Measuring data credibility and medical coding: a case study using a nationwide Portuguese inpatient database

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Abstract

Some countries have adopted the diagnosis-related groups (DRG) system to pay hospitals according to the number and complexity of patients they treat. Translating diseases and procedures into medical codes based on international standards such as ICD-9-CM or ICD-10-CM/PCS is at the core of the DRG systems. However, certain types of coding errors undermine this system, namely, upcoding, in which data is manipulated by deliberately using medical codes that increase patient's complexity, resulting in higher reimbursements. In this sense, ensuring data credibility in the context of upcoding is critical for an effectively functioning DRG system. We developed a method to measure data credibility in the context of upcoding through a case study using data on pneumonia-related hospitalizations from six public hospitals in Portugal. Frequencies of codes representing pneumonia-related diagnosis and comorbidities were compared between hospitals and support vector machine models to predict DRGs were employed to verify whether codes with discrepant frequencies were related to upcoding. Data were considered not credible if codes with discrepant frequencies were responsible for increasing DRG complexity. Six pneumonia-related diagnoses and fifteen comorbidities presented a higher-than-expected frequency in at least one hospital and a link between increased DRG complexity, and these targeted codes was found. However, overall credibility was very high for nearly all conditions, except for renal disease, which presented the highest percentage of potential upcoding. The main contribution of this paper is a generic and reproducible method that can be employed to monitor data credibility in the context of upcoding in DRG databases.

Keywords Data quality · Diagnosis-related groups · Clinical coding · Hospital administration · Data credibility · Support vector machine

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1 Background

In the Portuguese hospital management sector, all information concerning the patient's diseases, health status, disease progression, procedures, and treatments are routinely reported in health records, discharge notes, pathology, and surgical reports (Alonso et al. 2019). All this largely unstructured information is abstracted and translated into standard clinical codes representing the patient's diagnoses and procedures according to the International Classification of Diseases, Clinical Modification, ninth and tenth revisions (ICD-9-CM and ICD-10-CM) (Centers for Medicare and Medicaid Services 2014; Centers for Medicare and Medicaid Services 2019). Structured-coded clinical data will be further grouped into diagnosis-related groups (DRGs), generating a database to be used in several subdomains, ranging from healthcare management and decision-making (including resource use monitoring and billing) to research (discovering disease trends) (Alonso et al. 2019). In Portugal, the DRG system currently in use is the all-patient refined diagnosis-related groups (hereafter APR-DRG) (Administração Central do Sistema de Saúde 2014), which groups hospital cases, here referred as episodes, into specific clusters of patients (APR-DRGs) with similar resource use and costs (Averill et al. 2013; Mathauer and Wittenbecher 2013). The construction of APR-DRG is performed through a complex flowchart-based method supported by a specific software application ("APR-DRG grouper") that considers clinical data from each inpatient episode as inputs and assigns an APR-DRG for that episode based mostly on the clinical codes representing medical diagnoses and inpatient procedures present in the data, among other variables such as age, sex, and discharge status (Averill et al. 2013).

Each APR-DRG represents the patient's reason for hospital admission, either in terms of disease or procedure performed, and is usually associated with a predefined, standard price (Mathauer and Wittenbecher 2013). In fact, the algorithm assigns a severity of illness (SOI) level to each APR-DRG at the end of the classification process, which is a score ranging from one to four (1 minor, 2 moderate, 3 major, 4 extreme), representing increasing reimbursement demands for patients into the same APR-DRG (Averill et al. 2013). Secondary diagnoses representing comorbidities and complications are what typically drive SOI assignment, being thus relevant clinical features in the APR-DRG system (Aiello and Roddy 2017). At this point, it is necessary to recall that the Portuguese government pays hospitals according to an established list of reimbursement rates that are linked to each APR-DRG and SOI level (Ministério da Saúde 2017). Therefore, failures in the data representing codes of diseases and procedures will undoubtedly have an economic impact on hospitals.

1.1 Problem and case study

In Portugal, the process of creating the databases to feed the APR-DRG system relies on clinical coding, in which trained medical coders are in charge to interpret medical records and translate all patient's clinical information into diagnosis and procedure codes from the ICD-9-M and ICD-10-CM lists (Ministério da Saúde 2017). Figure 1 shows the information flow and data lifecycle related to the APR-DRG system, from patient's documentation to the creation of APR-DRG data.

Therefore, the credibility of all codes entered for each episode is critical to ensure a good performance of the APR-DRG system. The subjective generation of codes when interpreting medical records, however, can lead to data quality problems, namely, loss of objectivity and data credibility (Strong et al. 1997). This is of great concern in the context of DRG systems, as

several consequences could arise from the wide range of types of coding errors, including negative impacts on hospital finances and decreased reliability for reusing this data for clinical research and healthcare management. The most common types of coding errors include selecting the wrong principal diagnosis, omitting additional codes, and choosing less specific diagnosis and procedure codes (Reid et al. 2000). There are also deliberate coding errors, with the most common being denominated in the literature as upcoding, in which coders purposely miscode patient data to group episodes into higher-complexity DRGs to receive higher reimbursements (Dafny 2005; Silverman and Skinner 2004). For instance, Psaty et al. (1999) found that just adding a heart failure code as a complication to conditions such as acute myocardial infarction, pneumonia, or gastrointestinal hemorrhage would increase reimbursement to hospitals by over \$3000.00 on average. Exploring medical records to extract the most lucrative codes, including changes between the principal and secondary diagnosis, looking for reimbursable conditions, and exaggerating the choice of codes without supportive evidence in the patient's record are examples of upcoding practices (Pongpirul and Robinson 2013).

