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Original article

Comparison of comorbidity classification methods for predicting outcomes in a population-based cohort of adults with human immunodeficiency virus infection

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ABSTRACT

Purpose: We compared the John's Hopkins' Aggregated Diagnosis Groups (ADGs), which are derived using inpatient and outpatient records, with the hospital record-derived Charlson and Elixhauser comorbidity indices for predicting outcomes in human immunodeficiency virus (HIV)-infected patients.
Methods: We used a validated algorithm to identify HIV-infected adults ($n = 14{,}313$) in Ontario, Canada, and randomly divided the sample into derivation and validation samples 100 times. The primary outcome was all-cause mortality within 1 year, and secondary outcomes included hospital admission and all-cause mortality within 1–2 years.
Results: The ADG, Elixhauser, and Charlson methods had comparable discriminative performance for predicting 1-year mortality, with median c-statistics of 0.785, 0.767, and 0.788, respectively, across the 100 validation samples. All methods had lower predictive accuracy for all-cause mortality within 1–2 years. For hospital admission, the ADG method had greater discriminative performance than either the Elixhauser or Charlson methods, with median c-statistics of 0.727, 0.678, and 0.668, respectively. All models displayed poor calibration for each outcome.
Conclusions: In patients with HIV, the ADG, Charlson, and Elixhauser methods are comparable for predicting 1-year mortality. However, poor calibration limits the use of these methods for provider profiling and clinical application.

Introduction

Advances in the management of human immunodeficiency virus (HIV) infection have transformed the illness from one associated with high rates of mortality and inpatient utilization into a chronic illness characterized by an aging cohort of ambulatory patients living with multiple comorbid diseases [1–6]. In this context, there is an increased interest in the use of administrative health care databases to conduct population-based research examining patterns of health services utilization and health outcomes among persons living with HIV [7–9]. Because these studies are typically observational in nature, risk adjustment for morbidity burden is required.

Among the various methods available for summarizing the comorbidity of a population, the Charlson and Elixhauser comorbidity indices are commonly used for risk adjustment in observational studies conducted with administrative databases. The Charlson index was originally developed to predict mortality in hospitalized patients using data abstracted from the charts of general medicine inpatients and was subsequently adapted for use with administrative databases using International Classification of Diseases, ninth revision, (ICD-9-CM) diagnosis and procedure codes [10,11]. The weighted index is

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based on diagnosis codes for 17 conditions, each of which are assigned a value of 1, 2, 3, or 6, from which a summary score is computed for each patient. Like the Charlson index, the Elixhauser comorbidity index was developed to quantify the burden of comorbidity among hospitalized patients [12]. However, in lieu of a summary score, the Elixhauser index is computed using binary indicators (i.e. present or absent) for 30 different medical conditions. Although both the Charlson and Elixhauser methods have been validated in various settings and have been updated for use with International Classification of Diseases, 10th revision (ICD-10) codes [13–17], both measures were designed for use solely with inpatient administrative data, thereby limiting their utility in patients who are managed predominantly in outpatient settings. In contrast, the Johns Hopkins Adjusted Clinical Group (ACG) Case-Mix System uses administrative data that are derived from inpatient and outpatient encounters, thereby permitting risk adjustment in ambulatory and hospitalized patients [18–20]. The ACG system assigns each ICD-9 or ICD-10 diagnosis to one of 32 diagnosis clusters known as Aggregated Diagnosis Groups (ADGs). ADGs are similar in terms of severity, persistence over time, and expected need for health care utilization. Each individual may have between zero and 32 ADGs [21].

Although several risk-adjustment indices have been developed and validated for use in HIV patients, these measures have been developed using clinical data that are not routinely available in administrative databases [22–27]. There is therefore a need to compare the predictive validity of comorbidity measures derived from administrative health care data in a population of persons with HIV. Accordingly, we compared the ability of the ADG, Charlson, and Elixhauser methods to predict mortality and hospitalization in persons with HIV. We speculated that by virtue of being derived from both inpatient and outpatient administrative patient records, the ADG method would have superior predictive performance relative to either the Charlson or Elixhauser comorbidity indices.

