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Improvement of Diagnosis Coding by Analysing EHR and Using Rule Engine: Application to the Chronic Kidney Disease

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Abstract. Coding medical diagnosis in case mix databases is a time-consuming task as every information available in patient records has to be taken into account. We developed rules based on EHR data with the Drools rules engine in order to support diagnosis coding of chronic kidney disease (CKD) in our hospital. 520 patients had a GFR < 60 ml/min as estimated by the Cockroft-Gault formula and corresponded to 429 case mix database entries. We compared stays in which the patient was older than 12 and younger than 65 or 80 at the time of the stay. We concluded that our rules engine implementation may improve coding of CKD for 45.6% of patients with a GFR < 60 ml/min and younger than 65. When patients are older than 65 our rule engine may be less useful for suggesting missing codes of CKD because the estimation of GFR by the Cockroft-Gault formula becomes less reliable as patients get older.

Keywords. Clinical Coding, Electronic Health Records, Quality Improvement, Renal Insufficiency, Chronic

Introduction

Optimization of health-care related financial costs has become a major issue for stakeholders due to constant evolution and the introduction of new diagnosis and therapeutic technologies. Today, hospitals usually rely on DRG (diagnosis related groups) and case mix funding to manage these costs.

France has implemented a case mix system named the PMSI program (*Programme de médicalisation des systèmes d'information*) in 1989 [1], on which is based a prospective payment system since 2004. In order to allow homogeneous coding between different hospitals, the French case mix center ATIH (*Agence technique pour l'information hospitalière*) has written methodological guidelines for coding. These

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guidelines introduce regulatory requirements which are used by medical inspectors from the social insurance to check that coding is accurate based on hospital activity such as described in the patient's medical record.

The research hypothesis in this work is that electronic health records (EHRs) contain useful information to allow checking PMSI data collection. For example, some medical diagnosis may be checked in the EHR using results from biological data. As the number of possible rules that may associate clinical data to potential medical diagnoses is large, one solution would be to implement them within a business rule management system (BRMS).

We must distinguish three kinds of data present in EHR: (i) structured data, (e.g. birth date, biological data measure, biological investigation result, etc.), (ii) free text data (e.g. discharge summaries, medical report or clinical notes), and (iii) image data (e.g. radiograph, MRI, etc.). Scientific literature already provides use-cases presenting EHR as a source to support billing coding, by using free text, which has already proven to be valuable in term of patient information [2, 3], as well as structured data [4, 5]. In this paper, we evaluate if a BRMS may be used to support coding in the French PMSI. We focused our efforts on the diagnosis of chronic kidney disease.

1. Material and Methods

1.1. Chronic kidney disease

The French PMSI uses the International classification of diseases 10th revision (ICD-10) for coding diagnosis. In ICD-10, the code corresponding to chronic kidney disease (CKD) is N18. The main test associated with this code is the glomerular filtration rate (GFR). We used the Cockcroft-Gault formula presented in equation 1 to estimate the GFR:

$$GFR = [\ (140 - \text{age}) * \text{weight} / \text{blood creatinine}\ ] * \text{K} \tag{1}$$

In this case, the unit of measurement of the GFR is mL/min where the age is in years, weight in kilograms and blood creatinine in µmol/L. Finally, K is a constant equal to 1.23 for a male patient and to 1.04 for a female patient. According to the National Kidney Foundation (Washington, DC, US) definition, five stages are defined for chronic kidney disease as shown in table 1.

Table 1. Stages of chronic kidney disease with corresponding GFR range

Stage	Description	GFR (in mL/min)	ICD-10 code
1	Kidney damage (protein in the urine) and normal GFR	More than 90	N18.1
2	Kidney damage and mild decrease in GFR	60 to 89	N18.2
3	Moderate decrease in GFR	30 to 59	N18.3
4	Severe decrease in GFR	15 to 29	N18.4
5	Kidney failure (dialysis or kidney transplant needed)	Less than 15	N18.5

We chose to only take into account stages of CKD from 3 to 5, stages 1 and 2 relying on kidney disease markers in addition to the GFR.

1.2. Information needed from the electronic health record

We worked on Cristal Link, the EHR of the University Hospital of Saint-Etienne. Once the age, weight, gender and blood creatinine measurement have been located as a column of the database storing clinical data from the EHR, extracting them seemed an easy step. But even so, all these pieces of information, except gender, are depending on the date. We chose to consider each hospital stay independently, as the French system is based on hospital stays. In each stay, we looked if a blood creatinine measurement was prescribed to the patient and if a result had been issued. For each blood creatinine measurement, by basing our argument on the date of the blood sample, we gathered the last registered patient weight, preceding the sample and calculated the age of the patient at this date thanks to their birth date.

Finally, it only remained the gender of the patient to retrieve in order to estimate the GFR. It was pretty straight-forward as for the birth date, by accessing the patient demographics.

1.3. Implementation of the ICD-10 correspondences into rules

We chose Drools [6] as the rule engine for this work. The reasons of this decision were motivated by the successful use of Drools as rules engine to cope with a similar problematic [11], the possibility to use a domain specific language or a decision table as a way to represent conditional logic, the fact that Drools is written in Java, a programing language appropriate in our information system that relies on internet technologies for graphical display of clinical data. Finally, JBoss Drools is currently the most efficient BRMS benefiting from a free software license.