The main goal of this article was to assess the credibility of coded clinical data used in the APR-DRG system. We considered the definitions of data credibility according to ISO/IEC 25012, which states that credibility refers to “the degree to which data has attributes that are regarded as true and believable by users in a specific context of use. Credibility includes the concept of authenticity (the truthfulness of origins, attributions, commitments)” (ISO/IEC 25012 2006). In our case study, due to feasibility reasons and as a pilot for the methodology, upcoding was the only type of coding error explored. Therefore, in this study, we will assess data credibility in the specific context of upcoding. Moreover, for the sake of usability and understandability, our case study was limited to pneumonia-related conditions, which is a diagnosis area that has been regarded as a target of upcoding in the literature (Sjoding et al.

Fig. 1 The information flow and data lifecycle related to the APR-DRG system, from patient's documentation to the creation of APR-DRG data

2015; Hebert et al. 2005). The case study also includes comorbidities, which are secondary diagnoses representing the patient's preexisting conditions underlying the primary diagnosis. Comorbidities in the context of upcoding are not only relevant because they typically drive the determination of patient's severity within the APR-DRG algorithm, regardless of the medical field (Aiello and Roddy 2017), but also because adding more diagnoses such as comorbidities to make the patient's condition look more complicated is a typical upcoding practice (Pongpirul and Robinson 2013). It is important to highlight that the only way to confirm upcoding is by auditing the health records that originated all coded data. However, the audit is a very high resource and time-consuming process and could not comprise the totality of data. Rather, it is internally performed in random clinical processes (Barros and Braun 2017).

This article is the extended version of the paper presented at the "12th International Conference on the Quality of Information and Communications Technology," which described a method to measure the credibility of data used for APR-DRG classification in the context of upcoding (Pimenta et al. 2019). In the absence of historical audit data and medical records, the main contribution of our solution is to provide a fairly automatized, generic, and reproducible method to measure data credibility for APR-DRG classification in the context of upcoding. In particular, we restricted our case study to upcoding and pneumonia-related hospitalizations, but since our method is based on well-established statistical and machine learning methods, we reinforce that this method can be employed to measure data credibility in the context of other types of coding errors and for other clinical domains.

2 State of the art

Credibility can be defined as "the overall plausibility or reliability of the data and the degree to which data are perceived as credible can be influenced by validation from primary sources and the alignment of the data with current medical knowledge and user-perceived reality" (Feder 2018). Validation rules can be used to determine whether data values appear to be credible in terms of clinical or other natural perspectives. Validity checks to determine if specific elements within patient data were likely to be true include looking for elements with values that were outside biologically plausible ranges, changed implausibly over time (Weiskopf and Weng 2013). Study design involving multiple sites and databases can also be useful to evaluate data credibility (Weiskopf and Weng 2013). Lau et al. (2011) assessed data credibility by comparing inputted data from electronic health records with records and claim data held in other official databases. Frequency distribution of data can also be compared with other sources, such as nationally published disease incidence or prevalence rates, to assess credibility (Rea et al. 2013).

In this study, the presence of upcoding is the aspect undermining data credibility. Methods for upcoding detection in hospital data have been mixed. Most studies have employed chart review, which consists in recording and regrouping the original medical records that originated coded data to verify whether the newly coded episodes would be grouped into a different DRG (Hsia 1990; Hsia et al. 1992; Goodpasture et al. 2004; Reid et al. 2005) and whether these changes occurred by means of increasing or decreasing DRG complexity.

In the absence of the original medical records, authors differed in the methodology for upcoding detection. Silverman and Skinner (2004) estimated the levels of upcoding by calculating the ratio of the number of discharges grouped into a DRG representing respiratory infections and inflammations with complications by the sum of cases grouped into all other

DRGs representing respiratory ailments. This ratio was assessed over time and compared by the type of hospital ownership (not-for-profit, for-profit, and government hospitals). Hebert et al. (2005) assumed that a DRG commonly associated with a secondary diagnosis of pneumonia and influenza would pay less than if it had been reported as a principal diagnosis. In this sense, the authors investigated the DRG distribution in all claims with this condition listed as principal or secondary diagnosis over time.

