BRITISH COLUMBIA CENTRE for EXCELLENCE in HIV/AIDS

Providence HEALTH CARE How you want to be treated.

BRITISH COLUMBIA Ministry of Health

Identification algorithms and related considerations in using administrative data for epidemiology

populationdata BC

Webinar as part of the series:
Advanced Methods for the Analysis of Population-wide Administrative Health Data

Advanced Methods for the Analysis of Population-wide Administrative Health Data

This webinar series offered by Population Data BC in partnership with ICES will highlight the value of population-wide administrative data and related advanced analytic methods for health research.

IC/ES

June 28th 2022
Scott Emerson MSc
semerson@bccfe.ca

Declaration

I respectfully acknowledge that I am presenting from the traditional unceded territories of the Musqueam, Squamish, & Tsleil-Waututh peoples

http://res.cloudinary.com/simpleview/image/upload/v1589990523/clients/vancouverbc/Vancouver_Aerial_2017_1__72115131-4a31-42dc-b369-7a5ccec8273f.jpg

Data acknowledgement

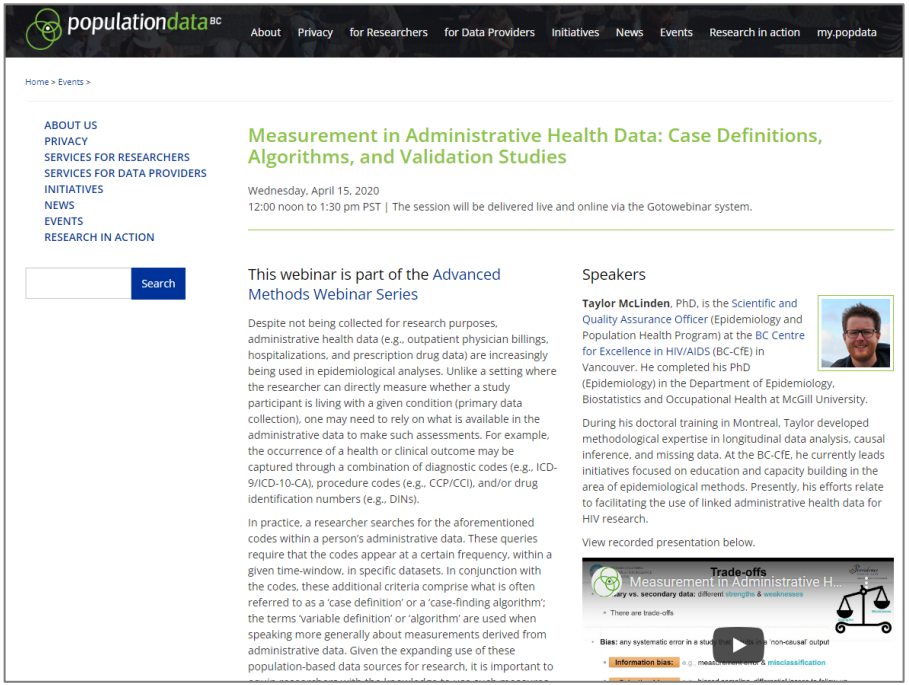
All inferences, opinions, and conclusions drawn in this presentation are those of the author, and do not reflect the opinions or policies of the Data Steward(s).

Previous webinar of interest…

- The current webinar builds upon a 2020 webinar:

Measurement in Administrative Health Data:
Case Definitions, Algorithms, and Validation Studies
(Presenter: Taylor McLinden, PhD; BC-CfE)

- An excellent, accessible introduction to administrative data and measurement considerations



https://www.popdata.bc.ca/events/etu/webinar/MAHD_Apr15_2020

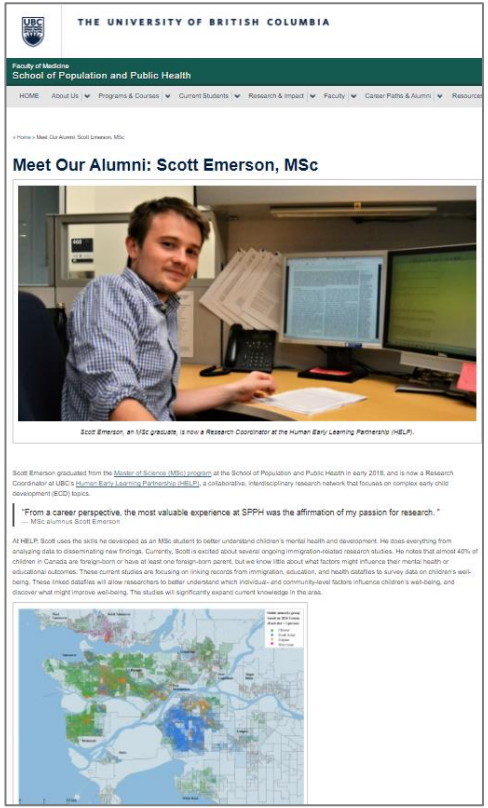
Context - my background

- **MSc in Epidemiology (UBC School of Population & Public Health [SPPH])**
  - Thesis examined validity evidence of a quality of life measure
  - Involved in several other concurrent projects using administrative data linkages

- **Prior experience includes various analytic, epidemiology related roles**
  - Analyst – ***UBC*** Human Early Learning Partnership (a child health research institute)
    - Projects leveraged administrative health + educational data linkages via **Popdata BC** (same building!)

HUMAN EARLY LEARNING PARTNERSHIP UBC

  - Epidemiologist – ***ICES*** *(Institute for Clinical Evaluative Sciences; Toronto)*
    - *Situated within two Programs: Populations and Public Health, & Primary Care and Health Systems*



Context - types of admin data projects I've supported

Longitudinal survey + DAD (hospitalizations)

J Urban Health (2020) 97:239–249
https://doi.org/10.1007/s11524-019-00406-9

The Association of Residential Instability and Hospitalizations among Homeless and Vulnerably Housed Individuals: Results from a Prospective Cohort Study

Anne M. Gadermann · Mohammad Ehsanul Karim · Monica Norena · Scott D. Emerson · Anita M. Hubley · Lara B. Russell · Rosane Nisenbaum · Stephen W. Hwang · Tim Aubry · Anita Palepu

DAD + OLIS (lab testing/results)

PLOS ONE

RESEARCH ARTICLE

Validating International Classification of Disease 10th Revision algorithms for identifying influenza and respiratory syncytial virus hospitalizations

Mackenzie A. Hamilton[1,2], Andrew Calzavara[1], Scott D. Emerson[1], Mohamed Djebli[1,2], Maria E. Sundaram[1], Adrienne K. Chan[2,3,4], Rafal Kustra[2], Stefan D. Baral[5], Sharmistha Mishra[3,6,7,8], Jeffrey C. Kwong[1,2,9,10,11,12]*

Census data + DAD + IRCC (immigration data) + MSP (healthcare practitioner billings)

Social Psychiatry and Psychiatric Epidemiology
https://doi.org/10.1007/s00127-022-02301-2

ORIGINAL PAPER

Neighbourhood context and diagnosed mental health conditions among immigrant and non-immigrant youth: a population-based cohort study in British Columbia, Canada

Scott D. Emerson[1] · Monique Gagné Petteni[1] · Joseph H. Puyat[2,3] · Martin Guhn[1] · Katholiki Georgiades[4] · Constance Milbrath[1] · Magdalena Janus[1,4] · Anne M. Gadermann[1,3]

Cross-sectional survey + MSP

JAMA Network Open

Original Investigation | Psychiatry

Association of Childhood Social-Emotional Functioning Profiles at School Entry With Early-Onset Mental Health Conditions

Kimberly C. Thomson, PhD; Chris G. Richardson, PhD; Anne M. Gadermann, PhD; Scott D. Emerson, MSc; Jean Shoveller, PhD; Martin Guhn, PhD

Cross-sectional survey + MSP + DAD + VitalStats Births

Child Psychiatry & Human Development (2020) 51:80–93
https://doi.org/10.1007/s10578-019-00912-6

ORIGINAL ARTICLE

Associations of Birth Factors and Socio-Economic Status with Indicators of Early Emotional Development and Mental Health in Childhood: A Population-Based Linkage Study

Martin Guhn[1] · Scott D. Emerson[1] · Dorri Mahdaviani[1] · Anne M. Gadermann[1]

IRCC + Cross-sectional survey + MoE (education data)

Journal of Ed

ISSN: 0022-0663

Thriving, Catching Up, Falling Behind: Immigrant and Refugee Children's Kindergarten Competencies and Later Academic Achievement

Monique Gagné and Martin Guhn
University of British Columbia

Magdalena Janus
University of British Columbia and McMaster University

Katholiki Georgiades
McMaster University

Scott D. Emerson and Constance Milbrath
University of British Columbia

Eric Duku
McMaster University

Carly Magee and Kimberly A. Schonert-Reichl
University of British Columbia

Anne M. Gadermann
University of British Columbia and Providence Health Care Research Institute, Vancouver, British Columbia, Canada

Context - my current role

- **Epidemiologist – Epidemiology & Population Health Program,**
  BC Centre for Excellence in HIV/AIDS (BC-CfE) – based at St Paul's Hospital, Vancouver

  - Providing consulting, educational, and analytic support to work leveraging administrative health data

  - Leading a monthly internal educational + resource-building presentation series: *Administrative Data Working Group*

  - Administrative data holdings include:
    - *MSP – healthcare practitioner billings (comparable to '**OHIP**' in Ontario)*
    - *DAD – hospitalizations + day surgeries*
    - *NACRS – emergency department use*
    - *PharmaNet – medication dispensations*

    In addition to linkages with clinical, treatment, socio-demographic, and survey data holdings from the BC-CfE

Overview

1. **Why transform administrative health data?**
   - Nature of data, when vs when not to consider transforming
2. **Identification algorithms**
   - Types (case-finding vs others), components, and examples
3. **Validity evidence of algorithms**
   - Methods for validation, data sources, and considerations
4. **Reporting and applying algorithms**
   - Considerations in reporting, describing patterns, implications

Why transform administrative health data?

