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Inpatients suffering from alcoholism automatically identified by electronic phenotyping

Griessbach Alexandra[a], Battegay Edouard[abc], Beeler Patrick E.[abc]

[a] Department of Internal Medicine, University Hospital Zurich and University of Zurich, Switzerland
[b] University Research Priority Programme "Dynamics of Healthy Aging", University Hospital Zurich and University of Zurich, Switzerland
[c] Centre of Competence Multimorbidity, University Hospital Zurich and University of Zurich, Switzerland

Background

Alcohol abuse disorder (AUD) refers to the drinking of alcohol that results in mental or physical health problems and is associated with poor medication adherence, economic costs, loss of productivity and psychiatric comorbidity. "Electronic phenotyping is the process of deriving phenotype information from incomplete sources of data, such as electronic health records" (doi:10.1038/nrg.2015.36). Since little is known about electronic phenotyping of AUD, we sought to develop an algorithm that automatically detects stays of AUD patients in structured clinical data.

Methods

In this retrospective analysis we used routinely collected electronic health record data of inpatients aged 18 years and older, discharged between august 2015 and August 2017 from a large tertiary care academic medical centre. The data included patient information (weight, height, age), laboratory values, length of stay, readmissions, intensive care unit (ICU) stays, medication orders, diagnoses and other information. The data were processed using structured query language (SQL) statements and R software. In the first steps, initial patient data were filtered using comprehensive alcohol specific ICD-10 diagnoses, in which SQL queries searched for strings matching the patient diagnoses (table 1). The list was further extended by matching diagnosis names/descriptions using name mapping tables. ICD-10 codes were chosen from the Centers for Disease Control and Prevention (CDC) – Alcohol-related ICD code lists and other resources, but nonspecific diagnoses such as stroke and hypertension were intentionally left out (table 1). Iterative refinements of the algorithm allowed for filtering increasingly specific and predictive features, such as AUD-associated medication orders (anatomic therapeutic class [ATC] codes), further diagnoses (ICD-10 codes), blood alcohol concentrations and the withdrawal assessment scale score (Wetterling; AES or AWS scale). The AES scale was introduced into the electronic health records in 2015, and only data generated after this point were ultimately considered. A total of 3064 patient stays comprised our gold standard AUD population. All positive predictive values (PPVs) of further potential factors for identifying AUD were calculated in relation to this gold standard. Stays in which the patient had undergone an AES assessment were found by searching for terms (%aes%). Blood alcohol concentrations were found in a similar manner by searching for the term "alcohol" and the unit "mmol/l". Medication orders and ICD-10 codes were identified by searching for the ATC/ICD-10 codes and their corresponding drug names with help of diagnoses and medication mapping tables (free-text option and misspellings of the medications and diagnoses entered by providers and the billing team). We generated SQL queries defining intersections in which the number of stays for each feature were determined. This resulted in four groups; AWS / gold standard intersection, blood alcohol concentration / gold standard intersection, F10 ICD codes / gold standard intersection and ATC medication / gold standard intersection, which enabled the calculation of the PPVs (fig. 1). Further analysis included separation of patient blood alcohol concentrations into heavy and moderate drinkers, with a cut-off value of 17.392 mmol/l (derived from the Federal Aviation Regulation – Virginia Polytechnic Institute and State University) and the F10% codes which define diagnoses related to alcohol consumption.

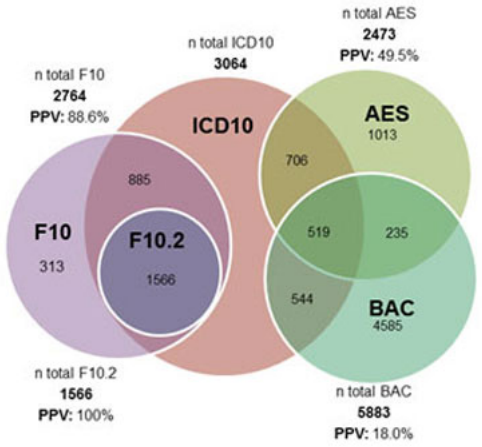
Results

By filtering of the raw data using the specific ICD-10 codes list, we identified a population of 3064 stays. The first intersection was generated using the F10% ICD-10 codes, which resulted in 2451 stays and a PPV of 88.6%. Of these stays, 1566 (PPV 100%) were associated with alcohol dependence disorder (F10.2). Using the AES scale, a second intersection was determined (1225 patients), which resulted in a PPV of 49.5%. The AES stays outside our gold standard population showed lower scale severity, blood alcohol concentration, length of stay and alcohol-related laboratory values such as aspartate and alanine transaminase and gamma-glutamyltransferase (ALT, AST and GGT). It is unclear why these patients had undergone an AES assessment and if they should be considered alco-