Aelvoet et al. (2009) employed fixed effects models to assess deviant coding behavior at the hospital level by examining the linear evolution over time of certain outcomes (e.g., number of days the patient spent in the hospital) of a set of diseases and conditions that are susceptible to increase the complexity of an episode. For cases of deviant coding, these targeted conditions were marked to direct the audit toward fraud-suspected cases. A Norwegian study also employed fixed effects models to assess variations in the number of patients treated within the different DRGs over time, taking into account changes in the national average cost per DRG offered to Norwegian hospitals during the studied period (Januleviciute et al. 2016). Fixed effects models were also employed by Dafny (2005) and Barros and Braun (2017) to investigate the existence of potential upcoding cases in hospital databases. In a similar assumption, an Italian study used a difference-in-differences method to test whether hospitals responded to changes in DRG prices, including by means of upcoding, and defined as the proportion of patients with complications (Di Giacomo et al. 2017).

The use of machine learning for upcoding detection in hospital databases was employed by Luo and Gallagher (2010) and Souza et al. (2018), also in the absence of original medical records or audit data, which is the case of our study. In both studies, an unsupervised method was employed by comparing different distributions of DRGs in several hospitals in order to filter data to be monitored for potential upcoding.

3 Methods

3.1 Generic method

To the best of our knowledge, this is the first study to measure the credibility of clinical data in the context of upcoding. More specifically, data credibility can be understood as the level of certitude that episodes in the datasets are free of upcoding, thereby representing the actual patient's clinical condition and severity and thus grouped into an APR-DRG accordingly. Considering the absence of the original medical records and past audit data, an unsupervised method based on statistical and machine learning techniques was designed and summarized in Fig. 2. Further details concerning the method for measuring data credibility are explained in Section 3.3.

3.2 Description of the data source

Data used in this study were extracted from the Portuguese National Hospital Morbidity Database, which contains inpatient and outpatient discharge data from all public hospitals from the National Health System (NHS) in Portugal. The Portuguese National Hospital Morbidity Database contains a comprehensive list of administrative, clinical, and demographic data fields. The main data attributes that are used for APR-DRG grouping were collected and considered in the method for data credibility measurement: principal and secondary diagnoses,

• Data quality measure name	Credibility of hospital clinical data for APR-DRG grouping
• Measurement function	$[1 - (A/B)] * 100$
• Quality measure elements	A= Number of pneumonia-related episodes in the dataset that are considered potential cases of upcoding B=Total number of pneumonia-related episodes in the dataset
• Measurement unit	Percent
• Measurement method	Inter-hospital variation in coding using Chi-squared test corrected for multiple comparisons. SVM models for APR-DRG classification to assess possibility of upcoding.
• Analysis model	Codes with a significantly higher frequency in at least one hospital were targeted as potential upcoding candidates. We considered p-values lower than Bonferroni threshold for multiple testing correction to identify these codes with abnormal frequencies. Using SVM models, we further evaluated the influence of candidate codes by assessing APR-DRG classification with and without the said codes.

Fig. 2 Summary of unsupervised method based on statistical and machine learning techniques

as well as inpatient procedures, specified according to the ICD-9-CM; discharge status, which is represented by a standard code indicating the patient's fate after the discharge, including departure to home, death and transfers to another hospital, or specialized services; and sex and age.

In this study, we analyzed data for 2015, which was the last year when ICD-9-CM was still used for coding diseases in Portugal. From 2016 onward, episodes were either coded in ICD-9-CM or in the newest revision, ICD-10-CM. Thus, we did not include more recent years to avoid further bias related to the transition between ICD versions. Moreover, in order to minimize the bias introduced by differences in the complexity of hospitals, we restricted our evaluation to six large hospitals with similar capacity and complexity, based on a standard categorization defined by the Portuguese NHS (Administração Central do Sistema de Saúde 2019). Furthermore, we selected all episodes with a principal or secondary diagnosis code from the ICD-9-CM list comprised in the interval of 480–488, which corresponds to pneumonia and influenza diagnoses. Comorbidities were selected according to the enhanced ICD-9-CM Charlson's definitions (Quan et al. 2005).

Since inpatient data used in this study were anonymized and only contained the discharge year, diagnosis and procedure codes, sex, age, discharge status, and an arbitrary episode identification number, there was no need for ethical approval and no data privacy law was violated.

3.3 Particularization of the method for data credibility measurement

In our method, the starting point to detect potential upcoding is by tracking diagnosis codes with an abnormally high frequency in a given hospital relatively to other hospitals. Data are considered not credible when an episode presents a diagnosis code with an abnormally high frequency in the hospital it was admitted to and if that code alone is responsible for increasing APR-DRG complexity and, thereby, hospital reimbursement.

The identification of codes with discrepant frequencies occurred in three phases. First, we compared hospitals regarding APR-DRG distributions using Chi-square test with Bonferroni correction for multiple comparisons, so that the proportion of episodes grouped into a specific APR-DRG in a given hospital is compared against all other facilities. Second, we compared APR-DRG distributions between hospitals, but now considering the SOI level and restricting to the APR-DRGs targeted in the first phase, which correspond to those APR-DRGs with an abnormally high frequency in at least one hospital. In the last phase, the same statistical test was employed to compare hospitals with regard to the frequency of individual codes representing comorbidities and pneumonia-related diagnoses among episodes grouped into the APR-DRGs targeted in the second phase. Following this analysis, all comorbidities and pneumonia codes that present a significantly higher-than-expected frequency in at least one hospital were targeted, as they might have led to potential cases of upcoding.

