Empowering Patient Risk Management Strategies: Validation the AHRQ Elixhauser Mortality Index on Italian Hospital Administrative Dataset

ANDREA, AF, Fidecicchi
Department of Public Health, University of Naples "Federico II", Naples, Italy

Teresa ANGELA, TAT, TRUNFIO*
Department of Advanced Biomedical Sciences, University of Naples "Federico II", Naples, Italy

ANTONIO, ADA, D'amore
A.O.R.N. "Antonio Cardarelli", Naples, Italy

Maria PIA, MM, Mannelli
A.O.R.N. "Antonio Cardarelli", Naples, Italy

ARIANNA, AS, Scala
Department of Public Health, University of Naples "Federico II", Naples, Italy

ABSTRACT

The study of patients' comorbidities is a fundamental element in risk analyses or quality assessment of health care systems. In addition to Charlson's index, which is the most widely used in the literature, there is Elixhauser's index, which analyses the comorbidities of patients in the administrative flow by identifying 29 categories, thus being more accurate and precise. The aim of this work was to validate the use of the Elixhauser measure and the AHRQ Elixhauser Mortality Index to estimate in-hospital mortality within the AORN 'A. Cardarelli' hospital in southern Italy. To do this, it was first necessary to create a special Python script for the identification of Elixhauser classes. From the classes, it was possible to obtain the index, which was then investigated through the implementation of logistic regression. The c-statistic of the index was 0.626, slightly lower than the mortality predicted with the extended version of the Elixhouser of 0.666, but still lower than the validation results available in the literature for other contexts.

CCS CONCEPTS

• **General conference proceedings, Health informatics, Health care information systems**;

KEYWORDS

Elixhauser, AHRQ Elixhauser Mortality Index, Logistic Regression, c-statistic, Python

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1 INTRODUCTION

The study of patient comorbidities is an important component of health research. Having a system available that is capable of dealing objectively and standardised with this variable can also help to describe and compare patients with each other within a population [1] or support risk estimates [2]. Comorbidity is associated with worse health outcomes and more complex clinical management. This therefore affects a fundamental element of clinical governance which is risk management, which must evolve towards a more responsive and systems-based system and the interaction people have on processes and less crisis-oriented.

Among the most popular ways of measuring comorbidities in health research are the Charlson measure (in its various adaptations) [3] and the Elixhauser measure [4]. The first index uses and defines 19 medical conditions and is the most widely used indicator in this context. The second, on the other hand, is a more recent model that works on 30 medical conditions by including some of them (such as hypertension, obesity, weight loss, and psychiatric disorders) that are excluded from the previous index [5] and that improve performance [6, 7]. Both use the list of comorbidities reported for each patient within the hospital discharge form, and thus the administrative flow, already coded according to International Classification of Diseases (ICD) diagnosis codes [8].

The original Elixhauser, in particular, was developed using the ICD, 9th Revision, Clinical Modification (ICD-9-CM) but has undergone several revisions over the years, such as version 3.0 posted on the website of the Agency for Healthcare Research and Quality (AHRQ) [9] which removed cardiac arrhythmias from the list of comorbidities, thus moving to 29 medical conditions or the updates which followed the use of the 10th Revision, Clinical Modification (ICD-10-CM) [10].

From these flags it is possible, by defining appropriate weights, to estimate in-hospital mortality [11, 12]. This parameter is commonly used as an indicator of healthcare quality [13], as done in the context of the European Collaboration for Healthcare Optimization (ECHO)

*Corresponding author: teresa.trunfio@gmail.com

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project [14] to compare the different healthcare systems of different nations.

Being able to calculate this parameter in real-time therefore becomes strategic for healthcare management. This evaluation adds to the techniques in use in healthcare to test, for example, the impact of COVID19 [15, 16], indoor air quality in hospitals [17], hospital infections [18, 19], biomedical data and signals [20, 21] or more managerial parameters such as hospitalization per pathology [22-24] or related to healthcare technology [25, 26].