Administrative data terminology

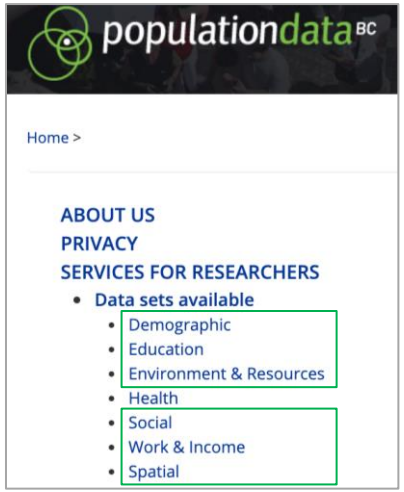
Administrative health data are sometimes instead termed:

- Health administrative data
- Routinely-collected data (broader term)
- Record linkage
- Health services utilization data
- Population data linkage
- Insurance/claims records
- Database studies
- Real world evidence (RWE)

https://www.bristol.ac.uk/golding/events/2019/optimising-the-use-of-routine-administrative-health-records-the-role-of-data-sc.html

Generally: any health-related data that is in administrative form
→ collected primarily for financial/budgeting/administrative reasons

** Increasingly, linkage to non-health databases can enrich health data i.e. environment, social services, immigration, education, census etc. **



https://www.popdata.bc.ca/index.php/data/listings

Trade-offs with administrative data


EDITORIALS

The Blessing and the Curse of the Administrative Database

Christina S. Boncyk, M.D.[1], Christina A. Jelly, M.D., M.Sc.[1], and Robert E. Freundlich, M.D., M.S.[1,2]

Strong representation	vs	Lacking clinical depth
- Particularly the case for Canadian provinces: Captures ~all current residents in a population and all public healthcare use (e.g., in British Columbia) - Relatedly, one can consider many years (even decades) of data		- Detailed, specific information about symptoms, condition (e.g., beyond simply 'having' healthcare use for X condition) - Often relying on ICD-based case definitions - which vary in accuracy (can be similar accuracy challenges when relying on other classification systems)

Remember: admin health data de facto only capture health care system interactions,
for some health events/conditions this will be a reasonable representation, but not for others

→ *Health occurs beyond what is recorded by healthcare encounters*

The structure of administrative data

Administrative health data often in raw structure – not immediately 'research-ready':

- There can be erroneous/canceled/corrected records
- Entered diagnostic codes may be provisional/query
- Artefacts due to changes in definitions/new fields being added or omitted
- Records are structured from a billing or resource use perspective
  - Rows may be redundant (e.g., 5 rows are duplicates with same diagnostic info)
  - Hospital stays spanning multiple facilities appear as separate rows per each transfer

Table. Example of Coding From Physician Documentation

	Documentation	Administrative Codes*	Interpretation of Codes
Physician A	85 male with diabetes mellitus, ischemic cardioembolic stroke caused by atrial fibrillation with hemorrhagic transformation	I63.4 (MRDx) I48.90 (DxType1) E11.52 (DxType3)	Cerebral infarction caused by embolism of cerebral arteries Atrial fibrillation, unspecified Type 2 diabetes mellitus with certain circulatory complications
Physician B	85 male, type 2 diabetes mellitus, stroke and hemorrhage on CT, atrial fibrillation	I61.9 (MRDx) I48.90 (DxType2) E11.52 (DxType3)	Intracerebral hemorrhage, unspecified Atrial fibrillation, unspecified Type 2 diabetes mellitus with certain circulatory complications

Scenario: 85-year-old man with diabetes mellitus type 2 admitted with an ischemic stroke with hemorrhagic transformation and is found to have atrial fibrillation on the second day of admission. CT indicates computed tomography; DxType, diagnosis type; and MRDx, most responsible diagnosis.

*These represent real codes generated by a coding specialist in a tertiary-care hospital based on hypothetical patient information.

Yu AY, Holodinsky JK, Zerna C, Svenson LW, Jetté N, Quan H, Hill MD. Use and utility of administrative health data for stroke research and surveillance. Stroke. 2016 Jul;47(7):1946-52.

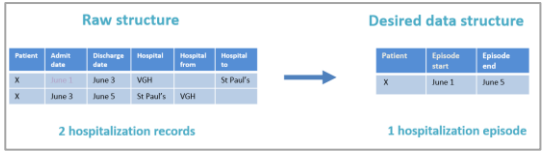
All to say…

Taking admin data at face value, assuming they are 'ready' for analysis … can be problematic

Why transform administrative data?

Failure to modify, transform admin data can introduce biases in the patterns of results

Examples (some of which will be unpacked later) –

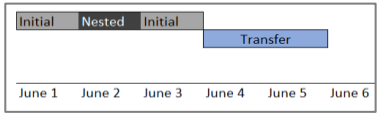


1. Taking healthcare records with diagnostic codes at face value:

- Over-estimates counts + rates of cases (or other health events)

2. Treating transfer-linked hospitalization records as separate hospitalizations:

- Over-estimates hospitalization counts + rates
- Under-estimates hospitalization length of stay (LoS)



3. Using a single source of emergency department use data without integrating others (in BC):

- Under-estimates emergency dept use counts + rates
- Mischaracterizes trends (depending on the types of ED use omitted)

When to transform administrative data

Given these challenges, it is often important to:
Consider certain approaches to modify / 'transform' the data
→ To generate more meaningful, less biased variables (+ therefore, less biased inferences)

Some elements/concepts in administrative data require NO transformation
Whether or not, and how, data should be transformed – depends on one's analytic goals

---

One example, with hospitalization records (Discharge Abstract Database [DAD]):

Goal = estimate hospital-level resource use: Use records as they are, reflect hospital-level focus

Goal = estimate hospitalization rates: Combine transfer-related hospital records into distinct 'hospitalization episodes of care'

A balanced perspective on admin data

- Researchers and clinicians alike exhibit – justified – skepticism about the validity evidence supporting administrative data…

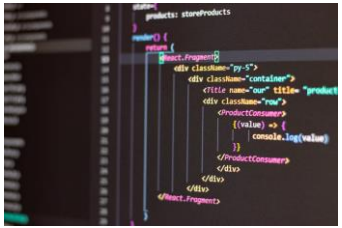
  " *However, when these data are **applied to an appropriate question with validated case definitions**, high-quality and reliable conclusions can be inferred* "

- Indeed, ICD codes: "**form the backbone structure of disease classification worldwide**"

Yu et al. Use and utility of administrative health data for stroke research and surveillance. Stroke. 2016;47(7):1946-52.

Identification algorithms

Identification algorithms



For the purpose of this talk – one can view an 'algorithm' in a broad sense:

Rules applied to transform data to obtain some desired information

It is an 'identification algorithm' as it ***identifies*** some characteristic, event, or health condition

Useful definition:
"a combination of values of routinely-collected variables that allow identification of cases of a given disease or other health event" (Ehrenstein et al. Clinical Epidemiology 2016: 8, 49-51)

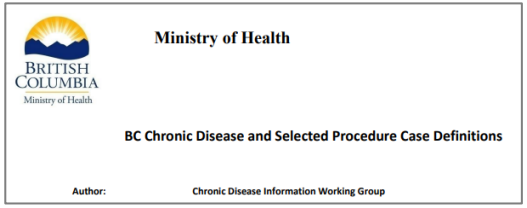
Identification vs case-finding algorithms

Case-finding algorithms

→ 'finding' / 'identifying' cases
(e.g., person with asthma, diabetes, HIV)

Also called:

Case definitions
Case identification
Case ascertainment algorithms
Administrative data algorithms


Ministry of Health

BRITISH COLUMBIA Ministry of Health

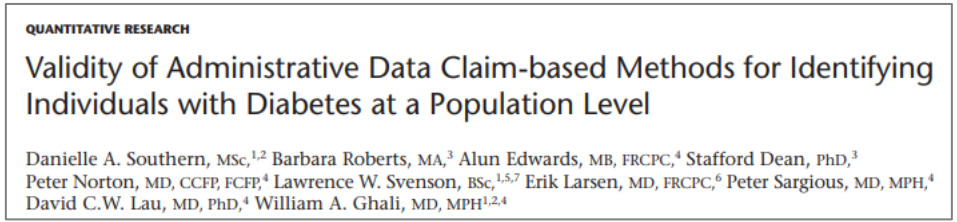
BC Chronic Disease and Selected Procedure Case Definitions

Author: Chronic Disease Information Working Group


RESEARCH

Development and validation of a case-finding algorithm for neck and back pain in the Canadian Armed Forces using health administrative data

François L. Thériault[a], Diane Lu[a] and Robert A. Hawes[a]


QUANTITATIVE RESEARCH

Validity of Administrative Data Claim-based Methods for Identifying Individuals with Diabetes at a Population Level

Danielle A. Southern, MSc,[1,2] Barbara Roberts, MA,[3] Alun Edwards, MB, FRCPC,[4] Stafford Dean, PhD,[3] Peter Norton, MD, CCFP, FCFP,[4] Lawrence W. Svenson, BSc,[1,5,7] Erik Larsen, MD, FRCPC,[6] Peter Sargious, MD, MPH,[4] David C.W. Lau, MD, PhD,[4] William A. Ghali, MD, MPH[1,2,4]

Examples of Canadian case-finding algorithms

Source	Condition (region)	Algorithm for healthcare use related to the condition *(e.g., physician visits with an MS diagnostic code)*
Widdifield et al (2015)	Multiple scelerois (ON)	5 physician visits within 24 months OR 1 hospitalization ever
Tu et al (2014)	Epilepsy (ON)	3 physician visits within 24 months OR 1 hospitalization ever
Yasseen III et al (2021)	Hepatitis B / C (ON)	1 physician visit (within ± 3 years of lab confirmation)
Lipscombe et al (2018)	Adult diabetes (ON)	1 physician visit OR 1 hospitalization AND 1 anti-diabetic prescription OR 1 diabetes fee code
Shiff et al (2017)	Childhood arthritis (MB)	2 physician visits within 24 months OR 1 hospitalization ever

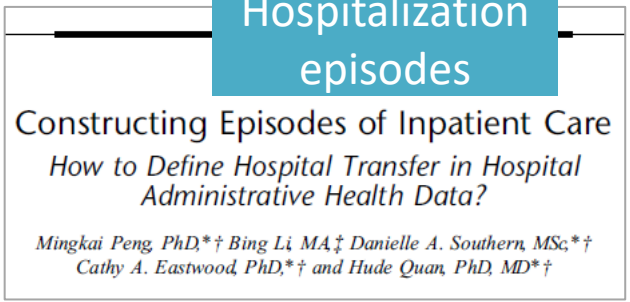
Identification algorithms: beyond solely '*cases*'

Algorithms can be used to identify other elements of interest (health or associated elements):

- **Other health events e.g.**
  - Hospitalization episodes-of-care
  - Emergency department visits (in BC)

- **Characteristics e.g.**
  - Visible minority group membership
  - Homelessness

Hospitalization episodes



Constructing Episodes of Inpatient Care

How to Define Hospital Transfer in Hospital Administrative Health Data?

Mingkai Peng, PhD,† Bing Li, MA,‡ Danielle A. Southern, MSc,*† Cathy A. Eastwood, PhD,*† and Hude Quan, PhD, MD*†*

Type of care provided

JOURNAL OF PALLIATIVE MEDICINE
Volume 20, Number 11, 2017

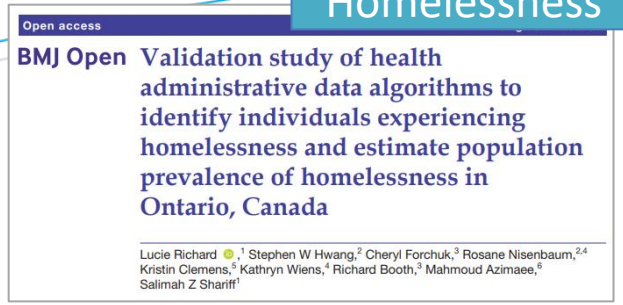
DOI: 10.1089/jpm.2017.0028

The Validity of Using Health Administrative Data To Identify the Involvement of Specialized Pediatric Palliative Care Teams in Children with Cancer in Ontario, Canada

Kimberley Widger, PhD,[1,2] Christina Vadeboncoeur, MD,[3–5] Shayna Zelcer, MD,[6] Ying Liu, MSc,[7] Alisha Kassam, MD,[8–10] Rinku Sutradhar, PhD,[7] Adam Rapoport, MD, MHSc,[1,10,11] Katherine Nelson, MD,[1,12] Joanne Wolfe, MD, MPH,[13,14] Craig Earle, MD, MSc,[7] Jason D. Pole, PhD,[7,15] and Sumit Gupta, MD, PhD[7,8,10,12]

Identification algorithms: beyond solely '*cases*'

Homelessness



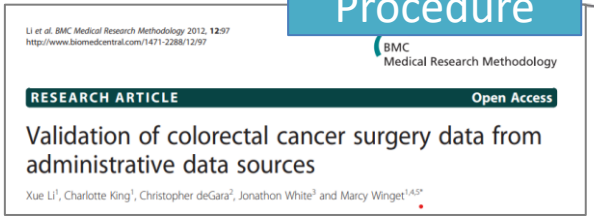
Open access

BMJ Open

Validation study of health administrative data algorithms to identify individuals experiencing homelessness and estimate population prevalence of homelessness in Ontario, Canada