To investigate whether the targeted codes could be associated with upcoding, we employed support vector machine (SVM) to build a model for APR-DRG classification. The SVM algorithm was introduced by Vapnik (1995) and is a consistently good classifier, being widely used as a classification method (Chu et al. 2008). Another important advantage of using SVM is that it can overcome high-dimensionality issues (Chu et al. 2008; Verplancke et al. 2008), which is the case of the APR-DRG classification problem. Other advantages of SVM include high accuracy, avoids overfitting, and accuracy and performance are independent of the number of features, and it presents a good generalization ability (Singh et al. 2016). Two SVM classification models were built to simulate the APR-DRG system:

- SVM-ONE to predict one out of the 17 APR-DRGs defined for classifying diseases or disorders of the respiratory system, based upon the APR-DRG version 31 (Averill et al. 2013).
- SVM-TWO to determine the SOI level. The APR-DRG assigned by SVM-ONE is used as an input variable for SVM-TWO.

3.4 Implementation details for SVM-ONE and SVM-TWO

Regarding the specification of variables for SVM-ONE, we included age as continuous attribute, sex, and discharge status as categorical attributes and all the existing ICD-9-CM diagnosis and procedure codes in the dataset. As SOI classification does not take into account sex and discharge status, SVM-TWO only included age as a continuous attribute and the APR-DRG itself as categorical attribute and all diagnosis and procedure codes. Each ICD-9-CM code was treated as an individual binary variable (“1” if the episode reported the code, “0” otherwise).

Using the constructed SVM models, we performed a sensitivity analysis to discover the role of each discrepant code on APR-DRG classification by removing the code from the original episode and assessing APR-DRG classification changes. If the exclusion of the code alone moves the episode to a lower complexity APR-DRG, then the episode is labeled as a potential case of upcoding. It is important to highlight that this verification can only be performed for secondary diagnosis codes, since the principal diagnosis is mandatory for APR-DRG grouping, so the exclusion of the principal diagnosis in the sensitivity analysis would simply invalidate APR-DRG grouping. Thus, to assess the role of principal diagnoses on APR-

DRG grouping, we simply studied the frequency distributions of the codes within each APR-DRG, instead of directly applying the SVM approach. Finally, as defined in Fig. 1, we estimated the percentage of potential cases of upcoding from the total number of episodes, for each hospital and disease (pneumonia-related condition or comorbidity), to calculate the levels of credibility.

Training and testing phases of SVMs, as well as sensitivity analyses, were performed using a Java program, which run in a Java Runtime Environment (JRE) 1.8.0_221 in combination with Java Standard Edition Development Kit (JDK) 1.8.0_221 and an open-source Weka library for Java, version 3.8.0. The integrated development environment used for implementing the Java code was Eclipse Mars 2. The running environment was a Windows 10 PC with a CPU Intel 1.80GHz and 16GB of RAM. We considered the algorithm for training the SVM models introduced by Platt (1998) and denominated sequential minimal optimization available in the Weka library for Java, considering default parameters, as detailed in the library's documentation.

3.5 Sensibility of the results: quality of the SVM models used for data credibility measurement

Data of 487,156 hospitalizations were used for training and testing the SVM models, which corresponds to all inpatient episodes due to respiratory system disorders occurred in the period of 2011–2015 in public Portuguese hospitals which were statically valid. This latter criterion refers to episodes within the length of stay interval determined for the APR-DRG they were assigned to (Ministério da Saúde 2017). Episodes due to respiratory system diseases were identified based upon a principal diagnosis list defined for the APR-DRG system (Averill et al. 2013). The chosen period comprises all available APR-DRG data coded according to the ICD-9-CM. Therefore, we considered this specific period to have access to the most comprehensive dataset to construct SVM models for APR-DRG prediction.

We trained the SVM models on two-thirds of the dataset and tested their performance on the remaining third. As evaluation metrics of the goodness of the models, we considered the percentage of correctly classified cases and weighted precision and recall. Estimates of precision and recall for each class (APR-DRG for SVM-ONE and SOI level for SVM-TWO) were weighed by the number of instances within each class, providing the weighted precision and recall, as follows:

$$\text{Weighted precision/recall} = \frac{\sum_i^n P_{Ci} * C_i}{\sum_i^n C_i} \quad (1)$$

where P_{Ci} is the precision or recall for class i ($i = 1, \dots, 17$ for SVM-ONE and $i = 1, \dots, 4$ for SVM-TWO) and C_i is the number of instances in class i . Weighting by class size provides a better estimate of overall performance of the SVM models, since the APR-DRG or SOI (classes) frequencies can be very different (e.g., certain APR-DRGs are much more frequent in the real world than others, and less severe episodes tend to be more prevalent).

We further tested the SVM models on unseen ICD-9-CM data from the year 2016 and estimated the percentage of correctly classified cases to add critical validation to the models in terms of generalization capacity.

