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Miscoding: a threat to the hospital care system. How to detect it?
Les erreurs de codage en tant que menace pour le système de soins hospitaliers: comment les détecter?

W. Aelvoet
Federal Service of Health, Food Chain Safety and Environment, Brussels, Belgium; Epidemiologie en Sociale Geneeskunde, Universiteit Antwerpen, Antwerp, Belgium; and Faculteit Geneeskunde en Farmacie, Vrije Universiteit Brussels, Brussels, Belgium.

N. Terryn
Federal Service of Health, Food Chain Safety and Environment, Brussels, Belgium

F.Windey,
Federal Service of Health, Food Chain Safety and Environment, Brussels, Belgium

M. Redivo
Federal Service of Health, Food Chain Safety and Environment, Brussels, Belgium

C. Faes
Center for Statistics, Universiteit Hasselt

Cell Audit
Federal Service of Health, Food Chain Safety and Environment, Brussels, Belgium

Corresponding author:
W. Aelvoet
Federal Service of Health, Food Chain Safety and Environment
Directorate-General for the Organisation of Health Care Establishments
Eurostation Bloc II - first floor -
Place Victor Horta 40 bte 10
B-1060 Brussels
Belgium
Tel +32 2 524.86.42; Fax +32 2 524.85.09
e-mail willem.aelvoet@health.fgov.be

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W. Aelvoet
Federal Service of Health, Food Chain Safety and Environment
Directorate-General for the Organisation of Health Care Establishments
Eurostation Bloc II - first floor -
Place Victor Horta 40 bte 10
B-1060 Brussels
Belgium
Tel +32 2 524.86.42; Fax +32 2 524.85.09
e-mail willem.aelvoet@health.fgov.be

Running title: Detection of miscoding

Abstract.

Background: Artificially influencing the case mix of hospitals may have several deleterious consequences for the hospital care system. One distinguishes over-evaluation (up-coding) and under-evaluation (under-coding) of the case mix. Apart from its financial consequences, miscoding may cause a fracture in epidemiologic time series and, by increasing artificially the severity of illness, may affect the assessment of the quality of hospital care, based on administrative data.

Methods: Fixed effects models were used to assess the evolution of length of stay at the national and the hospital level. To direct the audit towards fraud-suspected discharge abstracts 21 audit-triggering conditions were examined. Hereto, a method consisting in comparing a hospital's trend with the national trend was developed, using an interaction term between time trend and hospitals. To test this methodology fraud-directed audits were carried out in addition to the usual, at random audits.

Results: An important change in the mean LOS of the Belgian hospitals was identified, as well as evidence not only of improving coding practices, but also of up-coding, fraudulent under-coding and of numerous coding errors without financial impact. The coding errors, ascertained in the at random audit, resulted in a gain of the hospitals of 28.23 days in 258 stays, whereas in case of fraud-directed audits these figures amounted to 642.68 days in 334 stays.

Conclusion: Fraud-directed audit may constitute a valuable tool in the quality assurance of administrative databases, improving their use in epidemiology and assessment of the quality of care.

Key words: miscoding, administrative data, prospective payment system.

Résumé

Contexte : Les modifications artificielles du « case-mix » hospitalier peuvent engendrer des conséquences nuisibles pour le système de soins hospitaliers. Il importe d'effectuer une distinction entre sur-évaluation (« up-coding ») et sous-évaluation (« under-coding ») du « case-mix ». Outre un impact financier, les erreurs de codage peuvent provoquer un hiatus dans les séries temporelles, de même qu'elles peuvent, en accroissant artificiellement le degré de sévérité de la maladie, affecter l'évaluation de la qualité des soins hospitaliers à partir des données administratives.