Lucie Richard,[1] Stephen W Hwang,[2] Cheryl Forchuk,[3] Rosane Nisenbaum,[2,4] Kristin Clemens,[5] Kathryn Wiens,[4] Richard Booth,[3] Mahmoud Azimaee,[6] Salimah Z Shariff[1]

Procedure



Li et al. BMC Medical Research Methodology 2012, 12:97
http://www.biomedcentral.com/1471-2288/12/97

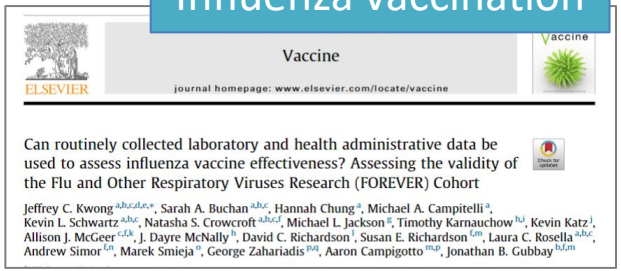
BMC Medical Research Methodology

RESEARCH ARTICLE Open Access

Validation of colorectal cancer surgery data from administrative data sources

Xue Li[1], Charlotte King[1], Christopher deGara[2], Jonathon White[3] and Marcy Winget[1,4,5*]

Influenza vaccination



Vaccine

ELSEVIER

journal homepage: www.elsevier.com/locate/vaccine

Can routinely collected laboratory and health administrative data be used to assess influenza vaccine effectiveness? Assessing the validity of the Flu and Other Respiratory Viruses Research (FOREVER) Cohort

Jeffrey C. Kwong[a,b,c,d,e,*], Sarah A. Buchan[a,b,c], Hannah Chung[a], Michael A. Campitelli[a], Kevin L. Schwartz[a,b,c], Natasha S. Crowcroft[a,b,c,f], Michael L. Jackson[g], Timothy Karnauchow[h,i], Kevin Katz[j], Allison J. McGeer[c,f,k], J. Dayre McNally[b], David C. Richardson[l], Susan E. Richardson[f,m], Laura C. Rosella[a,b,c], Andrew Simor[f,n], Marek Smieja[o], George Zahariadis[p,q], Aaron Campigotto[m,p], Jonathan B. Gubbay[b,f,m]

Injection drug use

International Journal of Drug Policy

ELSEVIER

journal homepage: www.elsevier.com/locate/drugpo

DRUG POLICY

Research Paper

Identifying injection drug use and estimating population size of people who inject drugs using healthcare administrative datasets

Naveed Zafar Janjua[a,b,c], Nazrul Islam[a,b,c], Margot Kuo[a], Amanda Yu[a], Stanley Wong[a], Zahid A. Butt[a,b], Mark Gilbert[a,b], Jane Buxton[a,b], Nuria Chapinal[a], Hasina Samji[a,d], Mei Chong[a], Maria Alvarez[a], Jason Wong[a,b], Mark W. Tyndall[a,b], Mel Krajden[a,c], for the BC Hepatitis Testers Cohort Team[1]

Visible minority groupings

Research

Classification of Canadian immigrants into visible minority groups using country of birth and mother tongue

Mohammad R. Rezai, Laura C. Maclagan, Linda R. Donovan, Jack V. Tu

Many Canadian identification algorithms are listed here: https://www.hdrn.ca/en/algorithm/

Examples of Canadian identification algorithms

Source	Event/characteristic (region)	Algorithm inputs
Sewitch et al (2013)	Screening colonoscopies (ON)	DAD, CCI (intervention/procedure codes)
Peng et al (2014)	Hospitalization episodes (AB)	Hospital records (DAD) linked wherein the discharge date occurred on the same date as a new admission date
Janjua et al (2018)	Injection drug use (BC)	MSP, DAD, prescription dispensings, MSP fee items
Richard et al (2019)	Homelessness (ON)	Indicators of homelessness (residence status, postcode, diagnostic etc fields) in DAD, NACRS, OHMS, Home care database, RAI, NRRS, Canadian Organ replacement registry

Example identification algorithm: Homelessness

Supplement Table 1 – Data Elements Indicative of Homelessness, Supportive Housing or Shelter Use

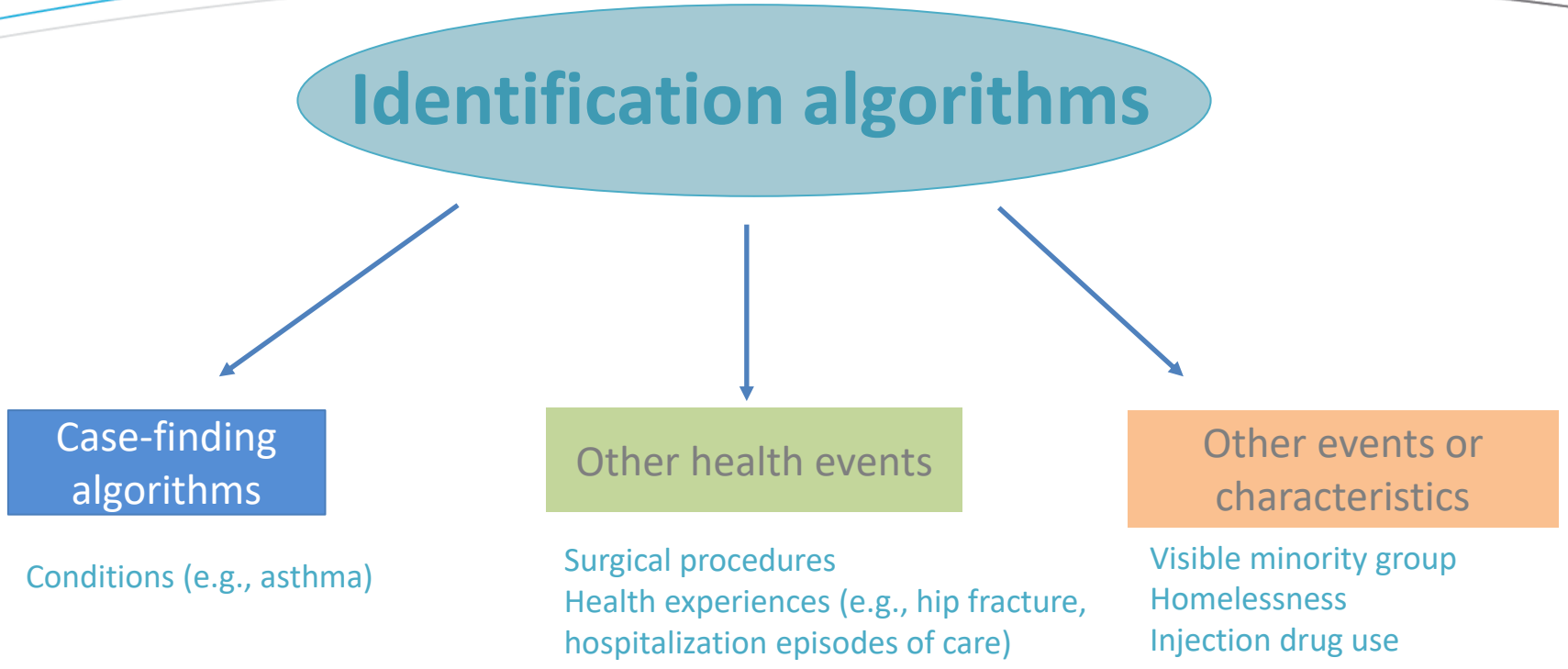
Database	Variable Name	Indicator Value	Description
DAD	HOMELESS	"Y"	Homelessness indicator
	INSTTYPE	"SH"	Institution Type = Supportive Housing
	DX10CODE1 to DX10CODE25	"Z590" or "Z591"	ICD-10 diagnosis codes for "Homelessness" and "Inadequate housing"
	CMGDIAG	"Z590" or "Z591"	ICD-10 diagnosis codes for "Homelessness" and "Inadequate housing"
	PSTLCODE	"XX"	Used to indicate transient/homeless patients
NACRS	DX10CODE1 to DX10CODE10	"Z590" or "Z591"	ICD-10 diagnosis codes for "Homelessness" and "Inadequate housing"
	RESTYPE	"3" or "4"	Residence Type = "Homeless" or "Shelter"
	PSTLCODE	"XX"	Used to indicate transient/homeless patients
OMHRS	PREDX10CODE to PREDX10CODE11	"Z590" or "Z591"	ICD-10 diagnosis codes for "Homelessness" and "Inadequate housing"
	POSTDX10CODE1 to POSTDX10CODE24	"Z590" or "Z591"	ICD-10 diagnosis codes for "Homelessness" and "Inadequate housing"
	PRIOR_RESIDENCE	"6"	Prior residential status = "Homeless (with or without shelter)"
	USUAL_RESIDENCE	"8"	Usual residential status = "Homeless (with or without shelter)"
	ADMITFROM	"8"	Admitted from = "Homeless (with or without shelter)"
	DISCHLIVING	"8"	Living arrangement at discharge = "Homeless (with or without shelter)"
	P5_Retired_2009	"6"	(Variable retired in 2009) Living arrangement = "Homeless (with or without shelter)"
	PSTLCODE	"XX"	Used to indicate transient/homeless patients
HCD	DXCODE	"V600" or "V601"	ICD-9 diagnosis codes for "Lack of housing" or "Inadequate housing"
	REQUEST_PROGRAM	"6"	Program Requested = "Supportive Housing"
	RESIDENCE_TYPE	"1604", "2200" or "3400"	Residence Type = "Other Supportive Living Unit", "Hostel/Shelter" or "No fixed address"
RAICA	B4	"8"	Expected residential/living status during service provision = "Homeless (with / without shelter)"
NRS	ALIVESET	"6"	Admission living setting = "Shelter"
	FLIVESET	"6"	Follow-up living setting = "Shelter"
	PRIM_DISCH_WAIT_REASON	"1.1"	Primary Discharge Wait Reason = "Assisted Living/Supportive Housing"
	SECND_DISCH_WAIT_REASON	"1.1"	Secondary Discharge Wait Reason = "Assisted Living/Supportive Housing"
CORR	PROVINCE_CODE	"XX"	"Transient/Homeless"
	HEALTH_CARD_PROVINCE_CODE	"XX"	"Transient/Homeless"

Supplement Table 2: Description of Case Ascertainment Algorithms

Name	Data Sources included[1]	Time Interval	Case Positive Condition(s)
1 indicator +/- 0 days	DAD NACRS OMHRS CORR RAICA HCD NRS	0 days before the encounter start or after the encounter end	1 positive ("homeless") indicator[2] in any of the included sources within the specified time frame
1 indicator +/- 15 days	DAD NACRS OMHRS CORR RAICA HCD NRS	15 days before the encounter start or after the encounter end	1 positive ("homeless") indicator in any of the included sources within the specified time frame
1 indicator +/- 45 days	DAD NACRS OMHRS CORR RAICA HCD NRS	45 days before the encounter start or after the encounter end	1 positive ("homeless") indicator in any of the included sources within the specified time frame
1 indicator +/- 90 days	DAD NACRS OMHRS CORR RAICA HCD NRS	90 days before the encounter start or after the encounter end	1 positive ("homeless") indicator in any of the included sources within the specified time frame
1 indicator +/- 180 days	DAD NACRS OMHRS CORR RAICA HCD NRS	180 days before the encounter start or after the encounter end	1 positive ("homeless") indicator in any of the included sources within the specified time frame

https://bmjopen.bmj.com/content/bmjopen/9/10/e030221.full.pdf
(supplementary info)

Identification algorithms and types



Unpacking nuances of identification algorithms

Unpacking identification algorithms: Inputs

Inputs

(e.g., diagnostic codes or drug identification numbers – for case-finding, but may be applicable to other types of algorithms)

- Multiple versions of diagnostic codes (and other classification systems) exist
  - (e.g., ICD-9, ICD-9-CM, ICD-10-CA, as well as jurisdiction-specific codes)
  - Example: a common diagnostic code for mood/anxiety conditions in BC is "**50B**" – this is a BC-specific code, not a standard ICD code

- With hospital records: Diagnostic 'typing' matters
  - (e.g., only the 'most responsible diagnosis' [MRD], or any diagnosis?)

