

Administrative database in Neurosurgery

- Similar reoperation rates in upper versus lower thoracic to pelvis instrumentation: an analysis of 7,300 patients utilizing a national administrative database
- Cancer Health Disparities Affecting Glioblastoma Survival in Ontario, Canada: A Population-Based Study
- National assessment of frailty impact on endovascular mechanical thrombectomy for minor to moderately severe large vessel occlusions per NIHSS
- Identifying associated comorbidities in the development of trigeminal neuralgia: A propensity-matched analysis of the National Inpatient Sample
- Stem cell therapy use in patients with dementia: a systematic review
- Prediction of seizure risk after repetitive mild traumatic brain injury in childhood
- Unplanned shunt readmission: what does it really look like?
- Time trends in spine surgery in Italy: a nationwide, population-based study of 1,560,969 records of administrative health data from 2001 to 2019



Large administrative [databases](#) have assumed a major role in [population-based study](#) examining [health care](#) delivery.

Important considerations in planning, developing, and maintaining a successful database

<https://www.ncbi.nlm.nih.gov/pmc/articles/PMC6304383/>

1. [Purpose/objectives](#) of database
2. [Stakeholders](#)/subject matter [experts](#)/users

- a. Intra- or interdisciplinary
- b. [Commitment](#)/involvement
3. [Scope](#) of database
 - a. Target patient [population](#)
 - b. Volume
 - c. Disease-, site- or treatment-specific
 - d. Cross-sectional vs. longitudinal
 - e. Database lifetime
 - f. Core dataset
4. Sources of data/links to other databases
5. Available infrastructure
6. Choice of database program/housing issues (interdependent with infrastructure available, issues of staffing, maintenance/enhancements/upgrades and cost)
7. Staffing
 - a. Background/training
 - b. Exact role
 - c. Retention
 - d. Cost
8. Governance plan
9. Quality assurance
 - a. The ALCOA data integrity test (Attributable, Legible, Contemporaneous, Original and Accurate)
 - b. Standardized data sources/definitions
 - c. Oversight plan
10. Compliance
 - a. Institutional review/ethical board approval
 - b. Issues of consent/authorization vs. waiver
 - c. Applicable policies and regulations at all levels (e.g., Code of Federal Regulations; Good Clinical Practice; Health Insurance Portability and Accountability Act [HIPAA and/or other applicable privacy

laws; institutional information security policies; other policies and regulations)

11. Assessment of initial feasibility and long-term viability (baseline and maintenance costs being major considerations)

Oravec et al.¹⁾ rightly bring up concerns about the [quality](#) of [diagnosis codes](#) that may impact the [internal validity](#) of studies using these [data](#). Quality improvement efforts by the institutions that manage these [databases](#), including the involvement of [neurosurgeon](#) input in database design, are one approach to address this issue. An opensource designation of neurosurgical diagnosis codes and relevant complications can also help standardize the way the field uses these [datasets](#). Additionally, like other types of retrospective data, analysis drawn from administrative databases can be used for descriptive and inferential analysis, but cannot establish [causality](#). This should be appropriately mentioned as a limitation in any [paper](#) that uses this type of data. These limitations, however, do not obviate the utility of administrative databases in answering particular types of questions and as hypothesis-generating tools. Descriptive and inferential analysis aside, the volume provided by administrative databases, which is unparalleled by any prospective dataset, is especially useful for the generation of predictive models. Ultimately, the goal of Harary et al. was to highlight the fact that administrative databases are an example of only one type of data that falls within the umbrella of “[Big Data](#),” and that they only begun to scratch the surface of what the data science, powered by Big Data and [artificial intelligence](#), can offer the neurosurgical community and patients²⁾.

Zhou et al. evaluated the [sensitivity](#), [specificity](#), [positive predictive value](#) (PPV) and [negative predictive value](#) (NPV) of [Cushing’s syndrome](#) (CS) etiology-related [ICD-10](#) codes or code combinations by comparing hospital [discharge administrative database](#) (DAD) with established diagnoses from medical records.

Coding for patients with [adrenocortical adenoma](#) (ACA) and those with [bilateral macronodular adrenal hyperplasia](#) (BMAH) demonstrated disappointingly low sensitivity at 78.8% (95% CI: 70.1% - 85.6%) and 83.9% (95% CI: 65.5% - 93.9%), respectively. BMAH had the lowest PPV of 74.3% (95% CI: 56.4% - 86.9%). In confirmed ACA patients, the sensitivity for ACA code combinations was higher in patients initially admitted to the Department of Endocrinology before surgery than that in patients directly admitted to the Department of Urology (90.0% vs 73.1%, $P = 0.033$). The same phenomenon was observed in the PPV for the BMAH code (100.0% vs 60.9%, $P = 0.012$). Misinterpreted or confusing situations caused by coders (68.1%) and by the omission or denormalized documentation of symptomatic diagnosis by clinicians (26.1%) accounted for the main source of coding errors.

Hospital [administrative database](#) is an effective data source for evaluating the etiology of [Cushing’s syndrome](#) (CS) but not [adrenocortical adenoma](#) (ACA) and [bilateral macronodular adrenal hyperplasia](#) (BMAH). Improving surgeons' [documentation](#), especially in the delineation of symptomatic and locative diagnoses in discharge abstracts; department- or disease-specific training for coders; and more [multidisciplinary collaboration](#) are ways to enhance the applicability of administrative data for CS etiologies³⁾.

References

1)

Oravec CS, Motiwala M, Reed K, et al. Big data research in neurosurgery: a critical look at this popular

new study design. Neurosurgery. 2017. doi: 10.1093/ neuros/nyx328

2)

Harary M, Smith TR, Gormley WB, Arnaout O. Letter: Big Data Research in Neurosurgery: A Critical Look at This Popular New Study Design. Neurosurgery. 2018 Jun 1;82(6):E186-E187. doi: 10.1093/neuros/nyy085. PubMed PMID: 29618111.

3)

Zhou J, Zhang M, Lu L, Guo X, Gao L, Yan W, Pang H, Wang Y, Xing B. Validity of discharge ICD-10 codes in detecting the etiologies of endogenous Cushing's syndrome. Endocr Connect. 2019 Jul 1. pii: EC-19-0312.R2. doi: 10.1530/EC-19-0312. [Epub ahead of print] PubMed PMID: 31340196.

From:
<https://neurosurgerywiki.com/wiki/> - **Neurosurgery Wiki**

Permanent link:
https://neurosurgerywiki.com/wiki/doku.php?id=administrative_database_in_neurosurgery

Last update: **2024/06/07 02:55**