Méthodes : Des modèles à effets fixes ont été utilisés pour évaluer l'évolution de la durée du séjour au niveau national et hospitalier. Afin de guider l'audit vers les dossiers de sortie suspectés de fraude, 21 conditions susceptibles de déclencher un audit ont été examinées. Dans ce but, une méthode a été développée, visant à comparer une tendance hospitalière avec la tendance nationale grâce à l'utilisation d'un terme d'interaction entre tendance temporelle et hôpitaux. La méthodologie a été testée en menant des audits spécialement orientés vers la détection de fraudes en plus des audits de routine « at random ».

Résultats : Il a été possible de mettre en évidence non seulement d'importants changements de la moyenne de la durée de séjour dans les hôpitaux belges et des preuves d'amélioration de la pratique de codage, mais aussi d' « up-coding », d' « under-coding » frauduleux et de nombreuses erreurs de codage sans impact financier. Alors que la méthode des audits « at random » a pu relever des erreurs de codage qui ont permis aux hôpitaux de gagner 28,23 jours sur 258 séjours, la méthode des audits spécialement orientés vers la détection de fraudes a identifié des erreurs ayant permis de gagner 642,68 jours sur 334 séjours.

Conclusion : L'audit spécialement orienté vers la détection de fraudes semble être un outil valable d'évaluation de la qualité des bases de données administratives afin d'améliorer l'utilisation de celles-ci en épidémiologie et dans l'évaluation de la qualité des soins.

Mots-clés : erreur de codage, données administratives, système de paiement prospectif

Miscoding: a threat to the hospital care system. How to detect it?

The original idea to use Diagnosis Related Groups (DRGs) as a measure of case mix, relied on the fact that, during the process of classifying a hospital stay into a particular DRG, length of stay (LOS), the dependent variable, correlated well with the total hospital costs.(1)

A few years after its introduction in 1975 a new hospital-acquired disease has been described, namely the systematically and deliberately overvaluing of the case mix, called “DRG creep”.(1) This phenomenon has been accelerated by the implementation of the Prospective Payment System (PPS), a system wherein hospitals receive a fixed reimbursement to treat patients with a given diagnosis, independently of the length of stay or the type of care, with the exception of certain patients with exceptionally high costs, the so-called outliers.(2;3) The reimbursement rates are set, for a given period of time, prior to the admissions giving rise to actual reimbursement claims. Thus PPS, by establishing a priori the reimbursement rates, facilitated the submission of discharge abstracts in the for the hospital most profitable way.(4)

Sources of creep are: misspecification, miscoding and resequencing of diagnoses. When in case of an admission for pneumonia, the attending physician selects against the rules an unrelated post-admission myocardial infarction as principal diagnosis one speaks of misspecification. A coder, coding a transient ischemic attack as a cerebro-vascular accident, and a member of the hospital staff, substituting the by the physician selected principal diagnosis of acute bronchitis into a diagnosis of chronic obstructive lung disease, are examples of respectively miscoding and resequencing.(5) Besides of up-coding its contrary, under-coding or the careless abstracting and coding leading to a lower DRG-assignment, has been described.(6) But here also, depending on the hospitals’ financing mechanisms, lucrative objectives may be pursued by a, this time, careful abstracting and coding leading to a lower DRG-assignment.

In Belgium for instance the reimbursement of hospitals is based on length of stay (LOS) which is compared with the national mean LOS of the same All-Patient-Refined-Diagnosis-Related-Group (APR-DRG), Severity of Illness (SOI) class and age class. According to APR-DRG version 15.0, the algorithm we use, SOI is categorised in four classes ranging from 1 (the lowest) to 4 (the highest severity).(7) In this context of reimbursement lengthy hospital stays are penalised. It may then be rewarding to under-code such discharge abstracts in order to be reclassified into another APR-DRG with a shorter LOS or lower SOI in the same APR-DRG, and to become an outlier, leading to the complete reimbursement.(8)

In addition to a PPS-inspired financing mechanism, the emergence of creep may have been facilitated during the introduction of the audit system in Belgium by the infrequently carried out audits and the restricted number of stays to be audited, consisting of an at random sample of 48 stays. In addition, due to loopholes in the law, no sanctions have yet been taken in case of creep. Finally, the evolution of the observed and the by case mix standardised national means of LOS showed a substantial decrease of the former and an increase of the latter.(8;9) These evolutions required an investigation to determine whether they consisted in a real gain in efficiency of the hospitals combined with an increase of its case mix, in an artefact caused by changing coding practices, or in a mix of both mechanisms.