Although there are many works in the literature on the calculation of the Elixhauser index, in the Italian context, which is very different from the American one both for different coding and for the number of secondary diagnoses included in the hospital discharge form, it is still not validated on a large-scale dataset. The aim of this work is to validate the use of the Elixhauser and of the mortality index developed by the AHRQ [27] in predicting intrahospital mortality in the AORN "A. Cardarelli" of Naples, the main hospital in the south of Italy.

2 METHODS

In order to calculate and validate the AHRQ Elixhauser Mortality Index, the following variables were extracted from the hospital discharge form flow:

- - Secondary diagnoses;
- - Diagnosis Related Groups (DRG);
- - Mode of discharge; and
- - Record number.

Records of 119751 patients treated within the AORN 'A. Cardarelli' of Naples from 2019 to 2023 were extracted. Patients with voluntary discharge, paediatric and obstetric admissions, patients transferred from other hospitals and those accessing the hospital for day surgery or day hospital were excluded. A variable called 'Mortality' was created from the mode of discharge, which is equal to 1 if the patient is discharged deceased and 0 in other cases.

2.1 Elixhauser comorbidity flags

Before calculating the selected mortality index, it was necessary to translate the vector of secondary diagnoses for each patient into a series of flags in accordance with Elixhauser's definition [4]. Since the Italian coding stopped at the ICD-9-CM of 2007 and the DRG system at version 24, it was not possible to use automatic tools available in programming environments such as R or online. For this reason, a special Python script was created. Using old code versions available on the AHRQ website [9] as a reference, two functions were first created: 1) for the classification of secondary diagnoses in the Elixhauser comorbidity classes; 2) for the classification of the DRG within the same classes. In both functions, a library of ICD-9-CM/DRG v.24 codes updated according to Quann et al. [28] was given, which through a succession of if-else constructs verifies that the diagnosis/DRG belongs to one of the defined classes. The DRG categorization serves to remove secondary diagnoses that are, however, directly related to the DRG and must therefore be excluded from the calculation. The main code developed in the Colab environment for faster sharing between researchers retrieves these two functions for each patient, removes the flags associated with directly correlated comorbidities and returns a vector of 29 variables consisting of 0/1 for each patient in output.

2.2 AHRQ Elixhauser Mortality Index

Having obtained the vector with the 29 flags associated with the Elixhauser comorbidities for each patient included in the dataset, it was possible to calculate the in-hospital mortality index. To do this, the coefficients developed by the AHRQ weighting each of the comorbidities present in Elixhauser were used. Table 1 shows the coefficients used.

2.3 Index assessment

To assess the performance of the index, a simple logistic regression was implemented. Similar to linear regression, it is used to estimate the relationship between a dependent variable and one or more independent variables. Specifically, logistic regression estimates the probability of an event occurring by applying a logit transformation to these, i.e. dividing the probability of success by the probability of failure. In our case, two logistic regression models were used:

- The first was implemented using the mortality variable as the dependent variable and the score value as the independent variable. The implemented equation is thus as follows: $logit\ y = b_0 + b_1x_1$;
- The second, on the other hand, retains actual Mortality as output y but uses the vector of Elixhauser's 29 comorbidities as independent variables. The equation representing the model is as follows: $logit\ y = b_0 + b_1x_1 + b_2x_2 + \ldots + b_{29}x_{29}$.

The c-statistic and the graph of the Receiver Operating Characteristic (ROC) curve were then used to evaluate the models' performance [12]. The c-statistic also called concordance measures the goodness of fit for binary outcomes in a logistic regression model and represents the area under the ROC curve. It is a value between 0 and 1; the closer it is to 1, the more predictive the model is. The ROC curve adds to this performance measure other assessments in terms of accuracy, sensitivity and specificity. These measurements are carried out over the entire range of permissible values. It measures the agreement between the test of interest and the presence/absence of a specific condition (in this case the death event) and thus represents the method of choice for validating a test or, as in this case, a predictive index. This phase of the analysis was conducted using the R software.