4 Results

4.1 Performance of SVM models (method for data credibility measurement)

Regarding the performance of the SVM models, considering the SVM-ONE, weighted recall and precision were both 0.994, and the percentage of correctly classified cases was 99.4%. For the second model, SVM-TWO, overall weighted recall and precision were both 0.893, with a percentage of correctly classified cases of 89.3%. When tested in ICD-9-CM data from 2016 (92,475 episodes), we used SVM-ONE and SVM-TWO simultaneously and compared with the original APR-DRG and SOI classifications. We verified that the SVM models together presented a high capacity of generalization, with a percentage of correctly classified cases of 88.4%. Supplementary Table 1 presents the detailed evaluation metrics results after the testing phase, for each possible class (APR-DRG and SOI levels).

4.2 Data credibility concerning upcoding

To detect diagnosis codes that could have been target of upcoding in the evaluated hospitals, we applied statistical tests in three phases. In the first phase, frequencies of APR-DRGs were compared between hospitals using Chi-square test with Bonferroni correction for multiple comparisons. We only compared frequencies of APR-DRGs with enough episodes to perform a robust Chi-square test, as defined in Yates et al. (1999) (contingency table with more than 80% of the cells presenting expected counts equal to five or more; the remaining 20% can present an expected count below five, as long as none are less than one). Significantly higher-than-expected frequencies were found for five APR-DRGs: APR-DRGs 120 (major respiratory and chest procedures), 130 (respiratory system diagnosis with ventilator support 96+ h), 137 (major respiratory infections and inflammations), 138 (bronchiolitis and RSV pneumonia), and 139 (other pneumonia). Detailed results of the first phase analysis are presented in supplementary Table 2. Our hypothesis is that discrepant frequencies of APR-DRGs between hospitals might be the first indicator of upcoding. However, as patient complexity and prices are mostly determined by APR-DRGs in combination with SOI, we further applied the same method in a second phase to compare the frequencies of the five discrepant APR-DRGs but now considering the SOI level. Only APR-DRGs and SOI levels with enough episodes to perform Chi-square test were further considered, reducing the analyses to three APR-DRGs, 137, 138 and 139, and combined with their respective SOI levels. All three APR-DRGs presented a significantly higher-than-expected frequency of a given SOI level in at least one hospital. Results of the second phase analysis are presented in supplementary Table 3.

Finally, in order to discover which codes might have been upcoded, we also compared hospitals with regard to the frequencies of individual diagnosis codes in a third phase analysis. To assess this inter-hospital variation in coding, for each discrepant APR-DRG, the frequency of each pneumonia-related diagnosis and comorbidity code was compared across hospitals using the same Chi-square-based approach. A total of six pneumonia-related diagnosis codes presented a significantly higher-than-expected frequency in at least one hospital: 482.42, methicillin-resistant pneumonia due to *Staphylococcus aureus*; 480.9, viral pneumonia, unspecified; 481, pneumococcal pneumonia; 482.9, bacterial pneumonia, unspecified; 485, bronchopneumonia, organism unspecified; and 486, pneumonia, organism unspecified. Regarding comorbidities, conditions with a significantly higher-than-expected frequency in at least one hospital were any malignancy, chronic pulmonary disease, renal disease, congestive

Table 1 Summary of the results of the three-phase analyses

Phase 1 – APR-DRGs with a significantly higher-than-expected frequency* in at least one hospital	Phase 2 – APR-DRG + SOI levels a significantly higher-than-expected frequency* in at least one hospital	Phase 3 – diagnosis codes with a significantly higher-than-expected frequency* in at least one hospital
APR-DRG 120 – major respiratory and chest procedures APR-DRG 130 – respiratory system diagnosis with ventilator support 96+ h APR-DRG 137 – major respiratory infections and inflammations APR-DRG 138 – bronchiolitis and RSV pneumonia APR-DRG 139 – other pneumonia	APR-DRG 137 – major respiratory infections and inflammations APR-DRG 138 – bronchiolitis and RSV pneumonia APR-DRG 139 – other pneumonia	Methicillin-resistant pneumonia due to <i>Staphylococcus aureus</i> (482.42) Viral pneumonia, unspecified (480.9) Pneumococcal pneumonia (481) Bacterial pneumonia, unspecified (482.9) Bronchopneumonia, organism unspecified (485) Pneumonia, organism unspecified (486) Any malignancy Chronic pulmonary disease Renal disease Congestive heart failure Dementia AIDS/HIV Myocardial infarction Moderate or severe liver disease Mild liver disease Cerebrovascular disease Metastatic solid tumor Hemiplegia or paraplegia Peripheral vascular disease Peptic ulcer disease Diabetes with chronic complication

*Bonferroni threshold for multiple testing correction

Table 2 Individual effects of each discrepant pneumonia-related diagnosis on APR-DRG classification

	Increased APR-DRG complexity (<i>n</i> of episodes)	Decreased APR-DRG complexity (<i>n</i> of episodes)	Total (<i>n</i> of episodes)
Principal diagnosis			
Methicillin-resistant pneumonia due to <i>Staphylococcus aureus</i>	0	0	102
Viral pneumonia, unspecified	0	53	54
Pneumococcal pneumonia	1	483	509
Bacterial pneumonia, unspecified	1	466	488
Bronchopneumonia, organism unspecified	0	449	455
Pneumonia, organism unspecified	1	6926	7059
Total	3	8377	8667
Secondary diagnosis			
Methicillin-resistant pneumonia due to <i>Staphylococcus aureus</i>	3	0	64
Viral pneumonia, unspecified	0	0	5
Pneumococcal pneumonia	5	0	34
Bacterial pneumonia, unspecified	26	0	78
Bronchopneumonia, organism unspecified	3	0	39
Pneumonia, organism unspecified	185	0	540
Total	222	0	760

heart failure, dementia, AIDS/HIV, myocardial infarction, moderate or severe liver disease, mild liver disease, cerebrovascular disease, metastatic solid tumor, hemiplegia or paraplegia, peripheral vascular disease, peptic ulcer disease, and diabetes with chronic complication.