In this study we present some statistical methods to assess the global evolution of the hospital system in terms of LOS and SOI, and to select purposefully the medical files to be audited in order to detect creep, as well as the first results of its in-the-field implementation.

Methods

Material

We used the Belgian Minimal Clinical Database (MCD) 2000-2003 (N= 11,743,945). It consists of anonymous discharge abstracts of every admission to all acute hospitals (N=114) in Belgium, with mainly following information: identification of the institution, patient data (age in years, gender and residence), stay data (year and month of admission/discharge, type of admission/discharge, LOS), main diagnosis, an unlimited number of secondary diagnoses and procedures.(10) Diagnoses and procedures are coded according to ICD-9-CM(11) and classified into APR-DRGs. (7)

Design of the study

1. Global assessment

The artificial increasing or decreasing of case-mix may provoke the classification of stays in the wrong APR-DRG and cause them to have an unusual LOS within the distribution of stays of that APR-DRG. Therefore, we modelled for the whole country and for each hospital the (weighted) difference between "observed" and "expected" mean LOS. Herein the expected mean LOS (ELOS) is an APR-DRG, SOI and age group adjusted mean, computed on the time period under consideration according to the prevailing financing regulation of the Belgian hospitals, whereas the observed mean (OLOS) is simply the mean of the stays. To establish an increasing case mix we also studied the evolution over time of the lowest SOI class.

Alongside of the aspect of the artificially influencing of the case-mix, we explored the so-called "Rest-DRGs", from which type 1 (APR-DRG 955 en 956) indicates the absence of (an acceptable) principal diagnosis and type 2 (APR-DRG 950, 951 en 952) flags stays mentioning an important surgical procedure not related to the principal diagnosis. In the latter case the stay is completely reimbursed.

Further, by judicious over- or under-coding it is possible to obtain the outlier status, leading to the complete reimbursement of the stay. Therefore we examined “small” outliers in SOI classes 3 and 4 in persons having left the hospital alive, and “big” outliers in SOI classes 1 and 2 as well.

2. Selection of triggering conditions

To guide the selection of the medical files to be audited, we tried to identify deviant coding behaviour using selected conditions or procedures susceptible, either to assign a stay to an APR-DRG with a lengthier mean LOS or to increase the SOI.(9) Based on frequency distributions of conditions, clinically judged prone to creep, we selected 21 conditions or procedures (Table 1) to be analysed in all the hospitals.

Precisely, two analyses are carried out on the triggering conditions: a first one focusing on the per-semester evolution of their rates (the trend), and a second one focusing on these rates of the entire time span of the study (the period).

3. At random versus fraud-directed audit

Our administration organised two types of audit on the MCD of the year 2003: on the one hand, at random audits in not fraud-suspected hospitals to assess their coding quality, and, on the other hand, fraud-directed audits. In the former audit 48 stays are to be scrutinised regarding the relevance of the choice of the principal and secondary diagnoses and the accuracy of the coding, whereas in the latter a secondary diagnosis is verified in 80 stays. Fraud-suspicion was based on the findings (1) of the global assessment and, subsequently, (2) of the analysis of the triggering conditions. We studied the agreement between auditor and audited regarding the choice of APR-DRG and SOI, and their influence on LOS. The audits were to be carried out in 102 hospitals, totalling 6154 stays. From these 90 records were lacking, and a further 987 one-day hospitalisations and 104 records from hospitals, financed by an alternative system, were not usable in this context. Finally our study concerned 4973 stays, from which 2158 stays were audited at random and 2815 fraud-detected.