3 RESULTS

Once the code had been extracted and the study dataset obtained, using the ad hoc created code a vector of 0/1 identifying the 29 Elixhauser comorbidity flags was obtained for each patient. From this vector, using the weights provided by the AHRQ model, the mortality index was calculated and its performance evaluated using, as described above, a simple logistic regression. In addition to this, a second logistic regression was implemented to evaluate the performance of the 29 Elixhauser comorbidity flags in predicting actual mortality. The results are shown in table 2.

As can be seen from the results, the 29 separate Elixhauser comorbidity flags perform slightly better than the index, but both do not reach the values of 0.7 found in the relevant scientific literature

Table 1: Index Weights for the AHRQ Elixhauser Comorbidity Index [27].

Comorbidity Measure	Weight	Comorbidity Measure	Weight
Acquired immune deficiency syndrome	0	Lymphoma	6
Alcohol abuse	-1	Fluid and electrolyte disorders	11
Deficiency anemia	- 2	Metastatic cancer	14
Rheumatoid arthritis/collagen vascular diseases	0	Other neurological disorders	5
Chronic blood loss anemia	- 3	Obesity	- 5
Congestive heart failure	9	Paralysis	5
Chronic pulmonary disease	3	Peripheral vascular disorders	3
Coagulopathy	11	Psychoses	- 5
Depression	- 5	Pulmonary circulation disorders	6
Diabetes, uncomplicated	0	Renal failure	6
Diabetes with chronic complications	- 3	Solid tumor without metastasis	7
Drug abuse	- 7	Peptic ulcer disease excluding bleeding	0
Hypertension (combine uncomplicated and complicated)	- 1		
Hypothyroidism	0	Valvular disease	0
Liver disease	4	Weight loss	9

Table 2: Comparison of Performance.

	c-Statistic	95% Wald Confidence Interval
All 29 Elixhauser comorbidity flags	0.666	0.655-0.676
AHRQ Elixhauser Mortality Index	0.626	0.615-0.637

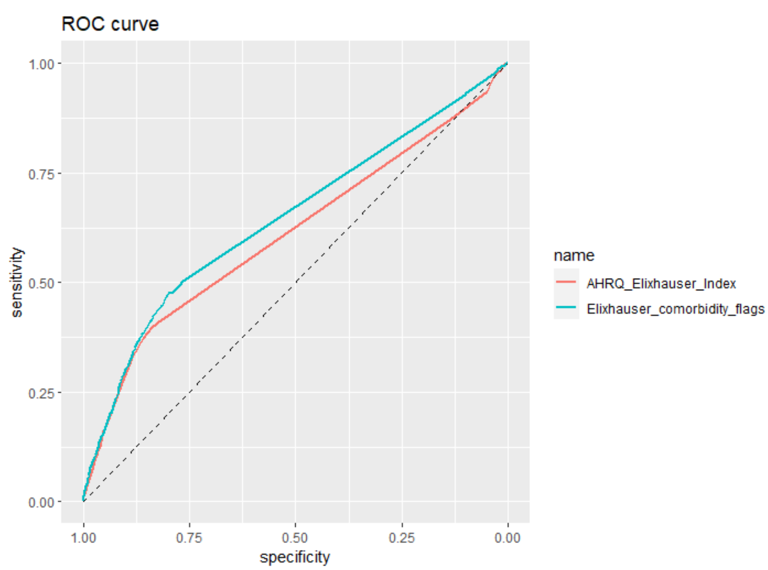

Figure 1: ROC Curve

[11, 12]. The same result is presented graphically through the ROC curve in Figure 1.
It is even more evident from the graph that in the aggregation of the flags for the realization of the index, part of the information content is lost.