Table 1 summarizes the results of the three-phase analyses, which resulted in a list of diagnosis codes with discrepant frequencies which could have been target of upcoding practices.

Table 3 Individual effects of each discrepant comorbidity on APR-DRG classification

Comorbidity	Increased APR-DRG complexity (<i>n</i> of episodes)	Decreased APR-DRH complexity (<i>n</i> of episodes)	Total (<i>n</i> of episodes)
Myocardial infarction	89	2	91
Congestive heart failure	830	1	831
Peripheral vascular disease	23	7	30
Cerebrovascular disease	247	5	252
Dementia	130	0	130
Chronic pulmonary disease	143	1	144
Rheumatic disease	29	2	31
Mild liver disease	30	7	37
Diabetes without chronic complication	350	1	351
Diabetes with chronic complication	44	2	46
Hemiplegia	67	1	68
Renal disease	3763	37	3800
Any malignancy	460	3	463
Moderate or severe liver disease	20	0	20
Metastatic solid tumor	421	2	423
AIDS/HIV	8	0	8
Total	6654	71	6725

In order to discover the role of the discrepant codes within the APR-DRG grouping process and thus investigate potential upcoding practices, we performed a sensitivity analysis using the SVM models to assess APR-DRG classification changes with and without the discrepant code. Table 2 summarizes the SVM results by indicating how many episodes were driven to a given APR-DRG by each one of the targeted pneumonia-related codes, either when those were coded as principal or secondary diagnosis, whereas Table 3 presents the results for comorbidities, which are conditions that can only be coded as secondary diagnoses.

Diagnosis code “pneumonia, organism unspecified” occurred in 7059 episodes, and, from this total, it was responsible for allocating 6926 episodes to an APR-DRG of lower complexity (APR-DRG 139) when coded as principal diagnosis, whereas it placed 185 episodes (out of 540) in an APR-DRG of higher complexity (APR-DRG 137) when coded as secondary diagnosis (Table 2). In fact, this tendency was observed for five pneumonia-related conditions, as 222 episodes (out of 760) were allocated to a higher complexity APR-DRG by simply being coded as secondary diagnosis (Table 2). Moreover, we observed that comorbidities generally increased APR-DRG complexity. In fact, comorbidities alone drove 6654 into higher-paying APR-DRGs (Table 3).

Table 4 shows, for each hospital and disease (pneumonia-related diagnosis or comorbidity), the number of hospitalizations flagged as potential cases of upcoding after the application of our criteria and the respective credibility levels, which in turn consist in the proportion of episodes that are not labeled potential cases of upcoding. Episodes are labeled as a potential case of upcoding case if they present a discrepant code that alone increases APR-DRG complexity. A total of 2916 episodes across the evaluated hospitals were targeted as potential upcoding cases, with the impact size varying depending on the hospital and diagnosis code (see Table 4).

At the hospital level, the occurrence of potential cases of upcoding was proportionally small, reaching around 1% of the cases for most of the targeted codes. Consequently, according to our method, overall data credibility levels across hospital databases were very high, with values higher than 99% for the clear majority of the diseases. However, for certain specific codes, we found that credibility levels were substantially lower, namely, for renal disease, which was the condition with the highest percentage of upcoding in all hospitals. In fact, credibility levels concerning renal disease were particularly low for hospital A (83.5%) and hospital F (57.8%).

5 Discussion of the findings

The credibility of coded clinical data in hospital administrative databases is a critical issue in APR-DRG systems and in other contexts where this data can be productively reused, namely, health care funding, research, decision-making, and quality of care assessment. Despite several existing problems, healthcare administrative data have a lot of potentials to produce quality indicators and health research (Jarman et al. 1999; Scott et al. 2004), and understanding the process of medical coding through data mining techniques, which was the basis for our method, have already been explored in the literature (Spangler et al. 2002) and may be useful to provide insights on the quality of coded data. The focus of this paper was to measure data

Table 4 Credibility levels in pneumonia-related hospitalization data, by diagnosis code