Diagnosis type definitions

The following are the diagnosis types and definitions used in the DAD-HMDB.

Value	Description	Definition
M	Most Responsible Diagnosis (MRDx)	A Diagnosis Type (M) is the one diagnosis or condition that can be described as being most responsible for the patient's stay in a facility. If there is more than one such condition, the one held most responsible for the greatest portion of the length of stay or greatest use of resources (e.g., operating room time or investigative technology) is selected.
1	Pre-Admit Comorbidity	A Diagnosis Type (1) is a condition that existed prior to admission, has been assigned an ICD-10-CA code and satisfies the requirements for determining comorbidity.
2	Post-Admit Comorbidity	A Diagnosis Type (2) is a condition that arises post-admission, has been assigned an ICD-10-CA code and satisfies the requirements for determining comorbidity.
3	Secondary Diagnosis	A Diagnosis Type (3) is a secondary diagnosis or condition for which a patient may or may not have received treatment, has been assigned an ICD-10-CA code and does not satisfy the requirements for determining comorbidity.
C	Quebec-specific value	For data year 2006–2007 onward, Diagnosis Type (C) has been assigned to Quebec records for diagnoses where CIHI cannot distinguish pre-admit comorbidities (Diagnosis Type 1s) from those that are most likely secondary diagnoses (Diagnosis Type 3s).
W, X, Y	Service Transfer Diagnosis	These are ICD-10-CA codes associated with the first, second or third service transfer, respectively.
4	Morphology Code	Diagnosis Type (4) morphology codes are derived from ICD-O (*International Classification of Diseases — Oncology*) codes describing the type and behaviour of a neoplasm.
5	Admitting Diagnosis	Diagnosis Type (5) can be used to code the admitting diagnosis when it differs from the most responsible diagnosis code.

https://www.cihi.ca/sites/default/files/document/diagnosis-type-definitions-en.pdf?version=1&modificationDate=1381930010000&api=v2

Unpacking identification algorithms: Inputs

- **Include only the exact diagnostic code(s), or all codes associated with a (parent) code**
  - (e.g., diabetes in ICD-9: "250", or accept codes starting with '250' i.e., 250.0, 250.1 etc ?)
  - Billing/data entry errors occur - sometimes there will be numbers or characters after the first 3 or few 'legitimate' digits
  - Leading or trailing zeros can occur with diagnostic codes (e.g., in MSP practitioner billing records in some years)

- **Does the nature and setting of the health event matter?**
  - (e.g., for health practitioner billings: practitioner specialty, outpatient vs inpatient vs emergency dept settings)

- **Do some records need to be omitted? If so, how?** (cancelations / corrections / reversals / duplicate information)
  - How is a unique event counted?
    - (e.g., physician visit: if a patient sees multiple physicians on the same date, how is that counted?)

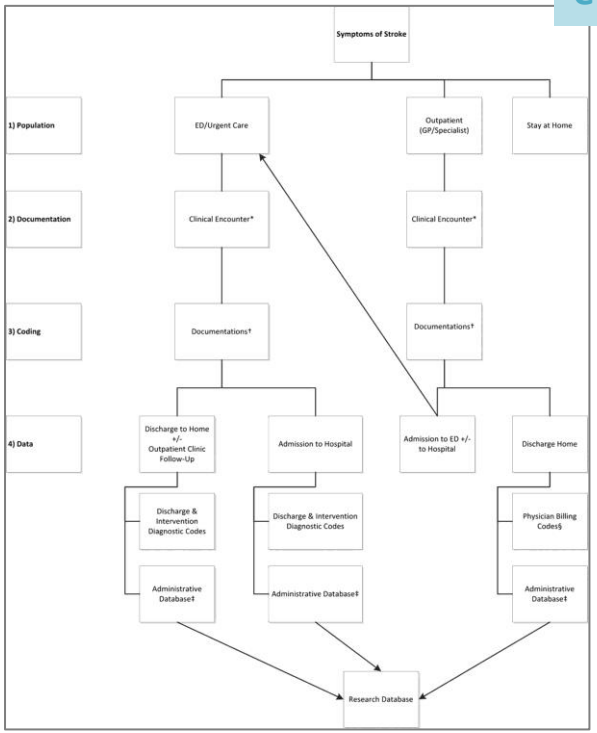
Number of physician visits within 1 year prior to the index date, defined as one visit per day per physician

https://bmjopen.bmj.com/content/bmjopen/9/10/e030221.full.pdf

  - What about out-of-province care? (e.g., patients from ON accessing healthcare in BC)

What appears in an admin health data record

- Info in data only represents the truth if the recorded diagnosis in a chart does
  - Example: 'unspecified' stroke related diagnostic codes are reported more commonly in rural vs urban clinical settings – which may reflect misclassification related to stroke diagnoses
- Much administrative health data collected for financial/budgeting purposes: thus, financial incentives may affect billing/coding – **upcoding**:
  - If a facility's reimbursement is based on case mix complexity, more complex disease codes may be entered, to increase the complexity of hospital case mix
  - The activation of healthcare practitioner fee items or other associated incentives may influence the frequency of a code/fee item being used over time



Health event

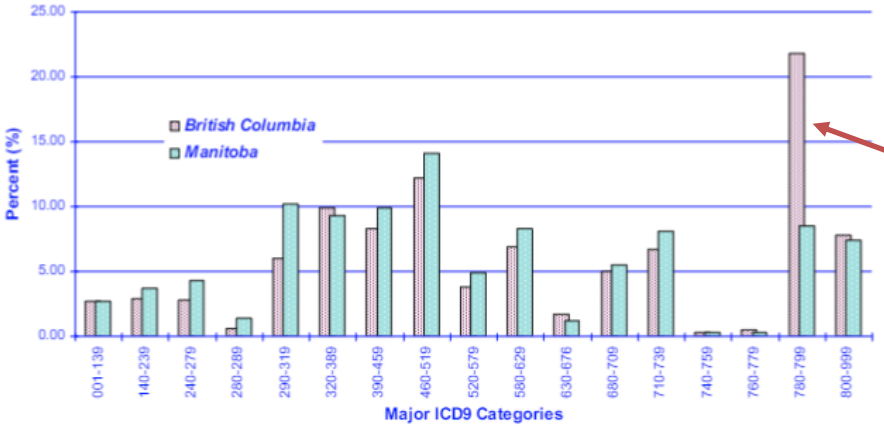
Analytic dataset

- McLintock K et al. The effects of financial incentives for case finding for depression in patients with diabetes and coronary heart disease: interrupted time series analysis. BMJ open. 2014;4(8):e005178.
- Yu et al. Use and utility of administrative health data for stroke research and surveillance. Stroke. 2016 Jul;47(7):1946-52.
- Pruitt Z et al Upcoding emergency admissions for non-life-threatening injuries to children. The American journal of managed care. 2013;19(11):917–24.

Landscape – inter-provincial differences

Jurisdictions can vary in terms of codes used and billing practices:

Figure 3.1: Percent Distribution of Paid Services across Major ICD9 Categories, Comparison between B.C. & Manitoba, 1993/94



https://www.popdata.bc.ca/sites/default/files/documents/data/MSP%20Diagnostic%20Codes%20paper.pdf

Hu (1996):
"two major diagnoses categories covered by these codes i.e. general symptoms (780-789) and nonspecific abnormal findings (790-796).

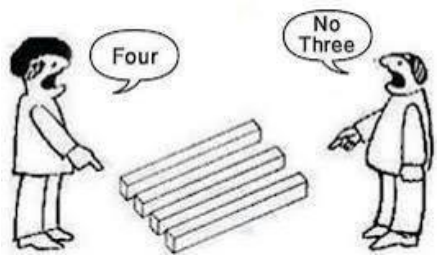
But more than 95% of the contribution to total services and amounts related to this diagnostic group (780 -799) are from codes 780-789 (general symptoms).

It seems, therefore, B.C. physicians are more likely to use this group of ICD codes as a diagnosis for these non-specific symptoms."

Note these data are ~20 years old …
the caveat about billing patterning potentially varying by jurisdiction may still apply

Jurisdictional differences: Mental illness example

Think of these bars as a health condition one is trying to measure (e.g., mood/anxiety disorders)



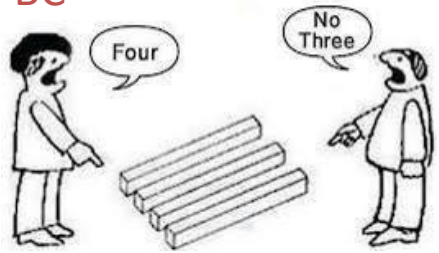
Mood/Anxiety disorder

Measuring mental illness example

BC definition – BCCDC / BC MoH

ICD-9/10	Description
F30	Manic episode
F31	Bipolar affective disorder
F32	Depressive episode
F33	Recurrent depressive disorder
F34	Persistent mood [affective] disorders
F38	Other mood [affective] disorders
F39	Unspecified mood [affective] disorder
F40	Phobic anxiety disorders
F41	Other anxiety disorders
F42	Obsessive-compulsive disorder
F43	Reaction to severe stress, and adjustment disorders
F44	Dissociative (conversion) disorders
F45	Somatoform disorders
F48	Other neurotic disorders
F68	Other disorders of adult personality & behavior
296	Affective psychoses
300	Neurotic disorders
311	Depressive disorder, not elsewhere classified
MSP DX Code 50B	Anxiety/Depression

BC Manitoba



Mood/Anxiety disorder

Manitoba definition – Manitoba health

Mood and Anxiety Disorders

The proportion of residents age 10 or older diagnosed with depression and/or anxiety disor der in a five-year period by any of the following:

- one or more hospitalizations with a diagnosis for depressive disorder, affective psychoses, neurotic depression or adjustment reaction: ICD–9–CM codes 296.2–296.8, 300.4, 309 or 311; ICD–10–CA codes F31, F32, F33, F341, F38.0, F38.1, F41.2, F43.1, F43.2, F43.8, F53.0, F93.0 or with a diagnosis for a manic disorder, anxiety state, phobic disorders, obsessive–compulsive disorders or hypochondriasis: ICD–9–CM codes 296.1, 300.0, 300.2, 300.3, 300.7; ICD–10–CA codes F40, F41.0, F41.1, F41.3, F41.8, F41.9, F42, F45.2
- one or more hospitalizations with a diagnosis for anxiety disorders: ICD–9–CM code 300; ICD–10–CA codes F32, F341, F40, F41, F42, F44, F45.0, F45.1, F45.2, F48, F68.0, or F99 AND one or more prescriptions for an antidepressant, anxiolytic or mood stabilizer: ATC codes N05AN01, N05BA, N06A
- one or more physician visits with a diagnosis for depressive disorder or affective psychoses: ICD–9–CM codes 296, 311
- one or more physician visits with a diagnosis for anxiety disorders: ICD–9–CM code 300 AND one or more prescriptions for an antidepressant, anxiolytic or mood stabilizer: ATC codes N05AN01, N05BA, N06A
- three or more physician visits with a diagnosis for anxiety disorders or adjustment reaction: ICD–9–CM code 300, 309

http://www.bccdc.ca/resource-gallery/Documents/Chronic-Disease-Dashboard/mood-anxiety-disorders.pdf

https://www.gov.mb.ca/health/annstats/as1819.pdf

Measuring mental illness example

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F42	Obsessive-compulsive disorder
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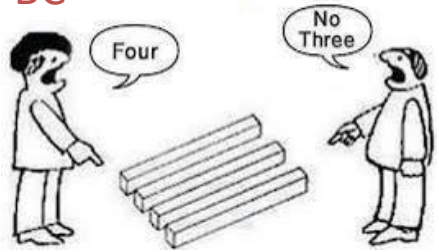
F45	Somatoform disorders
F48	Other neurotic disorders
F68	Other disorders of adult personality & behavior
296	Affective psychoses
300	Neurotic disorders
311	Depressive disorder, not elsewhere classified
MSP DX Code 50B	Anxiety/Depression

