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## HIMJ Reviewed articles

### Coding productivity in Sydney public hospitals

Vera Dimitropoulos, Adam Bennett and Jean McIntosh

#### Abstract

The aims of this study were to compare Sydney public hospitals regarding medical record coding times to compare observed coding times with coding times necessary to avoid backlog and to evaluate the impact on coding time of casemix complexity, coder age, experience, job satisfaction, employment status, and salary. Coding time (in minutes) for each medical record over a two-week period was documented by 61 coders employed in 13 hospitals: six principal referral (PR), six major metropolitan (MM), and one paediatric specialist (PS) hospitals. The mean coding time for each coder was estimated by averaging across coding times for all records during the two-week period. In order to compare hospital mean coding times, the hospitals were grouped into PR and MM/PS groups. The mean coding time necessary to avoid coding backlog (expected coding time) for each hospital group was based on the total number of annual separations and filled full-time equivalent coding positions. The observed mean coding time was longer in the PR group than in the MM/PS group ( $p = 0.019$ ); however, the observed coding time was within the expected coding time limit in both the PR and MM/PS groups. Casemix complexity tended to influence coding time, but neither age, experience, job satisfaction, employment status nor salary had any impact. In conclusion, the expected coding times, if reliable, indicate that coders in the two hospital groups were keeping coding up-to-date. Thus, the variation between hospital groups in coding time is of little importance, given that the main objective in coding productivity is to maintain the coding workload.

**Keywords:** coding productivity; coding workload; ICD-10-AM; medical records

High quality and timely data have become increasingly important with the introduction of various forms of casemix-based funding (Callen, Meehan and Tomornsak 1997a, p7). Due to the extensive use of coded data, attention has become focused increasingly on coder performance (Robinson, Williamson, Groom, Perry and Whitfield 1998, p130). Performance is measured in terms both of coding quality and coding productivity or output (Kaydos 1991, p30). Research to date has focused mainly on quality, but it has been stressed (Peters & Frischkorn 1984, p 14) that monitoring of output is also a vital issue. There is evidence that output in terms of coding speed varies between hospitals (Carter 1996) and is affected by coding method (manual or automated) (Lloyd and Layman 1997, p75; Dimitropoulos 1995), and type of coding format (for example, ICD-9-CM or ICD-10-AM) (Coopers & Lybrand 1997; Strauch 1998; Mair 1999). Other factors proposed to have an impact on coding time but which have not as yet been examined specifically, include casemix complexity (Watson and Gough 1991, p50; Eagar and Innes 1992, p94; Carter 1996, p27), coding experience, aptitude, and

competency, and adequacy of medical record documentation (Watson and Gough 1991, p50). While as yet no formal standards have been set for coding output, a method has been devised (Watson and Gough 1991, p51) to calculate, for a hospital, the coding output necessary to keep coding up-to-date. The methodology is based on the hospital's number of annual separations and filled full-time equivalent (FTE) coding positions.

The present study had three aims: (i) To compare public, acute care hospitals in Sydney, New South Wales regarding the average time taken to code a medical record; (ii) To compare the observed coding time with the coding time necessary to keep coding up-to-date; and (iii) To measure the impact on coding time of casemix complexity, coding method, and a coder's age, number of years of coding experience, job satisfaction, employment status (full-time, part-time, casual or contract), and salary.

## Method

### Study population and data collection instruments

The study sample consisted of clinical coders employed during June 1999 in public acute care hospitals with  $\geq$  150 beds in the Sydney Metropolitan area. Data on hospital bed size were obtained from the *NSW Public Hospital Comparison Data Book — 1997/98* (NSW Department of Health 1999). The Health Information Manager (HIM) in charge of the medical records department in each of the 19 hospitals with  $\geq$  150 beds was mailed an explanatory letter asking for the participation of all coders in the department and stressing confidentiality. The chief HIMs in 13 (68%) of the hospitals agreed for their coders to participate. All public hospitals are classified into peer hospital groups, for which similar performance is anticipated in terms of cost per standard unit of output (NSW Health Structural & Funding Policy Branch 1998, p1). The 13 hospitals fell into three peer group classifications: principal referral (PR) ( $n = 6$ ), major metropolitan (MM) ( $n = 6$ ), and paediatric specialist (PS) ( $n = 1$ ).

