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Variations in the recording of common health conditions in Australian hospitals

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Abstract

Objectives: To investigate the agreement between self-report and recording of six morbidities in administrative hospital data, quantify the between-hospital variation and identify predictors of positive agreement between the two data sources.

Setting and participants: Retrospective analysis of linked self-report and administrative hospital data for 32,832 participants in the large-scale cohort study (45 and Up Study), who joined the study from 2006-2009 and who were admitted to 313 hospitals in New South Wales, Australia, for an overnight stay, up to a year prior to study entry.

Outcome measures: Agreement between self-report and administrative hospital data and positive agreement among participants who self-reported any of the six morbidities.

Results: Agreement between data sources was good for diabetes (κ=0.79), moderate for smoking (κ=0.59), fair for heart disease, stroke and hypertension (κ=0.40, κ =0.30, κ =0.24, respectively) and poor for obesity (κ=0.09), indicating that a large number of individuals with self-reported morbidities did not have a corresponding diagnosis coded in their hospital records. Significant between-hospital variation was found (ranging from 8% of unexplained variation for diabetes to 22% for heart disease), with higher agreement in public and large hospitals, and hospitals with greater depth of coding.

Conclusions: The recording of six common health conditions in administrative hospital data is highly variable, and for some conditions, very poor. To support more valid performance comparisons, it is important to stratify or control for factors that predict the completeness of recording, including hospital depth of coding and hospital type (public/private), and to increase efforts to standardize recording across hospitals. Studies using these conditions for risk adjustment should also be cautious of their use in smaller hospitals.

Keywords: hospital data, morbidity, multilevel modeling, agreement

Article summary

Article focus

- Explore the agreement between administrative hospital data and self-report information for four clinical conditions, as well as smoking and obesity.
- Quantify the between-hospital variation in the level of recording of these conditions.

Key messages

- Good levels of agreement found only for diabetes, with other conditions exhibiting moderate to poor agreement.
- Better recording was found in public and large hospitals, and hospitals with greater depth of coding.
- Significant between-hospital variation in the levels of agreement, amplified when smaller and private hospitals are included.

Strengths and limitations

- Use of linked data from a large-scale cohort study and advanced multilevel modeling methods to comprehensively evaluate the recording of common health conditions in hospital data, and explore between-hospital variation.
- Limitations include the absence of 'gold standard' such as medical records.

Introduction

Most nations with advanced economies publicly report on the comparative performance of hospitals with a view to accelerating and informing efforts to improve quality and allowing patients to make informed choices. Diagnoses recorded in administrative hospital data are commonly used in the construction and case-mix adjustment of hospital performance metrics, as well as for risk adjustment in epidemiological studies.

The construction of reliable health metrics relies on statistical methods that take into account the degree to which patients treated in different facilities have different morbidity and risk profiles that predispose them to requiring different interventions or to achieving different outcomes. These statistical methods, known as case-mix or risk adjustment, account for patient-related factors that are above and beyond the immediate control of health care professionals.

Thus, properly constructed performance metrics fairly reflect differences in health care experiences, patient outcomes and risks of adverse events. There has been some criticism of case-mix adjustments because they are subject to measurement error, [1] but case-mix adjustment is still considered to be less biased than unadjusted comparisons. [2]

Most methods of case-mix adjustment rely principally on demographic and diagnostic information that is captured in administrative hospital data. [3] This approach may be sub-optimal [4 5] because evidence from many countries suggests that administrative hospital data underreport the morbidity information needed to fully account for differences between hospitals in patient-related factors that predispose them to differences in measured outcomes. [6-13] However, the impact of this underreporting on comparative measures of hospital performance depends on whether it varies systematically among hospitals, because of

differences in factors such as training or practice among coding staff, the comprehensiveness of clinicians' notes, or "upcoding" relating to funding models or incentives. [14]

This issue is relatively unexplored, aside from the work by Mohammed et al. [2] which reported a non-constant relationship between case-mix variables and mortality among hospitals in the UK, explained by differences in clinical coding and admission practices across hospitals. These variations in coding accuracy were shown to be related to geographic location and bed size, with small rural facilities performing better than large urban hospitals. [15 16] In Australia, variations in the reporting and coding of secondary diagnoses have been shown to exist in public hospitals among Australian states, [17] and also among hospitals within the state of New South Wales (NSW), with worse underreporting in private and rural hospitals. [3] However, the relative contributions of patient and hospital factors to these variations have not been identified, nor has this variation been formally quantified.

This study aimed to further investigate the nature and potential implications of underreporting of morbidity information in administrative hospital data, by: 1) measuring the agreement between self-reported morbidity information and coded diagnoses; 2) quantifying the amount of between-hospital variation in this agreement; and 3) identifying patient and hospital characteristics that predict higher or lower levels of agreement. We focused on clinical conditions common to case-mix and risk-adjustment models – diabetes, heart disease, hypertension and stroke. We also focus on smoking and obesity, due to their impact on health trajectories, rapid shifts in prevalence, substantial geographic variation in rates [18] and paucity of international evidence on completeness of coding.

