Development of a Risk-Adjusted In-Hospital Complication Rate (RAICR) using machine learning methods

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Background

- In-hospital complications are a key performance indicator in the assessment of healthcare results due to their close relationship with the quality of care.
- Their comparison between hospitals needs to consider many factors such as hospital characteristics or inter-patient variation.
- To generate an adjusted in-hospital complication rate will allow:
 - To describe the hospital episodes with complications.
 - To quantify the deviations between the observed vs expected complications.
 - To measure the contribution of specific groups of patients to the global complications rate of the hospital

Table 1 – Components of the models

General model						
 Includes: Hospitalizations Over 17 years of age or under 18 years of age with main diagnostic category 14 (obstetric) 	 Excludes: Episodes with vaginal birth procedures (AHRQ definition) Exclusion field > 0 	 Adjustment variables: Procedure maximum probability of complications Main diagnosis Secondary Diagnosis maximum probability of complications Admission circumstance DRG Type Age group Sex Hospital type Covid AHRQ Comorbidities 				
Obstetric model						
 Includes: Hospitalizations Women Age between 12 and 60 years Episodes with vaginal birth procedures (AHRQ definition) 	Excludes: - Exclusion field > 0	 Adjustment variables: Procedure maximum probability of complications Diagnosis maximum probability of complications Procedures: 10D07Z3 (forceps) and 0W8NXZZ (episiotomy) Gestation weeks Hospital type Diagnosis: 048.0 (post-term pregnancy) 066.0 (obstructed labor) 				
Pediatric model						
Includes: - Hospitalizations - Age between 29 days and 17 years	 Excludes: Episodes with vaginal birth procedures (AHRQ definition) Main diagnostic category 14 (obstetric) Exclusion field > 0 	 Adjustment variables: Procedure maximum probability of complications Main diagnosis Secondary Diagnosis maximum probability of complications DRG type Admission circumstance Age group Hospital type Procedures: 30233N1 (red blood cells transfusion) and 3E0G76Z (enteral nutrition) 				
Neonate model						
Includes: - Hospitalizations - Children under 29 days	 Excludes: Episodes with vaginal birth procedures (AHRQ definition) Exclusion field > 0 	 Adjustment variables: Procedure maximum probability of complications Main diagnosis Secondary Diagnosis maximum probability of complications Procedures: 30233N1 (red blood cell transfusion), 5A09557 (mechanical ventilation) and 009U3ZX (spinal canal drainage) Birth weight category Admission circumstance Gestational age 				

HSD130

Objectives

 This study aims to develop a between-hospital comparable Risk-Adjusted Inhospital Complication Rate (RAICR) using machine learning (ML) methods with data of hospitalization episodes from more than 150 hospitals from the Spanish National Health System.

Methods

- The dataset comprised 5 million hospitalization episodes extracted from the IQVIA's Anonymized Hospitalization Episodes Database (ICD-10 codes).
- Each episode was categorized as "complicated" or "not-complicated" according to Agency for Healthcare Research and Quality (AHRQ) criteria.
- Three types of complications were considered:
 - AHRQ patient safety indicators (≥18 years)
 - AHRQ Pediatric Quality Indicators (< 18 years)
 - Sentinel Complications (should never occur)
- ML techniques (ensemble algorithms complemented by modelling calibration methods) were used to develop a ML model to predict complication probabilities, considering patient and hospital characteristics, diagnoses, comorbidities, and information relative to the medical and surgical procedures associated to each episode.

Results

- Key variables helping to identify risk of complication were different for each of the four models, allowing to identify diagnoses and surgical procedures connected to complication risk under each of the four scenarios.
- Other variables such as age group, sex, type of hospital, COVID, and AHRQ comorbidities played a key role as well.
- Average sensitivity for the models behind the RAICR was 0.87 (max 0.98; min 0.70) and average specificity was 0.89 (max 0.99; min 0.75).

Table 2 – Performance of the ML models behind the new RAICR

General model Obstetric model Pediatric model Neonate model



- Four different models were developed: general, obstetric, pediatric, and neonate.
- The presented RAICR methodology calculates RAICR scores as the ratio between observed and expected (predicted by the model) number of complications (applicable at any level of granularity, e.g. hospital, procedure category, hospital department, etc.).

% Observed Complication episodes	0.50%	1.55%	0.19%	0.58%
Sensitivity	0.87	0.70	0.95	0.98
Specificity	0.90	0.75	0.91	0.99

Figure 2 – Cumulative Gains Curves



Conclusions

A new methodology supported by ML techniques was developed for the definition of four different RAICR (general, obstetric, pediatric and neonate) allowing interhospital comparisons and supported by high sensitivity and specificity in the models behind it.

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Interpretation of the graphics:

The graphs show the percentage of episodes with complications captured (Y axis) when considering the percentage (X axis) of the episodes with the highest probability according to the model.

For example, in the general model, the 5% of episodes with the highest probability according to the model include almost 80% of the complicated episodes in the data set.