Hospital A			
Disease	Number of potential cases of upcoding (n of episodes)	Upcoding proportion (%)	Credibility level (%)
Pneumococcal pneumonia	2	0.1	99.9
Bacterial pneumonia, unspecified	1	0	100
Pneumonia, organism unspecified	6	0.2	99.8
Myocardial infarction	5	0.2	99.8
Congestive heart failure	77	3.1	96.9
Cerebrovascular disease	22	0.9	99.1
Dementia	12	0.5	99.5
Chronic pulmonary disease	5	0.2	99.8
Mild liver disease	2	0.1	99.9
Diabetes without chronic complications	19	0.8	99.2
Diabetes with chronic complications	5	0.2	99.8
Hemiplegia or paraplegia	1	0	100
Renal disease	121	4.9	95.1
Any malignancy	33	1.3	98.7
Moderate or severe liver disease	2	0.1	99.9
Metastatic solid tumor	7	0.3	99.7
Overall (Mean)		0.8	99.2
Hospital B			
Disease	Number of potential cases of upcoding (n of episodes)	Upcoding proportion (%)	Credibility level (%)
Bacterial pneumonia, unspecified	1	0	100
Pneumonia, organism unspecified	4	0.1	99.9
Myocardial infarction	7	0.2	99.8
Congestive heart failure	59	2	98
Peripheral vascular disease	3	0.1	99.9
Cerebrovascular disease	21	0.7	99.3
Dementia	17	0.6	99.4
Chronic pulmonary disease	5	0.2	99.8
Rheumatic disease	1	0	100
Mild liver disease	2	0.1	99.9
Diabetes without chronic complications	26	0.9	99.1
Diabetes with chronic complications	4	0.1	99.9
Hemiplegia or paraplegia	4	0.1	99.9
Renal disease	478	16.5	83.5
Any malignancy	41	1.4	98.6
Moderate or severe liver disease	1	0	100
Metastatic solid tumor	10	0.3	99.7
Overall (Mean)		1.4	99.6
Hospital C			
Disease	Number of potential cases of upcoding (n of episodes)	Upcoding proportion (%)	Credibility level (%)
Pneumonia due to <i>Haemophilus influenzae</i>	1	0.1	99.9
Pneumococcal pneumonia	1	0.1	99.9
Pneumonia, organism unspecified	6	0.3	99.7
Myocardial infarction	22	1.3	98.7
Congestive heart failure	31	1.8	98.2
Peripheral vascular disease	1	0.1	99.9
Cerebrovascular disease	12	0.7	99.3
Dementia	5	0.3	99.7
Chronic pulmonary disease	11	0.6	99.4

Table 4 (continued)

Hospital A			
Disease	Number of potential cases of upcoding (n of episodes)	Upcoding proportion (%)	Credibility level (%)
Rheumatic disease	1	0.1	99.9
Mild liver disease	3	0.2	99.8
Diabetes without chronic complications	16	0.9	99.1
Diabetes with chronic complications	4	0.2	99.8
Hemiplegia or paraplegia	1	0.1	99.9
Renal disease	86	4.9	95.1
Any malignancy	18	1	99
Moderate or severe liver disease	2	0.1	99.9
Metastatic solid tumor	6	0.3	99.7
Overall (Mean)		0.7	99.3
Hospital E			
Disease	Number of potential cases of upcoding (n of episodes)	Upcoding proportion (%)	Credibility level (%)
Pneumonia, organism unspecified	3	0.2	99.8
Myocardial infarction	6	0.3	99.7
Congestive heart failure	24	1.2	98.8
Peripheral vascular disease	2	0.1	99.9
Cerebrovascular disease	12	0.6	99.4
Dementia	5	0.3	99.7
Chronic pulmonary disease	8	0.4	99.6
Rheumatic disease	3	0.2	99.8
Diabetes without chronic complications	16	0.8	99.2
Diabetes with chronic complications	2	0.1	99.9
Hemiplegia or paraplegia	8	0.4	99.6
Renal disease	85	4.4	95.6
Any malignancy	23	1.2	98.8
Moderate or severe liver disease	1	0.1	99.9
Metastatic solid tumor	7	0.4	99.6
Overall (Mean)		0.7	99.3
Hospital F			
Disease	Number of potential cases of upcoding (n of episodes)	Upcoding proportion (%)	Credibility level (%)
Methicillin resistant pneumonia due to <i>Staphylococcus aureus</i>	1	0	100
Bacterial pneumonia, unspecified	2	0.1	99.9
Bronchopneumonia, organism unspecified	1	0	100
Pneumonia, organism unspecified	2	0.1	99.9
Myocardial infarction	13	0.5	99.5
Congestive heart failure	119	4.6	95.4
Peripheral vascular disease	2	0.1	99.9
Cerebrovascular disease	45	1.8	98.2
Dementia	29	1.1	98.9
Chronic pulmonary disease	20	0.8	99.2
Rheumatic disease	3	0.1	99.9
Mild liver disease	6	0.2	99.8
Diabetes without chronic complications	75	2.9	97.1
Diabetes with chronic complications	5	0.2	99.8
Hemiplegia or paraplegia	13	0.5	99.5
Renal disease	1085	42.2	57.8
Any malignancy	49	1.9	98.1

Table 4 (continued)

Hospital A			
Disease	Number of potential cases of upcoding (<i>n</i> of episodes)	Upcoding proportion (%)	Credibility level (%)
Metastatic solid tumor	10	0.4	99.6
Overall (Mean)		3.2	99.8

credibility in the context of upcoding, using a case study on pneumonia-related hospitalizations. In the absence of medical records to verify the sources that originated coded data, as well as lack of historical audit data, we used an approach based on statistical analysis and machine learning to blindly detect potential upcoding. Our method only requires data on APR-DRG and the respective variables used for APR-DRG classification, namely, codes of diagnoses and procedures.