Includes 50B code
(a BC-specific value, not part of ICD system)

BC

Manitoba



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- one or more physician visits with a diagnosis for depressive disorder or affective psychoses: ICD–9–CM codes 296, 311
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- three or more physician visits with a diagnosis for anxiety disorders or adjustment reaction: ICD–9–CM code 300, 309

Nuances with ICD codes
(beyond first 3 values)

Incorporates medications

http://www.bccdc.ca/resource-gallery/Documents/Chronic-Disease-Dashboard/mood-anxiety-disorders.pdf

https://www.gov.mb.ca/health/annstats/as1819.pdf

Unpacking identification algorithms: Time

Time (e.g., for case-finding algorithms: the search window)

- Within which **search window** do the diagnostic codes (or other events) need to co-occur?
- What about stand-alone/ 'one-off' events? (i.e., if an algorithm includes a single physician visit for diabetes)
- Washout/clearance period (particularly for incidence: it can be necessary to ensure patients had no prior healthcare interactions condition for a certain period before a date of interest)
- **Lookback period** (how far back to 'look into' a person's records)
- Observation period: When does it start and end?
  - Did important changes occur within?
    - cohort effects, policy changes, data quality/coding changes etc.?

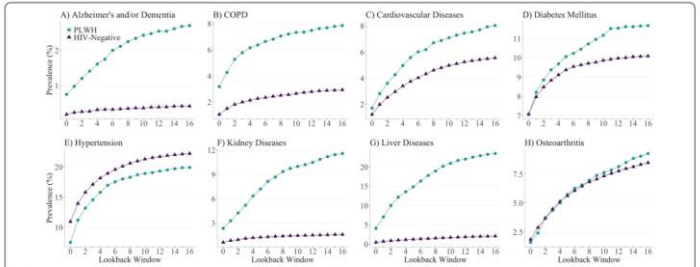
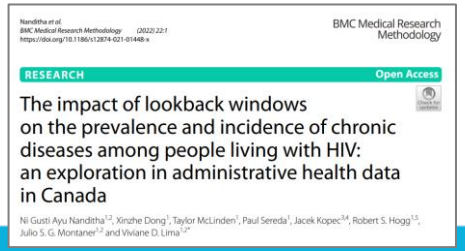


Fig. 2 Prevalence chronic diseases among people living with HIV and HIV-negative individuals in British Columbia, Canada for year 2012 across varying lookback windows. Note: PLWH: people living with HIV; COPD: Chronic Obstructive Pulmonary Diseases. Vertical scales differ for each graph for illustration purposes



Unpacking identification algorithms: Case study 1

To illustrate the idea of a **search window**, let's consider an example of ongoing work at the BC-CfE using **case-finding algorithms to identify persons living with HIV**

In this validation work, **HIV test data** was used as the reference ("gold standard") against which various case-finding algorithms were tested [more details on this soon…].

For several algorithms, we evaluated **co-occurrence of HIV-related physician visits** within defined search windows (time frame within which events co-occur)

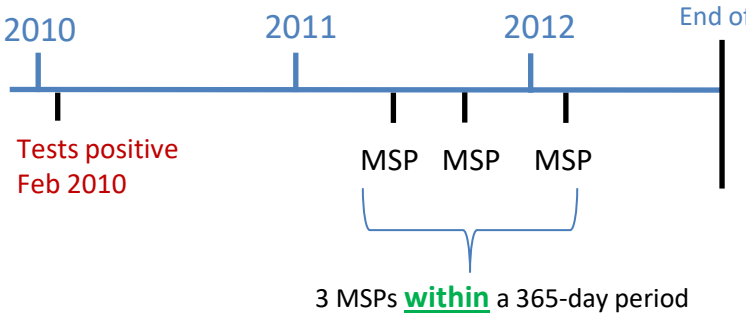
Let's use this example algorithm to demonstrate:

3 HIV-related physician visits within a 1-year (365 day) period

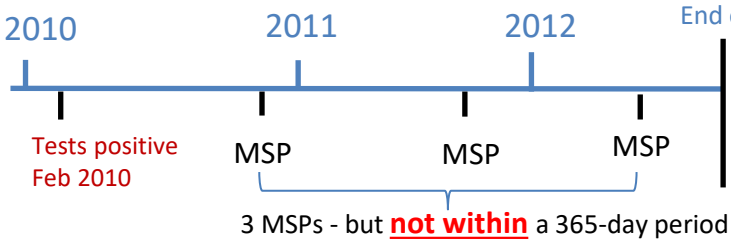
Example: Search window for HIV case-finding

MSP = HIV-related physician visit

- Looks *forward* from HIV+ test date for any occurrence of 3 HIV-related MSPs within a 1-year (365-day) period
  - MSPs can meet the criteria if they occur **AFTER** the HIV+ test date, BEFORE end of follow-up



Algorithm classifies person as HIV+
(true positive)



Algorithm classifies person as HIV-
(false negative)

Example: Search window for HIV case-finding

- Since a **single event** cannot be 'anchored' (or 'co-occur') relative to another event…
  - (i.e., for 3 MSPs occurring within a 365-day window, the time from 1st to 3rd MSP dates must be ≤ 365 days)

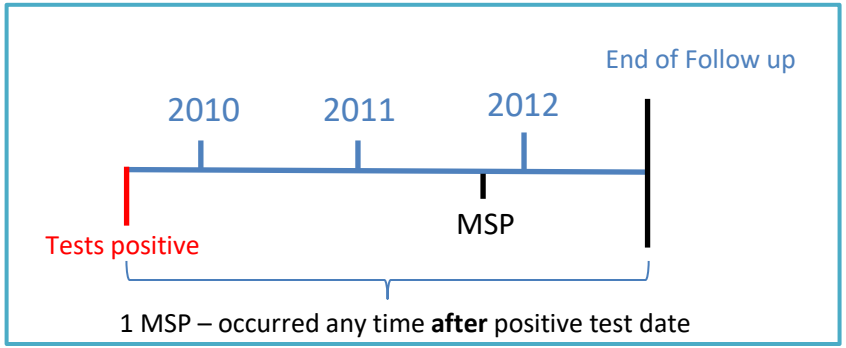
The search window for these 'single' events is '**ever**' i.e.

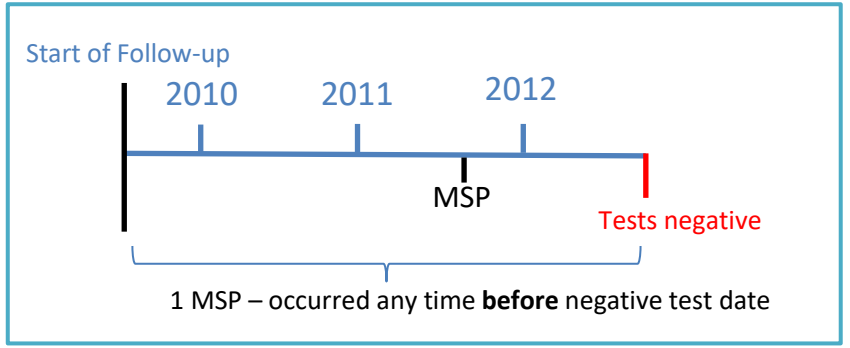
For positive tests, '1 MSP' is:

any MSP occurring *after* the HIV+ test date and *before* end of follow-up

For negative tests, '1 MSP' is:

any MSP occurring *before* the HIV- test date and *after* start of follow-up





Unpacking identification algorithms: Time

Although search windows within case-finding algorithms are a clear example where time/timeframe is important – it often matters for other types of identification algorithms:

Example:

Timing from discharge → next admission for combining hospitalization records into episodes of care

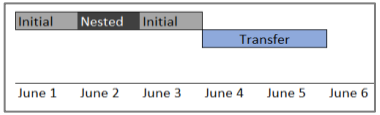


TABLE 1. Sensitivity and PPV for Transfer Case Definitions Using Different Time Gaps Between 2 Hospitalizations

		Time Gap Between 2 Consecutive Hospitalizations for the Same Patient					
		6 h		9 h		12 h	
	No. Transfer Cases	Sensitivity (95% CI)	PPV (95% CI)	Sensitivity (95% CI)	PPV (95% CI)	Sensitivity (95% CI)	PPV (95% CI)
Overall	21,830	93.3 (93.0, 93.7)	96.0 (95.8, 96.3)	96.7 (96.5, 97.0)	94.9 (94.6, 95.2)	97.9 (97.7, 98.1)	93.8 (93.5, 94.1)
Sex							
Male	10,597	93.2 (92.8, 93.7)	96.1 (95.7, 96.5)	96.5 (96.1, 96.8)	95.0 (94.5, 95.3)	97.8 (97.5, 98.1)	93.7 (93.2, 94.1)
Female	11,233	93.5 (93.0, 93.9)	95.9 (95.5, 96.3)	97.0 (96.6, 97.3)	94.9 (94.5, 95.3)	98.1 (97.8, 98.3)	94 (93.5, 94.4)
Age categories (y)							
≤20	977	87.9 (85.7, 89.9)	94.2 (92.5, 95.6)	93.7 (91.9, 95.1)	92.0 (90.1, 93.6)	96.4 (95.1, 97.5)	89.5 (87.4, 91.2)
21–35	1899	91.3 (89.9, 92.5)	93.8 (92.6, 94.8)	95.4 (94.4, 96.3)	91.4 (90.1, 92.6)	96.6 (95.7, 97.3)	88.3 (86.8, 89.7)
36–50	2304	91.5 (90.3, 92.6)	94.5 (93.5, 95.4)	95.4 (94.5, 96.3)	92.5 (91.3, 93.5)	97.2 (96.4, 97.8)	90.8 (89.6, 91.9)
51–65	4801	93.5 (92.7, 94.1)	96.2 (95.6, 96.7)	97.1 (96.6, 97.5)	95.2 (94.5, 95.7)	98.3 (97.9, 98.6)	94.3 (93.7, 95.0)
66–75	4256	93.6 (92.8, 94.3)	96.5 (95.9, 97.1)	96.9 (96.3, 97.4)	96.0 (95.4, 96.6)	98 (97.6, 98.4)	95.4 (94.8, 96.0)
>75	7593	94.9 (94.4, 95.4)	96.9 (96.5, 97.3)	97.6 (97.2, 97.9)	96.3 (95.8, 96.7)	98.4 (98.1, 98.7)	95.6 (95.1, 96.0)
Location of residence							
Rural	6791	89.6 (88.9, 90.4)	95.9 (95.4, 96.4)	95.0 (94.4, 95.5)	94.7 (94.2, 95.2)	97.0 (96.5, 97.4)	93.9 (93.3, 94.4)
Urban	15,039	95.0 (94.7, 95.4)	96.1 (95.8, 96.4)	97.5 (97.3, 97.8)	95.0 (94.7, 95.4)	98.4 (98.2, 98.6)	93.8 (93.4, 94.2)

CI indicates confidence interval; PPV, positive predictive value.