The coding managers and coders employed in the 13 hospitals were interviewed by postal questionnaire. The number of coder questionnaires sent equalled the number of coders working in the medical records department during a designated two-week period in July 1999. The coders were also requested to record on a coding productivity form their daily workload during these two weeks. The two-week study period represented an average pay period reflecting the typical roster for full-time, part-time and casual staff. All coding managers ( $n = 13$ ) in the 13 hospitals responded. In the PR hospitals, 38 out of 44 coders responded (86%) and in the MM/PS hospitals, 25 of 31 responded (81%), giving an overall response rate of 84%.

The coding manager's questionnaire asked questions on:

- the range of services provided by the hospital, and hence the range of cases to be coded;
- whether the hospital had a day surgery unit and, if so, the annual number of day surgery separations;
- the annual number of separations for the whole hospital; and
- the method of coding in the hospital's medical records department (whether manual or automated).

The coder's questionnaire included questions on:

- employment status (full-time, part-time, contract, or casual);
- salary (in \$10,000 increments);
- age;
- number of years of coding experience; and
- job satisfaction.

The questions relating to job satisfaction were adapted from the work of Shouksmith (1991, p359) and covered four aspects, namely satisfaction with:

1. salary;
2. co-workers (personal perceptions of their helpfulness, experience, knowledge, openness to discussion, willingness to assist and openness of mind);
3. the job as a whole (perceptions of job security and job qualities leading to personal growth); and
4. the work environment.

Each coder used the productivity form on a daily basis over the two-week period to record:

- the number of hours worked that day, excluding breaks;
- the number of inpatient records coded that day (including day-stay records); and the number of hours of that day spent doing other tasks.

In the study, coding was defined as the time spent abstracting and recording codes. Time spent indexing was not included, as it was not known whether a computerised encoder, with which the indexing can be performed simultaneously via an interface, was used in all study hospitals.

All coding was performed using the *International Statistical Classification of Diseases, 10<sup>th</sup> Revision, Australian Modification (ICD-10-AM), 1<sup>st</sup> edition*. The survey period was timed to be approximately one year after the changeover from the mostly numeric format of the Australian version of the *International Classification of Diseases, 9<sup>th</sup> Revision, Clinical Modification (ICD-9-CM)* to the alphanumeric format of ICD-10-AM (which is more than double the size of ICD-9-CM (NCCH, 1997, p19). This allowed for the learning curve associated with the change, on the assumption that time to adjust to using ICD-10-AM could vary among coders but would be achieved within one year (Innes, 1997). In order to ensure confidentiality, a number only was assigned to link the questionnaire and productivity form that identified each coder. Completed forms were sealed in an unidentified envelope.

In order to ensure satisfactory format, readability, and content validity of the questionnaires and the productivity form, the coding manager and two coders at one hospital were asked, before the mail-out, to complete the questionnaires applicable to them. The coders were also requested to trial the productivity form. Feedback from this led to amendments to the final documents mailed to participating hospitals.

### **Estimation of casemix complexity**

An average cost weight for top volume Diagnosis Related Groups (DRGs) was developed for each hospital and this was used as an

absolute indicator of the hospital's respective casemix complexity. Data for each hospital were obtained from the 1996/97 Inpatient Statistics Collection (ISC), using AN-DRG v.3.1. For each hospital, only DRGs with  $\geq 100$  cases were kept, with the exception of the following four DRGs:

- DRG 572: day stay renal dialysis, which is a simple procedure requiring only one code (Watson et al 1991, p50).
- DRG 780: chemotherapy, which requires only one code. In addition, as the number of chemotherapy separations is high and well outside the normal range, outlier values can distort results (Coakes and Steed 1999, p168; Tabachnick et al 1996, p133).
- DRG 940: planned same day rehabilitation.
- DRG 941: non-acute outpatient rehabilitation.

The rank order of casemix complexity (from greatest to least complex) was 1-6 in the six PR hospitals, 7-10, 12, 13 in the six MM hospitals, and 11 in the PS hospital.