For the subset of pneumonia-related hospitalizations, the overall impact size of upcoding observed in our findings seems to be in line with a systematic literature search conducted by Lungen and Lauterbach (2000), who estimated that upcoding was related with up to 1% of the inpatient care payments in Germany. However, this value is quite lower than the rates identified in a 1995–1996 coding audit in Australia, which revealed that an estimated 5.2% of the medical records were upcoded (Pongpirul and Robinson 2013). In the USA, it was found that one-third and one-half of the case-mix increase occurred due to upcoding in the periods 1986–1987 and 1987–1988, respectively (Carter et al. 1990; Carter et al. 1991). In Portugal, Barros and Braun (2017) analyzed the same Portuguese database used in this study and found that upcoding has occurred in public hospitals to increase their budgets, but the financial impact was quantitatively small.

Concerning pneumonia-related conditions, a total of six discrepant codes presented similar effects on APR-DRG grouping as they drove the classification into the APR-DRG 139 (see Table 2) when coded as principal diagnosis. Analyses based on SVM results showed that five out of the targeted six pneumonia-related conditions would have shifted these episodes to APR-DRG 137 when coded as secondary diagnosis (see Table 2), which is an APR-DRG with a higher complexity and reimbursement rate than APR-DRG 139. Thus, simply switching these conditions from principal to secondary diagnosis alone would result in more financial compensation to hospitals in the context of our case study. These cases should be watched more closely as they could be an indicator of upcoding practices, especially when a hospital presents a higher-than-expected frequency of such conditions coded as secondary diagnosis, rather than principal, relatively to its peers.

Comorbidities are secondary diagnoses with a high influence on SOI determination within the APR-DRG algorithm. In fifteen out of the seventeen evaluated comorbidities, at least one hospital presented a higher-than-expected frequency of cases. Adding more diagnoses, such as the patient's underlying comorbidities, is a typical upcoding practice, but only audit processes would determine whether the observed high frequencies are related to upcoding or whether

other hospitals are underreporting comorbidities. It is important to highlight that the number of Charlson comorbidities by inpatient episode increased by 48% in the period of 2000–2010 in Portuguese hospital databases, though this increasing trend was not equal for all comorbidities, as the proportion of episodes with AIDS/HIV and peptic ulcer disease has decreased over the studied period (Freitas et al. 2016). However, the proportion of episodes with Charlson's myocardial infarction, dementia, and renal disease has increased above 100% (Freitas et al. 2016). Those discrepancies in reporting certain comorbidities described by Freitas et al. (2016), which were also reported elsewhere in the literature among pneumonia hospitalizations (Chong et al. 2011), should be more closely monitored. In our case study, hospitals mostly differed in coding comorbidity renal disease, and a potential upcoding scenario should be investigated for hospital F, where this comorbidity alone drove the APR-DRG classification into a higher-paying APR-DRG in more than 40% of the episodes.

Overall, the number of cases flagged as upcoding by our method was proportionally small, and data credibility concerning upcoding was very high (see Table 4), indicating that data are credible enough and can be indiscriminately used for APR-DRG grouping in the context of pneumonia-related hospitalizations. However, this may not be true for some diseases, namely, renal disease, which appears to have a considerable influence in APR-DRG grouping. In fact, this condition accounted for the highest percentage of potential upcoding cases, having thus an important impact on data credibility. In fact, according to our method, data of patients with renal disease would be considered not credible for hospitals B and F.

As a limitation of our study, we mention that flagging possible upcoding cases was based upon results obtained with the direct application of SVM models. Therefore, existing errors or shortcomings associated with the SVM models might have influenced or been replicated in our results. Furthermore, we only evaluated credibility related to coding the six conditions and fifteen comorbidities in which at least one hospital presented a significantly higher-than-expected frequency of cases and did not consider possible coding issues related to other diagnoses or even inpatient procedures.

6 Conclusion

We identified potential upcoding in 2916 pneumonia inpatient episodes. We pose that measuring the level of credibility of the APR-DRG data allows hospital managers, providers, and stakeholders to better address this issue. In this article, we described and applied a method for credibility measurement regarding possible upcoding cases in pneumonia-related hospitalizations. According to our method, overall credibility levels were very high, and data can be considered credible and usable, except for data on renal disease. Hospitals significantly differed on reporting six pneumonia conditions and fifteen comorbidities, and we found a role of increasing APR-DRG complexity for these targeted codes, which thus should be investigated by means of audit. Furthermore, in the absence of historical audit data, our solution provided a fairly automated, generic, and reproducible method to measure data credibility for APR-DRG grouping, based upon well-established statistical and machine learning methods, which in turn could be applied to measure credibility concerning other types of coding errors, as well as for other diagnosis areas.

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