The calibration plot shown in Figure 2 shows precisely the trend of the prediction as a function of the actual data. The values of the AHRQ Elixhauser Mortality Index have been grouped so that each class has a mortality % of 1% or more.
From this graph it can be seen that the prediction generally underestimated the actual mortality, except for index values of 0 or

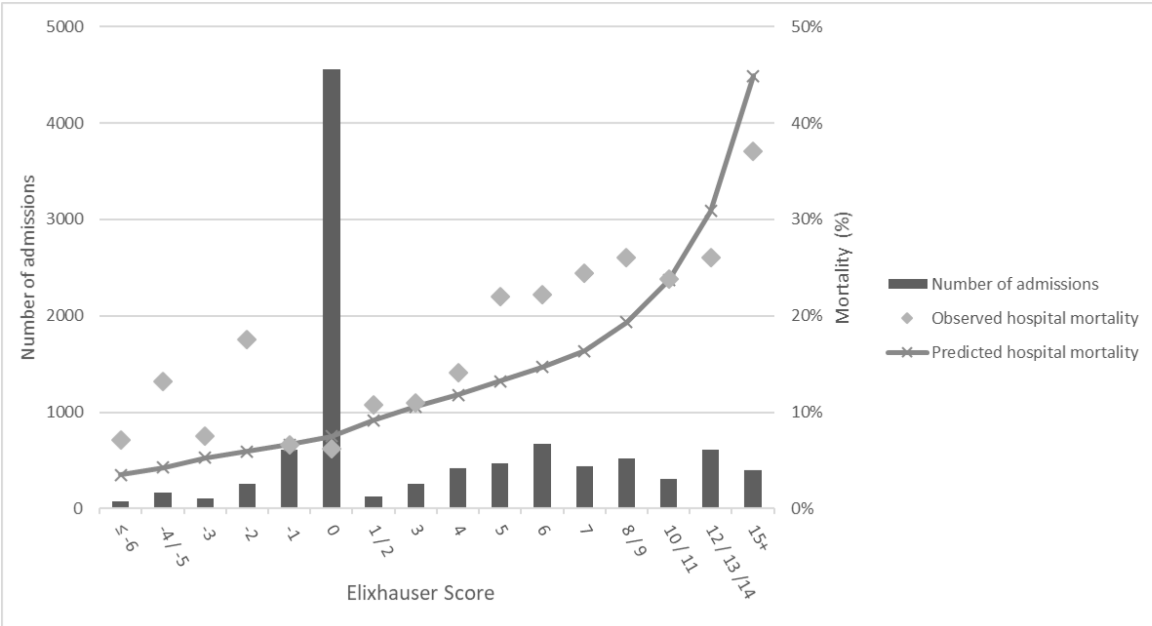

Figure 2: Calibration curve of Elixhauser index for predicting risk of hospital death. The graph shows for each class of the AHRQ Elixhauser Mortality Index the number of admissions (histogram), the % of observed mortality (♦) and the % of mortality predicted by the logistic regression model in that class (*).

higher 10 / 11. Another interesting finding was that the Italian case history shows a less wide range of score values than the data in the literature [12].

4 DISCUSSION AND CONCLUSION

The problem of clinical characterization of the patient is an issue of significant interest in the clinical literature. The use of standardized indices may be the key to solving it. Indeed, Elixhauser et al. [4] proposed in their first study a vector of 29 comorbidities obtained from the secondary diagnoses in the hospital discharge form flow. From this vector, several indices capable of predicting in-hospital mortality were defined, such as that of the AHRQ which is the subject of this study.

The aim of this work is to validate the use of this index in the Italian context, and in particular in that of the AORN 'A. Cardarelli' of Naples (Italy), which is characterized by a classification and identification of secondary diagnoses that is strongly different from the reference context found in the literature.

First of all, a Python code was created to translate the list of secondary diagnoses extracted from the hospital discharge forms into the vector of the 29 comorbidities identified by Elixhauser. Once the vector was obtained, the weights provided by the AHRQ index were applied to obtain a synthetic mortality index.

Our study shows that the c-statistic results are lower than in the literature [11, 12] and that the index performed worse than the decomposed comorbidity vector. The mortality prediction tended to overestimate the true value for both low and high index values. This phenomenon may be attributable to the different distribution of patients in the various classes, which inclined in our study to focus on the central values.

Several reflective insights derive from the results obtained, which will be the subject of future developments. The validity of the index shows the need to create specific weights for the Italian context, characterized by a coding that is still obsolete (ICD-9-CM) and by a lower number of secondary diagnoses detected for each patient (in Italy only 5 secondary diagnoses are included) compared to the contexts in which the index was defined.

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