### Statistical analysis

The unit of analysis was the average number of minutes taken to code a record. Coding time per record was calculated by firstly subtracting from each coder's working day the number of hours spent performing other duties; the number of minutes (converted from hours) spent coding was then divided by the number of records coded in the day to arrive at the average number of minutes taken to code a record that day. For each coder, the sum of the average coding times for each day, divided by the number of days worked during the two-week period, gave the overall average time per record. It was inappropriate to test for variation in coding time among the individual hospitals within a peer group, as the number of coders in most hospitals was smaller than the number of hospitals in the peer group ( $n = 4 - 8$  coders per PR hospital, and  $2 - 4$  coders per MM hospital). Thus, comparison was made only between the hospital groups. The casemix complexity of the PS hospital was in the MM range; therefore, this hospital was included in the MM group for analysis because the level of casemix complexity appeared associated with hospital peer group. The *t*-test was used to check for any difference in coding times between coders in the PR and the MM/PS hospital groups. The mean coding times of two coders from a PR hospital were more than 5 standard deviations (SD) from the hospital group mean coding time and were thus in the extreme range; therefore, they were excluded, leaving for analysis the coding times of 61 coders. Thirty-six coders worked in the PR hospitals and 25 coders worked in the MM/PS hospitals. The average coding time, per record, necessary to keep coding up-to-date in each hospital group was estimated according to the method devised by Watson and Gough (1991), and was termed the 'expected coding time'. The methodology involved dividing the total number of annual separations in 1999, per hospital group, by the total number of full-time equivalent (FTE) coding positions per group, to obtain the number of records to be coded per FTE in 1999. This figure was then divided by 220 (representing the number of working days in the year after leave entitlements) to arrive at the expected number of records coded per working day. The number of minutes per working day (equating to 480, given an FTE of 1.0 = 40 hours/week (Kemp 1994, p95) and thus eight hours per day) was divided by the expected number of records, per hour, to estimate the expected number of minutes per record.

A multiple regression analysis was used to evaluate the ability of casemix complexity, age, years of experience, job satisfaction, employment status, and salary to influence coding time. This assessed the association between each factor (that is, each independent variable) and coding time (the dependent variable), with the influence of the other factors held constant (Munro 1997, p258). It was found that all coding was performed using a 3M encoder; therefore, the impact of coding method could not be examined. One assumption underlying multiple regression is that independent variables should not correlate highly (Tabachnick and Fidell 1996, p131); therefore, age of the coder and years of experience were combined into a single variable (age/years experience), as they were found to be linked. The standard multiple regression model was used because there were no logical or theoretical grounds on which to rank any one variable higher than another (Cohen and Cohen 1975) and there was no good reason to use another technique (Tabachnick and Fidell 1996, p153). The values for 56 coders (74.7% of those eligible) were used in the regression analysis because the two coders with outlier values were excluded from all analyses and five other coders (also from PR hospitals) failed to answer most questions relating to the independent variables. All data were entered into a Microsoft Access 97™ database. The regression analysis was performed using SPSS for Windows v.9.0.

## Results

### Mean coding time per record

The average coding times per record for the PR and MM/PS hospital groups were 13.59 (SD 3.9) and 11.31 (SD 3.3) minutes, respectively. The mean time for the PR group was significantly longer at the 2% level than that for the MM/PS group ( $t = 2.41$ ,  $df = 59$ ,  $p = 0.019$ ). The mean difference between the coding times was 2.28 minutes (95% Confidence Interval (CI) 0.38 - 4.18). [Table 1](#) shows that the observed mean coding times were shorter than those expected by 0.44 and 2.07 minutes in PR and MM/PS hospitals, respectively.

**Table 1. Number of annual separations and filled FTE coding positions, and the expected and observed coding times, in the PR and MM/PS hospitals**

Hospitals	Total separations (1999)	Total FTEs (1999)	Expected no. of minutes/record	Observed no. of minutes/record
PR	291,692	38.75	14.03	13.59
MM/PS	176,455	22.36	13.38	11.31

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The results of the multiple regression analysis are shown in [Table 2](#). From the  $\beta$  and  $p$ -values it is seen that no factor under study affected time taken to code a record at the 5% level of significance. It is seen, however, that casemix complexity tended to be associated

significantly with coding time ( $p = 0.09$ ). The value of  $R^2$  indicates that only 8.6% of any differences in coding time between the hospital groups is explained by the factors of interest combined.

**Table 2. Extent and significance of the impact on coding time of casemix complexity, coder age/experience, job satisfaction, employment status, and salary as shown by regression analysis**

Independent variable	Standardised coefficient $\beta$	t	Significance of t (P)	$R^2$
Casemix complexity	0.24	1.72	0.09	N/A
Age/experience	-0.18	-0.13	0.90	N/A
Job satisfaction	-0.1	-0.71	0.48	N/A
Employment status	0.15	0.92	0.36	N/A
Salary	-0.12	-0.70	0.49	N/A
All variables	N/A	N/A	N/A	0.086