Methods

Data sources

We obtained data from Ontario's administrative health care databases, which are available at the Institute for Clinical Evaluative Sciences through a data sharing agreement with the Ontario Ministry of Health and Long-Term Care. Specifically, we used the Ontario Health Insurance Plan (OHIP) database to identify claims submitted by physicians to the provincial universal health insurance program. To receive payment for services rendered, physicians must submit the name, date of birth, and OHIP card number of the individual patient seen, the service provided (i.e., a service code), and a single diagnosis code on each claim. For OHIP claims, the diagnosis code is a truncated three-digit version of the corresponding ICD-9 code. We obtained hospitalization data from the Canadian Institute for Health Information Discharge Abstract Database (CIHI DAD), which contains information from all acute care hospital separations in Ontario. Each hospitalization record includes the patient OHIP number, dates of admission and discharge from the hospital and up to 25 diagnoses contributing to a given admission, coded by trained health information professionals using standard ICD-10 diagnosis and procedure codes. We obtained basic demographic information, including age, sex, and date of death, from the Registered Persons Database, a registry of all Ontario residents eligible for health insurance. Finally, we used the Ontario Mental Health Reporting System (OMHRS) database to identify admissions to adult-designated inpatient mental health beds in psychiatric and nonpsychiatric facilities in Ontario. Each record in the OMHRS contains data regarding psychiatric and nonpsychiatric diagnoses, as well as reasons for admission and discharge. These databases were deterministically linked in an anonymous fashion using encrypted health card numbers and have been previously used for the validation of comorbidity indices in populations of Ontario residents with chronic diseases [28–31].

Study population

We identified adults in Ontario aged 18 years and older who were living with HIV as of April 1, 2009 from the Ontario HIV database, an administrative data registry of Ontario residents with diagnosed HIV infection, which was generated using a previously validated case-finding algorithm [32]. The definition of three physician claims with an ICD-9 code for HIV infection (042, 043, and 044) within a 3-year period has a sensitivity and specificity of 96.2% (95 confidence intervals 95.2%–97.9%) and 99.6% (95% confidence intervals 99.1%–99.8%), respectively, for identifying persons with HIV who are regular users of primary care. Due to the use of administrative health care databases, complete follow-up was available for all individuals.

For each patient, we determined the Charlson comorbidity score and presence of Elixhauser comorbidities using hospitalization data obtained from the CIHI DAD for all admissions occurring in the 2 years preceding the index date, April 1, 2009. We obtained mental health and addiction diagnoses for the Elixhauser comorbidities from the OMHRS database in addition to the CIHI DAD and OHIP physician claims database. Following common practice, individuals who had not been hospitalized in the previous 2 years had their Charlson score set to zero and values for each of the 30 Elixhauser comorbidities designated as absent [33]. We used the Johns Hopkins ACGs case-mix assignment software (Sun Microsystems Inc., Santa Clara, CA) to determine the presence or absence of each of the 32 ADGs for a given patient using all diagnostic codes listed in the CIHI DAD and OHIP databases in the 2 years preceding the index date.

Outcomes

The primary outcome was death from any cause within 365 days of the index date (April 1, 2009). Secondary outcomes included hospitalization from any cause within 365 days of the index date and death from any cause between days 366 and 730 after the index date among individuals who survived for at least 1 year.

Statistical analysis

To evaluate the predictive performance of each comorbidity classification scheme in a sample that was independent of the sample in which regression models were derived, we used a random number generator to divide the overall sample into approximately equal-sized derivation and validation samples. In the derivation sample, we used a series of "base" and "comorbidity-adjusted" multivariable logistic regression models to assess the predictive performance of each comorbidity measure. Specifically, the base model for each outcome included age (in years), sex, neighborhood income quintile, and number of years in the Ontario HIV database, whereas comorbidity-adjusted models included all the variables in the base model in addition to either the Charlson comorbidity index (as a continuous variable), indicator variables denoting the presence or absence of the 30 Elixhauser comorbidities or indicator variables denoting the presence or absence of the 32 ADGs. The discriminatory performance of each model developed in the derivation sample was assessed in the derivation and validations samples using the c-statistic, which is equivalent to the area under the receiver operating characteristic curve for dichotomous outcomes [34]. We repeated the process of randomly splitting the original sample into derivation and validation samples 100 times, applying the coefficients from each derivation