Peng et al. Constructing Episodes of Inpatient Care. Medical Care. 2017 1;55(1):74-8.

Table 2 Lengths-of-stay in hospital and ICU, by combination method

	No combining of abstracts or records	≤ 1 day gaps		≤ 2 day gaps	
		Indication of inter-hospital transfer		Indication of inter-hospital transfer	
		Used	Not used	Used	Not used
	Method 1	Method 2	Method 3	Method 4	Method 5
Hospital LOS (days)					
Mean ± SD	16.7 ± 33.6	21.5 ± 41.7	21.9 ± 43.8	21.5 ± 41.7	21.9 ± 42.1
Difference vs. Method 1	–	28.7%	31.1%	28.7%	31.1%
Median (IQR)	8 (4–16)	9 (4–21)	9 (5–21)	9 (4–21)	9 (5–21)
Difference vs. Method 1	–	12.5%	12.5%	12.5%	12.5%
ICU LOS (hours)					
Mean ± SD	89.1 ± 141.8	98.8 ± 172.7	99.0 ± 173.0	100.3 ± 175.1	100.5 ± 175.3
Difference vs. Method 1	–	10.9%	11.1%	12.8%	12.9%
Median (IQR)	48.8 (24.0-97.3)	53.3 (24.0-106.3)	53.3 (24.0-106.5)	54.2 (24.0-108.7)	54.3 (24.0-108.9)
Difference vs. Method 1	–	9.2%	9.2%	11.1%	11.3%

LOS, length-of-stay; *SD*, standard deviation; *IQR*, interquartile range.

Fransoo et al. Constructing episodes of inpatient care: data infrastructure for population-based research. BMC Medical Research Methodology. 2012;12(1):1-6.

Unpacking identification algorithms: Case study 2

Algorithm	Criteria for combining hospital records into hospitalization episodes	Fields used from DAD [hospitalizations]
Raw records	No adjustment / combining of hospital records – FOR REFERENCE	n/a
Dt_base	Nested or overlap by >1 day [all other definitions build on this criteria]	Solely dates (discharge and admit)
Dt_0day	same day admit vs prior discharge date	
Dt_1day	up to 1-day diff between admit vs prior discharge date	
Hp_0day	same-day admit vs prior discharge date AND populated hospTO+hospFROM fields	dates + inter-hospital transfer (hospTO / hospFROM)
Hp_0day_any	same-day admit vs prior discharge date AND some agreement of hosp IDs	
Hp_0day_strict	same-day admit vs prior discharge date AND strict agreement of hosp IDs	
Hp_1day	up to 1-day diff between admit vs prior discharge date AND populated hospTO+hospFROM fields	
Hp_1day_any	up to 1-day diff between admit vs prior discharge date AND some agreement of hosp IDs	
Hp_1day_strict	up to 1-day diff between admit vs prior discharge date AND strict agreement of hosp IDs	
Tr_0day	same-day admit vs prior discharge date AND populated hospTO+hospFROM fields AND transfer flag present	dates + inter-hospital transfer + transfer indicator (disposition type)
Tr_0day_any	same-day admit vs prior discharge date AND some agreement of hosp IDs AND transfer flag present	
Tr_0day_strict	same-day admit vs prior discharge date AND strict agreement of hosp IDs AND transfer flag present	
Tr_1day	up to 1-day diff between admit vs prior discharge date AND populated hospTO+hospFROM fields AND transfer flag present	
Tr_1day_any	up to 1-day diff between admit vs prior discharge date AND some agreement of hosp IDs AND transfer flag present	
Tr_1day_strict	up to 1-day diff between admit vs prior discharge date) AND strict agreement of hosp IDs AND transfer flag present	

Validity evidence of algorithms

The importance of being valid

Validity is often assumed, rather than evidenced

- **Validity is not a static property of a measure** (e.g., a case-finding algorithm)
  - Embedded within context → may be valid in one setting/population, but not in others
  - Validity can vary over time → codes activated/ended; transition to new ICD versions

'Off-label' use…

- Taking an algorithm 'validated' in one context, then applying it elsewhere i.e.
  - Using a mood-anxiety disorder case-finding algorithm from Ontario and apply it in BC
  - Many ICD-based algorithms for mental health, 'validated' on adults but applied to children

'Gold' standard vs algorithm

1. A gold standard (aka 'reference standard')
    - The best measure available to indicate whether a person has a condition; typically this is the closest thing (one has available) to the 'truth' (within reason!) – but does not need to be 'perfect'

In our case study: HIV lab tests (other examples include EMRs, charts)

2. A tool or comparator (aka 'test', but that confusing term as our *gold standard* source = HIV 'test')
    - A tool that attempts to classify whether a person has a condition of interest; this tool is the 'thing' being validated

The algorithm: Some pattern of recorded healthcare use that may characterize HIV+ status *(e.g., 3 HIV-related physician visits within a 1-year period)*

Our aim was to 'validate' the algorithm against HIV lab test results

A valid algorithm will accurately classify:

lab-confirmed HIV+ persons as HIV+

lab-confirmed HIV- persons as HIV-

Common metrics for assessing validity of algorithms

'Gold standard' classification

Algorithm classification

		Disease ⊕	Disease ⊖	Predictive Value	
Test	⊕	**A** True Positive (TP)	**B** False Positive (FP)	Positive Predictive Value (PPV) $\frac{TP}{TP+FP} = \frac{A}{A+B}$	Total Positive Results (A + B)
	⊖	**C** False Negative (FN)	**D** True Negative (TN)	Negative Predictive Value (NPV) $\frac{TN}{FN+TN} = \frac{D}{C+D}$	Total Negative Results (C + D)
Sensitivity & Specificity		Sensitivity $\frac{TP}{TP+FN} = \frac{A}{A+C}$	Specificity $\frac{TN}{FP+TN} = \frac{B}{B+D}$		
		All diseased patients (A + C)	All non-diseased patients (B + D)		

Among patients classified as diseased by the algorithm, what % are truly diseased?

Among patients classified as non-diseased by the algorithm, what % are truly non-diseased?

Among diseased patients, what % are classified as diseased by the algorithm?

Among non-diseased patients, what % are classified as non-diseased by the algorithm?

A 'perfect' algorithm would have absolute agreement with the 'gold standard' classification
(i.e., 0 false positives and 0 false negatives)

https://step1.medbullets.com/stats/101006/testing-and-screening

Example: Validity evidence for HIV case finding algorithms

- Goal = Evaluate the validity of a case-finding algorithm for HIV using a validation sub-sample
  i.e., how well our algorithm (healthcare records) corresponds to our 'gold' standard (lab tests)

- **Algorithm =** combination of administrative healthcare records within a certain time frame
  (e.g., 3 HIV-related physician visits within a 1-year period)

- **We leverage these data sources, which are linked as part of the STOP HIV/AIDS program (see link below):**
  - **BCCDC: BC Centre for Disease Control, Provincial HIV/AIDS Surveillance Database** (HIV lab test results) **= our gold standard**
  - **MSP: Medical Services Plan Payment information file** (HIV-related physician visits) **&**
    DAD: Discharge Abstract Database (HIV-related hospital visits) **= our algorithm**

Seek and Treat for Optimal Prevention of HIV/AIDS
STOP HIV/AIDS

http://bccfe.ca/stop-hiv-aids/about

Example: Assessing validity evidence

		Gold standard [BCCDC lab test result]	
		HIV + (10,000 obs)	HIV – (10,000 obs)
Algorithm (MSP,DAD)	HIV+	**True positive (9,000)**	False positive (100)
	HIV-	False negative (1,000)	**True negative (9,900)**
		Sensitivity = Algorithm-classified HIV+ / Lab-confirmed HIV+ = $\frac{9{,}000}{10{,}000}$ = 90% Among lab-confirmed HIV+ persons, the algorithm classified 90% as HIV+	**Specificity** = Algorithm-classified HIV- / Lab-confirmed HIV- = $\frac{9{,}900}{10{,}000}$ = 99% Among lab-confirmed HIV- persons, the algorithm classified 99% as HIV-

* Fictious numbers to illustrate concept *

Additional measures of validity (many many exist…)

Other core validity measures in this context are the following:

C statistic: (aka concordance statistic) is the area under curve (AuC), weights sensitivity and specificity equally;

1 = perfect at correctly classifying 'true' HIV status; 0.5 = no better than random chance

For binary tests, 'hand calculation': (sensitivity + specificity) / 2 Cantor & Kattan (2000)

Positive predictive value (PPV) and *Negative predictive value* (NPV) are other common validity metrics, but:

To be accurate, they require (HIV) prevalence in the validation sub-sample to be comparable to general population (clearly *NOT* the case for a validation sub-sample of persons with HIV lab tests who tested positive)…

For our ongoing validity work with HIV case-finding – we do NOT calculate PPV/NPV

Antoniou* 2011's HIV case-finding algorithm study – also did not estimate PPV/NPV because the HIV prevalence in their validation sub-sample was much higher than the prevalence in general population

*Antoniou T, Zagorski B, Loutfy MR, Strike C, Glazier RH. Validation of case-finding algorithms derived from administrative data for identifying adults living with human immunodeficiency virus infection. PloS one. 2011 Jun 30;6(6):e21748.

Sensitivity vs specificity trade-off

- Generally, there is a **trade-off between sensitivity and specificity**:
  - A highly sensitive algorithm will detect virtually all HIV+ persons in our data
  - if an algorithm has lower specificity, however, some truly HIV- persons will be misclassified as HIV+

Consider an algorithm defining HIV+ as 1 HIV-related MSP in a 3-year period:

- High sensitivity → most HIV+ persons likely have had 1 HIV-related physician visit during a 3-year period

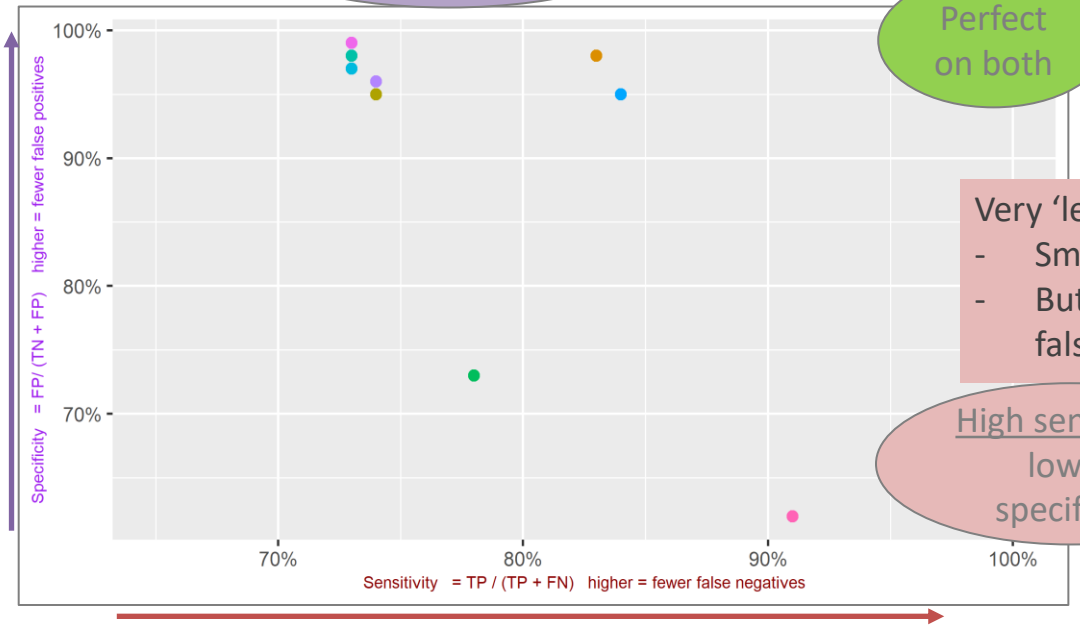
- Lower specificity → some HIV- persons will have had 1 HIV-related physician visit during a 3-year period
  *** a *single* HIV-related physician visit could be billing error or otherwise: not ongoing HIV care

- **Impact** = this algorithm would provide a considerably inflated estimate of the number of persons with HIV+

Sensitivity vs specificity trade-off

Very 'strict' algorithms:
- Small % false positives
- But moderate % of false negatives

High specificity lower sensitivity



Perfect on both

Very 'lenient' algorithms:
- Small % false negatives
- But moderate % of false positives

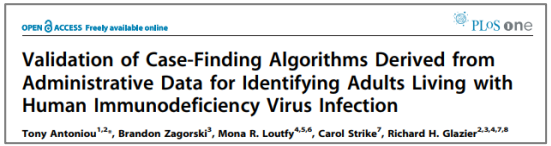
High sensitivity lower specificity

*** Each dot = an algorithm; data from Table 2:**
Hamilton et al Validating International Classification of Disease 10th Revision algorithms for identifying influenza and respiratory syncytial virus hospitalizations. PLoS One. 2021. 7;16(1):e0244746.