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## Discussion

The results show that coders in the PR group of hospitals took longer, on average, to code their records than those in the MM/PS group. However, while the estimated mean difference between the average coding times for the two hospital groups was 2.28 minutes, the 95% CI indicates there is 95% confidence that the difference could be as little as 0.38 minutes and as great as 4.18 minutes; that is, that the true difference lay somewhere in that range. The extent of significance of difference ( $p = 0.019$ ) was due to consistently longer, rather than markedly longer, coding times in PR hospitals. The expected mean coding times show that, given the number of annual separations and filled FTE coding positions in the two hospital groups, the coding time required to avoid backlog was, in any case, longer in PR than in MM/PS hospitals, although only by around half a minute. In this study the coders, knowing that their rate of work would be scrutinised, albeit anonymously, and having to keep track of their output, may have worked faster or slower than usual. However, the finding that the observed mean coding time was ahead of the expected in both hospital groups, and appreciably ahead in the MM/PS group, suggests, assuming the study period's workload was representative of 1999, that the coders in both groups were coping quite well with the work required of them. In this study, the main feature shown to distinguish between the PR and MM/PS groups was the level of casemix complexity. Although the claim that casemix complexity has an impact on coding time (Watson and Gough, 1991, p76; Eagar and Innes, 1992, p96; Carter, 1996, p27; Callen, Meehan and Tomornsak, 1997b, p73), is based on conjecture rather than evidence, it is arguably plausible. It stands to reason that, due to a

greater proportion of patients with multiple medical conditions and a greater proportion staying longer in hospital, the discretely greater casemix complexity associated with the PR hospitals would cause their records, on the whole, to be longer and more complex than MM/PS hospital records (and thus to take longer to code). The lack of a significant association at the 5% level between casemix complexity and coding time could be due to the fact that in Sydney hospitals it is not the policy to randomise allocation of records among coders; those who code more slowly may be more likely (and perhaps encouraged) to code the simpler, shorter records. This practice could balance out coding times across the more and less complex records. If this phenomenon does exist, it can be speculated that the longer mean coding time in the PR hospitals was due to a higher ratio of longer, more complex records to faster coders in the PR hospitals than in the MM/PS hospitals. It seems logical that such manipulation of record distribution could obscure associations of coding time with factors such as age or experience, and employment status. However, these factors, together with job satisfaction and salary, are seen to have exerted absolutely no impact on coding time with the effect of casemix complexity taken into account (all  $p$ -values  $>0.35$ ). It is noted that small sample sizes can cause a type II error; that is, failure to detect a significant association when one is present. An increase in sample size can correct this by increasing the power of the analysis (Bradford Hill, 1980). With a population of only 56 coders, the impact of casemix complexity on coding time was significant at the 10% level; hence it is possible, for instance, that with a larger number of coders a significance level of 5% would have been reached.

Coding output previously has been studied in terms of the number of records coded per month (Callen, Meehan and Tomornsak 1997b), per day (Dimitropoulos and Ryan-Thomas 1995; Dunn 1996; Lloyd and Layman 1997; Lorence 1999), per hour (Carter 1996) and, as in the present study, the number of minutes per record (Wendler 1987; Mair 1999). Only one survey, that by Carter (1996), is comparable to the present in that it is Australian, it examined coding time across several hospitals, took into consideration hospital size (and thus casemix complexity, albeit very indirectly), and used in estimates of coding output only the hours actually spent coding. Among the regional Victorian hospitals studied by Carter that had annual separations in the 1,000 to 10,000+ range, the mean coding time increased as hospital size (and thus, presumably, casemix complexity) decreased. This is an opposite finding to that of the present study. Carter concluded that the reason for this is not readily explained. However, in these hospitals, both manual and automated coding methods were used, with an apparent positive correlation between usage of DRG Grouper or encoder and hospital size. It has been shown previously that automated encoding improves coding speed (Lloyd and Layman, 1997). Therefore, it may be that across the hospitals (if, in fact, hospital size and casemix complexity were linked), the positive effect on coding time of advanced coding technology counteracted the negative effect exerted by increased length and complexity of the medical record.

## Conclusion

In conclusion, while coding time was found to be longer in the Sydney PR hospitals than in the MM/PS, it is logical that this should be the case. On the assumption that the effect of casemix complexity on coding time may have been masked by the way in which records

were distributed to the coders, casemix complexity is suggested as the possible cause of the difference in coding times. This is suggested despite the fact that it was found that coding time was not associated with casemix complexity at the 5% significance level. However, the main objective in coding productivity is maintaining the coding workload; thus, if the expected coding times are reliable indicators of coding requirements, the factor over-riding all is that coders in both hospital groups were seen to be working at a pace that was more than adequate to keep coding up-to-date, especially in the major metropolitan hospitals. The factors that are personal to individual coders working in Sydney public hospitals, that may affect time taken to code a medical record, remain unknown.

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