Statistical methods to identify fraud-suspected hospitals

Given focus is on the whole of the Belgian hospitals and given our interest in identifying outlying hospitals, we used so-called fixed effects models. (12;13) Hierarchical models, usually taking the form of so-called random-effects models, would have been an alternative.(14) However, these models are not conceived to identify outliers. Further, the theory dealing with outliers has to be developed for linear mixed models and it is impossible to identify outliers in non-linear mixed models.(14;15) Finally, in the random-effects models the hospitals in the set of data are considered a random sample from the larger population of all hospitals, contrary to the facts in our study.

A multivariate analysis of repeated-measures data(16)was carried out to assess the evolution over time of the system. The same analysis, extended with an interaction term between a linear time trend and individual hospitals, was conducted to identify hospitals with an abnormal coding behaviour. More precisely, we compared the slope of each hospital's time trend with that of the other hospitals using linear contrasts.(16-18) In a linear mixed model, conceived to account for correlation within the data, we also fitted the difference between OLOS and ELOS to assess the system's evolution over time.

In case of a logistic regression the interaction term between time trend and hospitals has to be understood as an evaluation of log-odds ratios, i.e. the neperian logarithm of the odds ratios, wherein the log-odds ratio of a stay, with a principal diagnosis of trigger condition Y, belonging to a particular hospital Z versus the whole of Belgian hospitals in year X is not unvarying over time but has to be multiplied by a factor to obtain this log-odds ratio in year X

+ 1. This factor on the contrary is constant, thus the name trend, as long as we are working with log-odds ratios, but is no longer constant after taking antilogs to get odds ratios. The interested reader is referred to the book of Hosmer and Lemeshow for full statistical details of this modelling.(19)

To illustrate the concept of contrasts, consider the comparison of four hospitals. Custom hypothesis tests can be performed by specifying an L vector for testing the hypothesis $L\beta = 0$, indicating that the trends of the hospitals to be compared do not differ. In a first step we compare the trend (β_1) of hospital 1 (H1) with the mean trend of all the hospitals (H1, H2, H3, H4). The null hypothesis is then: H_0: $1\beta_1 = (1\beta_1 + 1\beta_2 + 1\beta_3 + 1\beta_4)/4$, with β_i being the trend for the *i*th hospital. In next steps we repeat this process for each of the hospitals and finally we fit the matrix of contrasts in our regression analyses. In Figure 1 we illustrate graphically the presence or otherwise of interaction between linear time trends. We do not observe an interaction between hospitals one (H1) and two (H2) (parallel lines), whereas it exists between these hospitals and both hospitals three (H3) and four (H4) (the lines are no longer parallel).

Because of the simultaneous multiple comparisons – 114 hospitals are compared with each other – we divided the alpha of the null hypothesis under study by the number of comparisons, in this case the number of hospitals (the so-called Bonferroni-correction(20;21)).

To detect outliers we also used the Mahalanobis distance, (20;22-25) which is a probabilistic distance, akin to a squared z-score: $z = (x-\mu)/\sigma$, where x = the observed value, μ = the mean, and σ = the standard deviation of the hospital values.