Specificity for rare diseases

- Particularly for low prevalence diseases (like HIV), even a small decrease (e.g., 1%) in specificity could misclassify a large # of persons as false positive if the algorithm is applied to the general population

- Antoniou 2011 (p.4) presents an example to illustrate this:


OPEN ACCESS Freely available online PLoS one

Validation of Case-Finding Algorithms Derived from Administrative Data for Identifying Adults Living with Human Immunodeficiency Virus Infection

Tony Antoniou[1,2*], Brandon Zagorski[3], Mona R. Loutfy[4,5,6], Carol Strike[7], Richard H. Glazier[2,3,4,7,8]

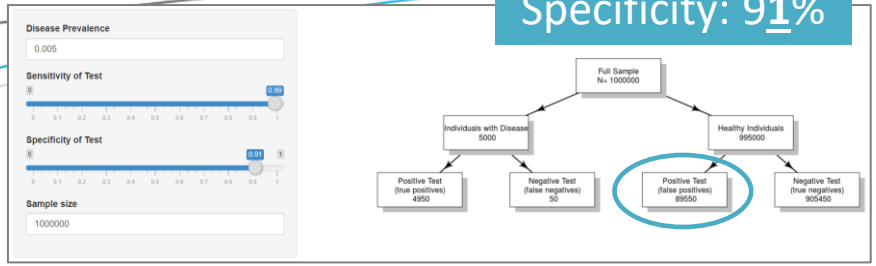
Imagine there are 5,000 HIV+ persons in a population of 1 million residents –

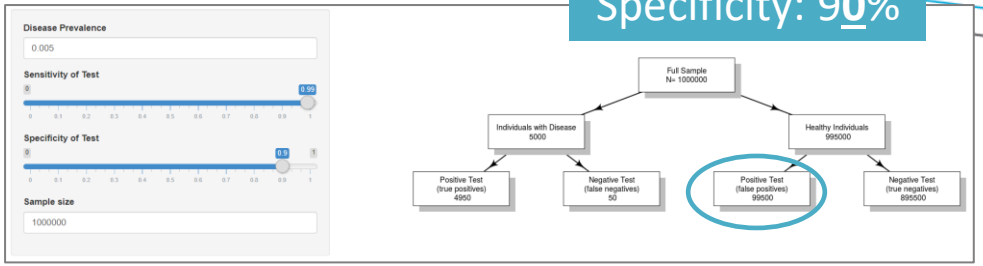
Per each 1% drop in specificity, an additional ~**10,000** HIV- persons could be misclassified as HIV+ (false positives)

Per each 1% drop in sensitivity, an additional ~**50** HIV+ persons could be misclassified as HIV- (false negatives)

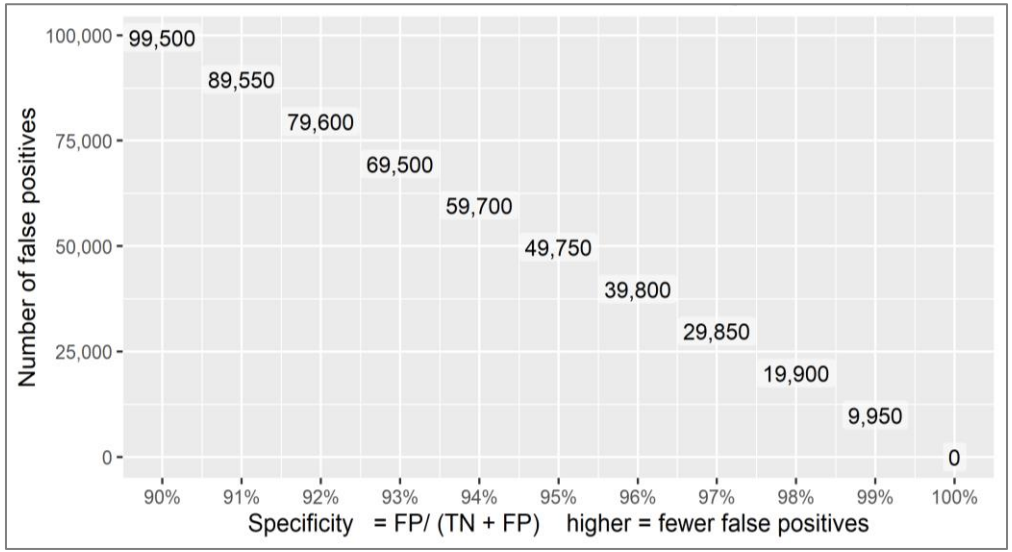
*Antoniou T, Zagorski B, Loutfy MR, Strike C, Glazier RH. Validation of case-finding algorithms derived from administrative data for identifying adults living with human immunodeficiency virus infection. PloS one. 2011. 30;6(6):e21748.

Specificity for rare diseases: Example





https://neurotroph.shinyapps.io/Sensitivity-Specificity/



Each 1% drop in specificity adds ~10,000 false positives

Eligibility (for validation metrics)

- Important to consider the eligibility/inclusion criteria for an algorithm validation study
  - This decides the denominator for sensitivity or specificity estimates + can impact all estimates

- Several administrative health data algorithm validation studies require participants in the validation analysis to be recent healthcare users

  e.g., *Antoniou 2011** required patients to:

  - a) have first visited their physician ≥ 3 years before index date (chart abstraction), and
  - b) have had ≥ 2 physician visits OR 1 complete physical examination during the 3-year study period)

- In our ongoing HIV case-finding work: **Require a 1-year min follow-up (presence in BC)**
  - This had negligible impacts on specificity, but tangible improvements to sensitivity – **reducing false negatives**
  - (omitting from the sensitivity denominator those with little (<1 year) follow-up after their positive test, who are therefore less likely to record any healthcare visits and hence appear as a false negative)

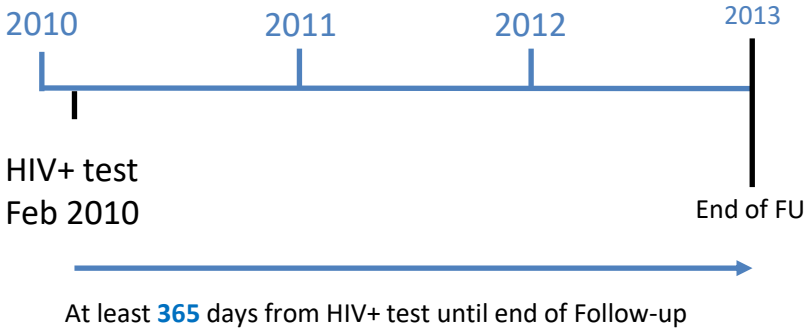
*Antoniou T, Zagorski B, Loutfy MR, Strike C, Glazier RH. Validation of case-finding algorithms derived from administrative data for identifying adults living with human immunodeficiency virus infection. PloS one. 2011;6(6):e21748.

Eligibility – for *positive* test dates (sensitivity)

Eligible records are all persons who have at least X days between HIV+ date and *end* of follow-up

e.g., eligible person for a 365-day window: HIV+ date = 01FEB2010, end of follow-up = 01FEB2013 (≥ 365 days) ✓

- All those eligible will be in the lab-confirmed **positive** column



✓

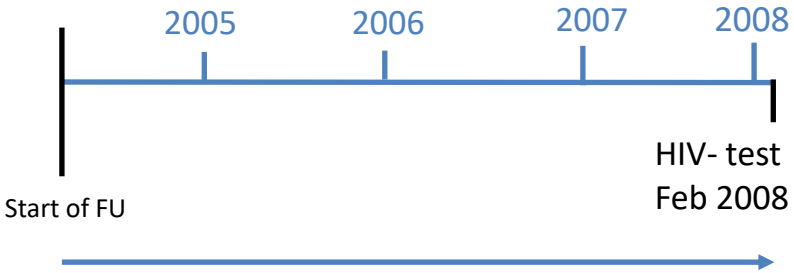
Eligible: included in HIV+ column
i.e. **part of denominator for sensitivity calculation**

		BC CDC lab test result	
		HIV +	HIV -
Algorithm (using MSP+DAD)	HIV+	**True +**	False +
	HIV-	False -	**True -**

Eligibility – for *negative* test dates (specificity)

Eligible records are all persons who have at least X days between HIV- date and *start* of follow-up
e.g., eligible person for a 365-day window: HIV- date = 01FEB2010, start of follow-up = 01FEB2004 (≥ 365 days) ✓

- All those eligible will be in the lab-confirmed **negative** column



At least 365 days from start of Follow-up until HIV- test date

✓

Eligible: included in HIV- column
i.e. **part of denominator for specificity calculation**

		BC CDC lab test result	
		HIV +	HIV -
Algorithm (using MSP+DAD)	HIV+	True +	False +
	HIV-	False -	**True -**

Reporting and applying algorithms

Reporting results

- Given the variation and complexity of identification algorithms:
  - **Clarity and transparency** are central guiding principles
  - Regardless of the approaches/definitions/assumptions you use – **describe them clearly**

- Aim to present a protocol such that a reader would understand what you did, how you did it, any assumptions made, and fundamentally: **How to reproduce it**

Several guidelines exist, including checklists to help ensure comprehensive reporting:

- **RECORD** (*REporting of studies Conducted using Observational Routinely-collected health Data*)
  - Benchimol EI, Smeeth L, Guttmann A, Harron K, Moher D, Petersen I, Sørensen HT, von Elm E, Langan SM, RECORD Working Committee. The REporting of studies Conducted using Observational Routinely-collected health Data (RECORD) statement. PLoS medicine. 2015; 6;12(10):e1001885.
- **STARD** (*Standards for Reporting of Diagnostic accuracy*) – adapted for administrative health data
  - Benchimol EI, Manuel DG, To T, Griffiths AM, Rabeneck L, Guttmann A. Development and use of reporting guidelines for assessing the quality of validation studies of health administrative data. Journal of Clinical Epidemiology. 2011;64(8):821-9.