Correspondence:
Patrick E. Beeler, MD, Department of Internal Medicine, University Hospital Zurich and University of Zurich, Raemistrasse 100, CH-8091 Zurich, Switzerland, patrick.beeler[at]usz.ch

holics. Further analysis will include AUD correlations with the AES severity scale (AES assessment – Universitäre Psychiatrische Dienste Bern; stratification of scale) and the differences in characteristics between the groups. The third intersection was made using alcohol specific ATC medication codes (disulfiram, calcium carbimide, acamprosate, naltrexone and nalmefene), in which only 27 stays were identified, resulting in a PPV of 29.6%. Disulfiram was the most frequent medication order. The medications most frequently used to treat AUD patients include benzodiazepine derivatives; however, they are often used for various other conditions and are therefore unspecific and unusable as an electronic phenotyping predictor. Data profiling of features specific to gold standard population showed that AUD patients had a "foot print" of medication orders such as being frequently prescribed vitamin B and laxatives. Blood alcohol concentration determined a fourth intersection and resulted in 1063 patient stays (PPV 18.0%). The mean blood alcohol concentration of our gold standard inpatient population was 25.428 mmol/l, substantially higher than the mean value for all patients (including the gold standard population) who had their blood alcohol measured (11.69 mmol/l). Blood alcohol is typically measured in all patients who are admitted to hospital after an accident, which could account for the large number of stays not found in our gold standard group, potentially explaining the low PPV.

Figure1: Intersections and positive predictive values (PPV) of AES scale, blood alcohol concentration (BAC) and "F10" diagnoses with ICD-10 gold standard population.



Discussion and conclusions

We developed an electronic phenotyping algorithm from which we can identify patients suffering from AUD. Using our gold standard population for testing predictive data features, the F10.2 ICD code showed the highest PPV with 100%. Whereas some of the PPVs are low, e.g., medications, there is always a trade-off between increased number of patients and specificity. We found further potentially interesting features, such as a high number of prescriptions of vitamin B and laxatives for these inpatients, as well as increased blood alcohol concentration in our gold standard population. Further research will look at inpatient characteristics such as age, sex, blood alcohol concentration, length of stay, readmissions, severity of AES and the influence of multi-morbidity. Prospectively, the algorithm could be used to identify potential AUD patients and prepare clinicians for such cases. It is estimated that up to 42% of patients admitted to general hospitals, and one third of patients admitted to hospital ICUs have some form of AUD but only a small proportion of these are identified upon admission (doi:10.1111/ane.12671.). A refined algorithm may identify alcoholics according to data generated by previous hospital stays, baseline characteristics, laboratory values and be implemented into clinical decision support systems.

Disclosures
No potential conflict of interest relevant to this article was reported

Table 1: Alcohol-specific ICD-10 codes – gold standard.

ICD10	Diagnosis	Stays (n)
F10.1	Harmful use	560
F10.2	Dependence syndrome	1566
F10.24	Alcohol dependence with alcohol-induced mood disorder	0
F10.25	Alcohol dependence with alcohol-induced psychotic disorder with delusions	0
F10.3	Withdrawal state	186
F10.4	Withdrawal state with delirium	318
G31.2	Degeneration of nervous system due to alcohol	47
G62.1	Alcoholic polyneuropathy	111
G72.1	Alcoholic myopathy	1
I42.6	Alcoholic cardiomyopathy	11
K70.0	Alcoholic fatty liver	69
K70.2	Alcoholic fibrosis and sclerosis of liver	22
K70.3	Alcoholic cirrhosis of liver	789
K70.4	Alcoholic hepatic failure	98
K70.9	Alcoholic liver disease, unspecified	20
K86.0	Alcohol-induced chronic pancreatitis	115
Z50.2	Alcohol rehabilitation	5