Results

Global assessment

The computed values of OLOS and ELOS in the Belgian hospitals changed from respectively 7.36 and 6.94 in 2000 to 6.87 and 7.32 in2003, resulting in an important decrease of 0.87 days in the difference between OLOS and ELOS. The mixed model approach resulted in a very similar linear trend of –0.976days /year (SE=0.01), amounting to –0.8928 days during that time span. The multivariate analysis of repeated-measures regarding the ratio of OLOS/ELOS indicated a significant trend of 0.98/year ($p < 0.0001$) and the presence of 10, Bonferroni-corrected outlying hospitals. Also, the analysis of the Mahalanobis distance revealed significant heterogeneity between hospitals (Figure 2). Thus three hospitals displayed a deviant distance with probability ≤ 0.000442 (= 0.05/114), four other hospitals could have been considered to have a deviant distance with probability > 0.001 and ≤ 0.01, and seven others had probabilities ≤ 0.05 and > 0.01. Regarding the “Rest-DRGs” we found national decreasing trends, respectively of 0.54 (0.40-0.70) in type 1 and 0.88 (0.86-0.90) in type 2. We also observed, compared with the national trend of SOI=1, a statistically significant decreasing trend in 35 hospitals and a statistically significant increasing trend in 47 hospitals. Further we found in 6 hospitals less and in 22 hospitals more “small” outliers than nationally. Regarding the “big” outliers these numbers respectively amounted to 11 and 25. The number of hospitals with more outliers was significantly higher for both the “small” ($p= 0.0025$) and the “big” ($p=0.018$) outliers than with less outliers.

Finally, we combined the fraud-suspected endpoints (global assessment) of the multivariate analysis, Mahalanobis distance, trend of SOI=1, “big” and “small” outliers, into one common endpoint. We obtained for each hospital a score, totalling the number of conditions for which it was fraud-suspected (Table 2).

Triggering conditions

Lacking a good classification of hospitals' case mix, which renders the interpretation of period odds ratios difficult, we focussed on trend. The national trend was significantly increasing for 12 of the triggering conditions, significantly decreasing for 2 and remaining stationary for 7 of them. In table 2 we present the distribution of the number of fraud-suspected conditions by hospital.

At random versus fraud-directed audit

We found an impressive 38.6% of the at random and 44.0% of the fraud-directed stays with disagreement regarding codes, from which approximately 7/10 did not result in a change of APR-DRG, SOI and LOS (Table 3). 56% of stays of the fraud-directed audits, selected because of an abnormal evolution, were correctly coded, which reveals at least a partial improvement of coding, evolving from a previous under-coding to an actual correct coding. The occurrence of relatively more cases of disagreement (RR= 1.14; 95% CI [1.07-1.22]) in the fraud-directed setting comes as no surprise. We observed the reverse phenomenon regarding changes in APR-DRG with or without changes of SOI (RR=3.03; 95% CI [2.33-3.93]). This might have been expected, because in this type of audit all diagnoses and procedures are verified and not only a single secondary diagnosis, which is the case in a fraud-directed audit. The fraud-directed audits revealed more frequently a change of SOI (RR=1.72; 95% CI [1.39-2.12]) and these changes resulted more often in a decrease of SOI (RR=1.59; 95% CI [1.35-1.88]). In the at random audits the proportion (0.56) of stays with decreasing SOI is not significantly different from 0.5 (p = 0.2273), whereas in case of fraud-directed audit this figures amount to 0.89 (95%CI [0.85-0.92]) and p <0,0001.

In case of disagreement between auditor and audited we detailed it by triggering code (Table 4) as well. Chronic airway obstruction (496), morbid obesity (278.01), acute respiratory failure (518.81), chronic renal failure (585), and decubitus ulcer (707.0) seemed to be efficient fraud-detectors. Acute posthemorrhagic anaemia (285.1) and anaemia, unspecified (285.9) seemed to be poor fraud-detectors but rather detectors of careless coding.

Discussion

Using fixed effect models it showed possible to identify an important change in (the difference between) the observed and expected means of the Belgian hospitals. Both at random and fraud-directed audits revealed the existence of numerous coding errors without financial impact. Moreover the fraud-directed audits, by determining an upward trend in correct coded discharge abstracts, revealed an at least partial shift towards correct coding. Also, the coding errors ascertained in the at random audit seemed to be bi-directional, resulting in a slight gain of the hospitals of 28.23 days in 258 stays, whereas in case of fraud-directed audits these figures amounted to 642.68 days in 334 stays, justifying our fraud-suspicion regarding those hospitals. These findings may have contributed to the observed changes in mean LOSses.

