)

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Acronyms and Abbreviations

ALoS	Acceptable Level of Safety
COPD	Chronic Obstructive Pulmonary Disease
DCSI	Diabetes Complications Severity Index
EHR	Electronic Health Records
ICD-9	International Classification of Diseases, Ninth Revision
ICD-10	International Classification of Diseases, Tenth Revision
LLM	Large Language Model
LOINC	Logical Observation Identifiers Names and Codes
OSA	Obstructive sleep apnea
SNOMED	Systematized Nomenclature of Medicine
UMLS	Unified Medical Language System

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