Given the information on correspondence between GFR estimation ranges and stages of the CKD, we implemented the rules in two ways: (i) in a Drools rule file (DSLR) paired with a domain specific language (DSL) file (an example of one rule is shown in Fig. 1) and (ii) in a decision table formatted in XLS (not presented in this paper for a matter of space). Subsequently, anyone, even without programming skills, can write rules by using the documented natural language expressions.

Language Expression	Rule Language Mapping	Scope
GFR more than {ll} mL/min	p: Patient(getDFG() >= {ll})	[condition]
GFR less than {ul} mL/min	Patient(getDFG() < {ul})	[condition]
Display ICD-10 code "{code}"	System.out.println("The patient suffers from a disease whose ICD-10 code is {code}");	[consequence]

```
rule "Kidney damage and mild decrease in GFR"
    when
        GFR more than 60 mL/min and
        GFR less than 90 mL/min
    then
        Display ICD-10 code "N18.2"
end
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Figure 1. DSL and DSLR snippets for a rule.

2. Results

On one hand, we executed our rule engine with rules explained previously on every stay including a blood creatinine measurement during the month of January 2014. Thus, 533 stays present all components required to estimate GFR and are linked with a

GFR which is less than 60. By searching in the PMSI database, we found 429 acute care stays among the initial 533. This difference of 104 stays is explained by the fact that the PMSI database does not contain the stays for rehabilitation, psychiatry, and long term care.

In a second phase, we considered all stays for which the hospitalized patient was older than 13 and younger than 80 at the time of the stay. This choice was motivated by the works of Pierrat *et al.* [7] concluding that the Cockcroft-Gault formula is not the best suited for children and of Rimon *et al.* [8] about the poor results of Cockcroft-Gault formula for octogenarian in-patients. We end up with a set of 203 stays noted as set 1, whereas 9 stays concerned children younger than 12 or less, and 217 stays for which the patient was older than 79. We also decided to take into account the work of Garg *et al.* [9] to add another perspective to these results by also considering the 46 stays, noted set 2, in which patients were older than 12 and younger the 65 at the time of the stay.

The evaluation of our rules engine implementation was structured around the exclusion criteria of the "renal failure" diagnosis family of the ICD-10, containing the N17, N18 and N19 codes. Thus, N17 and N19 codes were considered, as well as, N99.0, O00-O07, O08.4, P96.0, O90.4, D59.3, K76.7, O90.4, and R39.2 codes. We checked if these diagnoses describing alternative clinical situations associated with renal failure were coded instead of N18. Consequently, 33.5% of the stays from set 1 were coded with N18 or at least another code associated with renal failure. The proportion increased to 54.4% for stays from set 2. Among sets 1 and 2, stays coded with a N18.* code represent respectively 27.1% and 45.7%. More precisely, 13.8% and 28.3% of stays from set 1 and set 2 were coded with a code among N18.3, N18.4 and N.18.5. About the exclusions of the N17-N19 diagnosis family, stays coded with N17 represent 5.9% in set 1 and 10.9% in set 2. The R39.2 code is used in 4.4% and 2.2% in set 1 and set 2 respectively. Finally, the other codes were not used for the stays at the exception of 1 stay coded with N99.0 among set 1 (0.49%).

3. Discussion

Results show diagnoses associated with renal failure are more often coded in patients older than 12 and younger than 65 that have a GFR < 60 mL/min than in patients between 12 and 80 with similar estimations of GFR as calculated by the Cockcroft-Gault formula. When patients are older than 65, the Cockcroft-Gault formula becomes a worse predictor of the true GFR and it is not sure that such approach may allow accurate suggestions of coding in older patients. Moreover, this approach has some limitations.

Firstly, the information needed to infer a CKD diagnosis corresponds to a basic situation where a medical diagnosis may be checked using a single value of a clinical data. However, we have to face more complex cases as described in the ATIH guidelines, e.g. malnutrition that takes into account one of different conditions such as a specific weight loss during a certain amount of time, a value of BMI or albumin to infer a diagnosis code among E44.0, E44.1 and E43. Implementing complex rules is required before we can claim that such approach may be generalized to the whole ATIH guidelines. Secondly, the GFR cannot be estimated when the blood creatinine is not measured. Lacking this measurement implies that we cannot determine precisely if the N18 code should be added or not. Thirdly, inference on structured data is sufficient in the case of N18 but it is not the case for every ICD-10 code. For example, result of a blood glucose test is not specific enough to be confident in a diagnosis of diabetes mellitus. In this case, the only remaining solution seems to mine free texts hosted in the EHR. Analysis of free text data has proven to be useful, for example to identify diabetes mellitus, Parkinson's disease, or asthma using discharge summaries [10], to extract Diagnosis Procedure Combination codes [11], or even to infer the diagnostic code [12]. Thus, using NLP tools could improve the rules implementation.

Nevertheless, we are confident that a business rule management system could be a good basis to implement a tool to help and check diagnosis codes. This is motivated by the possibility to allow healthcare professionals to write rules in their own language, for example using DSL in Drools, but also by the fact that progresses in natural language processing seem promising to extract useful information from free texts of EHR.

Consequently, we plan to implement new rules based on Schwartz and Modification of Diet in Renal Disease formulas, respectively for children younger than 12 and patients older than 80. Then, we ought to implement complex pieces of the ATIH guidelines into Drools rules, as well as a text miner in the future.

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