Creep as well as under-coding may have several deleterious consequences for the hospital system. Moreover since the financing mechanism in our country is from a closed envelope type, fraud by one hospital might have negative consequences in the financing of the other ones. In addition to these financial consequences, it may cause a fracture in epidemiological time series (26), and may affect the assessment of the quality of care in hospitals, based on administrative data. More precisely, it may distort the co-morbidity and severity of illness and hence bias risk-adjustment. Finally, miscoding may cause problems when interpreting the evolution of important characteristics of the hospital care system such as the seriousness of the pathology.

However, evidence shows that is possible to contend against the up-coding-facilitating effect of PPS. For instance the implementation of measures such as mandatory attestation by the attending physician of the mentioned diagnoses and procedures, together with the action of peer review organisations have been proven to achieve a reduction of the misspecification part of creep.(5;27;28)

The main strength of our study being its longitudinal approach, allowing the setting-up of fraud-directed audits, our exploratory approach nevertheless suffers from several limitations. Our choice of the triggering conditions, based on clinical judgment, is perfectible in the sense that a systematic search based on the algorithm assigning the SOI class might probably be more efficient. Further, it is not impossible that the linear time trend we used would always have achieved the best possible fit of the model. However we believe that the achieved fits are sufficiently good to allow routinely performed screenings for deviant coding behaviour to be efficient. Also, the fact of having had to focus on trend may have caused since long fraudulent hospitals to have reached a no longer increasing level of up-coding and thus escaped the detection procedure. This shortcoming may be corrected for by using input from at random audits and by elaborating a case mix classification of the hospitals.

Another weakness of our study consists in a possible, difficult to measure lack of inter-observer agreement between our auditors, which may have led to different appreciations regarding the same type of coding problem. Indeed, inter-observer variability is a well-known drawback of peer review(29;30), which we try to control by intensive case discussions between the auditors, by elaborating and referring to national guidelines, and by setting up a system of appeal in case a hospital would find itself unjustly considered fraudulent.

Finally, due to the temporarily limited number of auditors it was not yet possible to compare properly at random and fraud-directed audits and hence to assess the relative efficiency of the latter audit. Indeed such objective would have required audits of both types, conducted in the same hospitals during the same period, an objective we intend to realise the next few months.

Appendix: Interpretation of an OR by interaction between a continuous and a categorical variable

When there exists an interaction between a risk factor and another variable, the estimate of the odds ratio for the risk factor depends on the value of the variable that is interacting with it. Let F be a risk factor (here: the hospitals), X be a continuous variable (here: the evolution in time). The logit for this model is evaluated at F=f en X=x:

$g(f,x) = ß_0 + ß_1f+ß_2x+ß_3f*x$

Hosmer and Lemeshow[19] propose following three steps procedure leading to the desired OR:

1) $g(f_1,x) = ß_0 + ß_1f_1+ß_2x+ß_3f_1*x$, and
$g(f_0,x) = ß_0 + ß_1f_0+ß_2x+ß_3f_0*x$

obtain the log-odds ratio by computing their difference

2) $\text{Log OR} = ß_1(f_1-f_0) + ß_3x\ (f_1-f_0)$

exponentiate the log-odds ratio

3) $\text{OR}= \exp[ß_1(f_1-f_0) + ß_3x\ (f_1-f_0)]$

If the risk factor F is dichotomous, then this formula reduces to:

$$\ln[\text{OR}(F=1,F=0,X=x)] = ß_1+ß_3x,$$

which is the case in our study, since we are comparing one hospital (F=1) with the whole of the Belgian hospitals (F=0). Focus is given to $ß_3x$ the evolution over time of the log-odds ratio (the trend) of a specific hospital versus the whole of the Belgian hospitals. Given the unknown case mix of the hospitals, we are essentially interested in the evolution of the odds ratio and less in its actual value. Therefore outliers were identified according to the trend.

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