Reporting validity results – Benchimol (2011)

- Benchimol et al (2011) provide recommendations specifically regarding conducting + reporting validity studies with administrative data

ELSEVIER

Journal of Clinical Epidemiology 64 (2011) 821–829

Journal of Clinical Epidemiology

REVIEW ARTICLES

Development and use of reporting guidelines for assessing the quality of validation studies of health administrative data

Eric I. Benchimol[a,b,c,d,e,f,g,*], Douglas G. Manuel[a,h,i,j,k], Teresa To[a,c,d], Anne M. Griffiths[b,e], Linda Rabeneck[a,d,l], Astrid Guttmann[a,d,e,m]

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[c]Child Health Evaluative Sciences, The Hospital for Sick Children, Toronto, Ontario, Canada

Table 4
Summary of recommendations based on results of systematic review and assessment of study quality

A. The term "health administrative data" should be added as MeSH and EMBASE subject headings and should be included as a key term in all studies using health administrative data.
B. Complete description of the validation cohort should include age, a description of the disease or health condition being studied, the distribution of disease severity (if applicable), and the geographic location or jurisdiction in which the validation cohort is located.
C. Where possible, revalidation of identification algorithms should take place in other jurisdictions before application in those jurisdictions' administrative data to ensure accuracy.
D. The training and job description of personnel interpreting the reference standard in a validation study and those personnel should be blinded to elements of administrative data when interpreting the reference standard. If two or more personnel are involved, statistics of consistency of reference standard interpretation should be reported (e.g., kappa coefficient).
E. Cross-tabulation of results should be included in the results section of articles, allowing for readers to assess the power and confidence intervals of the results.
F. Statistics describing diagnostic accuracy of algorithms should be described in the methods section, and at least four markers of diagnostic accuracy (with 95% CIs) should be reported.
G. Where PPV and NPV are reported, the prevalence of disease in the validation cohort should equal the prevalence of disease in patients contained within health administrative databases.

Reporting validity results – Benchimol (2011) appendix

Supplemental Data 1. Checklist of reporting criteria for studies validating health administrative data algorithms. This document can be printed and used as a guide for authors of validation studies and for users of the literature to evaluate the completeness of reporting of validation studies.

TITLE, KEYWORDS, ABSTRACT
Identify article as study of assessing diagnostic accuracy
Identify article as study of administrative data
INTRODUCTION:
State disease identification & validation one of goals of study
METHODS:
Participants in validation cohort:
Describe validation cohort (Cohort of patients to which reference standard was applied)
• Age
• Disease
• Severity
• Location/Jurisdiction
Describe recruitment procedure of validation cohort
• Inclusion criteria
• Exclusion criteria
Describe patient sampling (random, consecutive, all, etc.)
Describe data collection
• Who identified patients and did selection adhere to patient recruitment criteria
• Who collected data
• *A priori* data collection form
• Disease classification
• Split sample (i.e. re-validation using a separate cohort)

METHODS (cont.):
Test Methods:
Describe number, training and expertise of persons reading reference standard
If >1 person reading reference standard, quote measure of consistency (e.g. kappa)
Blinding of interpreters of reference standard to results of classification by administrative data e.g. Chart abstractor blinded to how that chart was coded
Statistical Methods:
Describe methods of calculating/comparing diagnostic accuracy
RESULTS:
Participants:
Report when study done, start/end dates of enrollment
Describe number of people who satisfied inclusion/exclusion criteria
Study flow diagram
Test results:
Report distribution of disease severity
Report cross-tabulation of index tests by results of reference standard

RESULTS (cont.):
Estimates:
Report at least 4 estimates of diagnostic accuracy
Diagnostic Accuracy Measures Reported:
• Sensitivity
• Spec
• PPV
• NPV
• Likelihood ratios
• Kappa
• Area under the ROC curve / c-statistic
• Accuracy/agreement
• Other (specify)
Report accuracy for subgroups (e.g. age, geography, different sex, etc.)
If PPV/NPV reported, ratio of cases/controls of validation cohort approximate prevalence of condition in the population
Report 95% confidence intervals for each diagnostic measure
DISCUSSION:
Discuss the applicability of the validation findings

*Not all criteria may be applicable for all projects…

but many will be

Table 4. Validation of top-performing ICD-10 influenza and RSV

ICD-10 Algorithm	TP	FP	FN	TN
FLU1 Algorithm[a]				
0–4	751	69	378	8,975
5–19	379	24	223	2,264
20–34	295	15	156	2,719
35–49	518	28	228	4,116
50–64	1,405	78	544	10,545
65–74	1,772	115	652	11,793
75–84	2,683	160	931	14,105
85+	2,952	164	887	13,714

Hamilton et al Validating International Classification of Disease 10th Revision algorithms for identifying influenza and respiratory syncytial virus hospitalizations. PLoS One. 2021. 7;16(1):e0244746.

10 considerations for reporting identification algorithms

1. When reporting validity results: Provide n as well as % for: FP, TP, FN, TN

2. Examine/characterize: “false” cases i.e., false positives and false negatives *(example in link below)*

3. Provide multiple metrics (and 95% CIs); including PPV/NPV, if cohort prevalence =~ to general pop

4. Relatedly: Estimate prevalence of outcome in validation sub-sample vs target population

5. Provide goal-oriented algorithm options e.g.:
   ‘high sensitivity’, ‘balanced’ etc.

Table 2 the validity of the algorithms

Algorithm	Sensitivity (%, 95 CI)	Specificity (%, 95 CI)	PPV (%, 95 CI)	NPV (%, 95 CI)
High sensitivity	94.2 (90.1–98.4)	93.7 (91.5–95.9)	79.2 (72.5–85.8)	98.5 (97.3–99.6)
High PPV	75.2 (67.5–82.9)	98.3 (97.2–99.5)	91.9 (86.6–97.3)	94 (91.9–96.1)
High accuracy	85.1 (78.8–91.5)	97.3 (95.8–98.7)	88.8 (83.1–94,5)	96.3 (94.6–98)
Balanced sensitivity and PPV	89.3 (83.7–94.8)	96.2 (94.5–97.9)	85.7 (79.6–91.8)	97.2 (95.8–98.7)
Balanced specificity and NPV	91.7 (86.8–96.6)	94.5 (92.5–96.6)	81.0 (74.5–87.6)	97.8 (96.5–99.2)

Xu et al. Development and validation of case-finding algorithms for recurrence of breast cancer using routinely collected administrative data. BMC cancer. 2019;19(1):1-0.

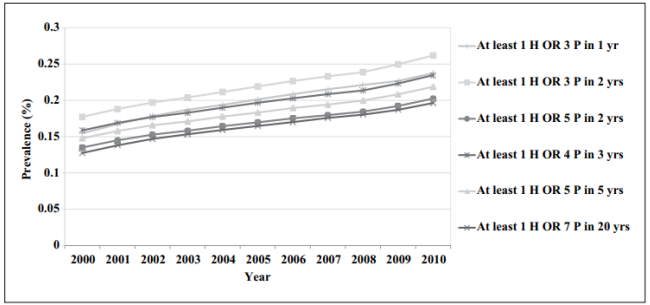

Figure 1. Age-and-sex standardised MS prevalence estimates, across different administrative data case definitions. H: hospitalization for MS; MS: multiple sclerosis; P: physician billing claim for MS; yr: year.

Widdifield et al. Development and validation of an administrative data algorithm to estimate the disease burden and epidemiology of multiple sclerosis in Ontario, Canada. Multiple Sclerosis Journal. 2015;21(8):1045-54.

10 considerations for reporting identification algorithms

6. Operationalize the details of the identification algorithm clearly:

- *diagnostic codes* (e.g., '250'; explain why certain ones may have been excluded)
- *versions* (e.g., ICD-10 vs ICD-10-CA; jurisdiction-specific codes [e.g., BC has '50B'])
- *type of diagnostic code* (e.g., physicians vs other healthcare practitioners; outpatient. vs inpatient care)
- *how codes were queried* (e.g., codes starting with '250' vs '250' per se)
- *search window* (e.g., events occurring in calendar/fiscal year; 'co-occurring' within x months of each other; how one-off events handled)

7. When possible, provide codes, macros [SAS], functions [R] etc. relevant to the algorithm/definitions

Note. Some algorithms are proprietary (e.g., certain comorbidity indices are purchases)

10 considerations for reporting identification algorithms

8. Describe/characterize validation sub-sample; how it compares to target population
   → can help shed light on potential biases (e.g., selection bias, generalizability)

9. Where applicable: visualize the patterns of findings and trends, especially across strata of interest
   → Can help clearly demonstrate patterns, findings (compared to a dense table per se)

10. Contextualize + caveat the application of algorithms:

- Algorithms will likely perform differently given length of available lookback/follow-up data
- Many case-finding algorithms are de facto dependent on healthcare use →
  what about subpopulations who may tend to under-use healthcare?
  (e.g., for some types of healthcare use, such groups may be: young men; first-generation immigrants)

Additional resources

Many Canadian identification algorithms are listed here, from the Health Data Research Network Canada: https://www.hdrn.ca/en/algorithm/

As part of data quality and cleaning checks for practitioner billings (which houses diagnostic codes, and is thus a core component of many identification algorithms), some MSP cleaning is typically required:

For cleaning records from the MSP Payment Information File (healthcare practitioner billings), there is useful code presented on the 'Code Snippets' section of the my.popdata.bc.ca website (https://www.popdata.bc.ca/researchers/resources/Snippets).

→To access: One can sign up for an account for free : https://my.popdata.bc.ca/account/register/

Also, PopData Research in Action pages showcase past examples of researcher projects using administrative data generally - https://www.popdata.bc.ca/ria

The pure and simple truth is rarely pure and never simple

EDITORIAL

Editorials represent the opinions of the authors and JAMA and not those of the American Medical Association.

Finding Pure and Simple Truths With Administrative Data

Mary S. Vaughan Sarrazin, PhD
Gary E. Rosenthal, MD

The pure and simple truth is rarely pure and never simple. —Oscar Wilde

ADMINISTRATIVE DATA HAVE BEEN USED TO ASSESS quality of care and variations in health care delivery for nearly 3 decades. Indeed, administrative data have provided important insights on racial disparities in care,[1] geographic differences in utilization,[2] and variations in outcomes across hospitals.[3] In the absence of national clinical registries, administrative data will continue to be an important source of information about health care delivery in the United States because of their ready availability, low cost, and ability to span multiple years and health care settings. Moreover, in contrast to data from randomized controlled trials, administrative data reflect real-world treatment settings and unselected populations. However, users must be aware of the inherent limitations of administrative data to avoid erroneous conclusions.

In this issue of *JAMA*, Lindenauer and colleagues[4] illustrate the complexity in deciphering simple temporal trends in hospital mortality for pneumonia. Using a nationally representative database—the Nationwide Inpatient Sample—the authors found that the rate of hospitalizations with a

tively pure and simple measurements may be marred by a failure to appreciate the dynamic circumstances that affect how *International Classification of Diseases, Ninth Revision, Clinical Modification* (*ICD-9-CM*) codes are recorded. These issues go beyond pneumonia and may have affected many studies based on administrative data. For example, relative decreases in risk-adjusted hospital mortality between 2000 and 2007 for congestive heart failure (CHF), acute myocardial infarction (AMI), and stroke have also been reported—49%, 36%, and 26%, respectively.[5] Given that this study identified patients using principal diagnoses, it is possible that the reported decreases also resulted from changes in coding practices in which patients with more severe disease were given other principal diagnoses (eg, pulmonary edema or respiratory failure for CHF).

Nuances in the assignment of principal and secondary diagnoses can also affect assessments of hospital performance. Since 2005, the Centers for Medicare & Medicaid Services (CMS) has monitored the provision of recommended care to patients hospitalized with AMI, CHF, pneumonia, and chronic obstructive pulmonary disease (COPD). Because sampling of patients for specific performance measures is usually defined by principal diagnoses,[6] the sequencing of *ICD-9-CM* codes may affect performance assessments. For example, a study by Wu et al[7] in 2002 reported lower use of aspirin, heparin, β-blockers, and primary angioplasty among AMI patients with CHF com-

Thank you

always learning…

Happy to connect, discuss, collaborate, share ideas on anything administrative data related!

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