Methods

Data sources

The 45 and Up Study

The 45 and Up Study is a large-scale cohort study involving 267,153 men and women aged 45 years and over from the general population of NSW, Australia. The study is described in detail elsewhere. [19] Briefly, participants in the 45 and Up Study were randomly sampled from the database of Australia's universal health insurance provider, Medicare Australia, which provides near complete coverage of the population. People 80+ years of age and residents of rural and remote areas were oversampled. Participants joined the Study by completing a baseline questionnaire (available at https://www.saxinstitute.org.au/our-work/45-up-study/questionnaires/) between January 2006 and December 2009 and giving signed consent for follow-up and linkage of their information to routine health databases. About 18% of those invited participated and participants included about 11% of the NSW population aged 45 years and over. [19] Exposure-outcome relationships estimated from the 45 and Up Study data have been shown to be consistent with a large random survey of the same population. [20]

The NSW Admitted Patient Data Collection (APDC)

The APDC includes records of all public and private hospital admissions ending in a separation, i.e. discharge, transfer, type-change or death. Diagnoses are coded according to the Australian modification of the International Statistical Classification of Diseases and Related Problems 10th Revision, ICD-10-AM. [21] Up to 55 diagnoses codes are recorded on the APDC, including the principal diagnosis and up to 54 additional diagnoses. Additional diagnoses are defined as 'a condition or complaint either coexisting with the principal diagnosis or arising during the episode of care' and should be interpreted as conditions that affect patient management. [22]

The APDC from 1 July 2000 to 31 December 2010 was linked probabilistically to survey information from the 45 and Up Study by the NSW Centre for Health Record Linkage (www.cherel.org.au) using the 'best practice' protocol for preserving privacy. [23]

Study population

The study population comprised patients aged 45 years and above who participated in the 45 and Up Study and who had an overnight hospitalisation up to 365 days prior to filling out the baseline 45 and Up Study survey. NSW is home to 7.4 million people or one-third of the population of Australia.

Measuring morbidity

We examined four health conditions (diabetes, heart disease, hypertension and stroke) and two health risk factors (obesity and smoking), referred to hereafter collectively as "morbidities". For each participant, these health conditions were measured using self-report and administrative hospital data.

Self-reported morbidities were ascertained on the basis of responses to questions in the baseline 45 and Up Study survey. Diabetes, hypertension, stroke and heart disease were identified using the question "Has a doctor ever told you that you have [name of condition]?". Participants who did not answer the question were excluded from analyses (n=1,242).

Smoking was classified on the basis of answering "yes" to both of the questions "Have you ever been a regular smoker?" and "Are you a regular smoker now?". Participants' responses to the questions "How tall are you without shoes?" and "About how much do you weigh?" were used to derive body mass index (BMI), defined as body weight divided by height

squared (kg/m^2). The World Health Organization's [24] classification system was used to categorize individuals as obese (BMI $\geq 30 kg/m^2$).

Morbidity information in administrative hospital data was ascertained using all 55 diagnosis codes in the APDC records (ICD-10-AM: E10-E16 for diabetes, I20-I52 for heart disease, I60-I69, G45, G46 for stroke, I10-I15 and R03.0 for hypertension, F17.2 or Z72.0 for smoking and E66 for obesity).

Predictors of agreement

We explored both patient- and hospital-level factors as predictors of agreement between the two data sources.

Patient-level factors were self-reported in the 45 and Up Study baseline survey and included age, sex, education, country of birth, income and functional limitation. Functional limitation was measured using the Medical Outcomes Study – Physical Functioning scale, [25] and classified into 5 groups: no limitation (score of 100), minor limitation (score 95-99), mild limitation (score 85-94), moderate limitation (60-84) and severe limitation (score 0-59).

Facility-level factors were type of hospital (public/private), hospital peer group (akin to hospital size defined by number of case-mix weighted separations, [26] which includes hospital remoteness in the classification), remoteness of hospital and depth of coding. Remoteness of the Statistical Local Area in which the hospital was located was classified according to the Accessibility/Remoteness Index of Australia (ARIA+), grouped into four categories (major city, inner regional, outer regional, remote/very remote). [27] Depth of hospital coding was the mean number of additional diagnoses coded for each hospital, calculated using all overnight hospitalizations for the full 45 and Up Study cohort from 2000 to 2010, and divided into four groups at the 25^{th}, 50^{th} and 75^{th} percentile. Hospital peer

groups were divided into 5 categories: principal referral (≥25,000 separations per year), major (10,000-24,999 separations per year), district (2,000-9,999 separations per year), community (up to 2,000 separations per year) and other (non-acute, un-peered hospitals). Missing information was treated as a separate category for any variables with missing data.

Statistical methods

We examined patient-level agreement between data sources for each of the six morbidities individually, as well as for their 15 two-way combinations. We compared the self-reported responses (yes/no) with all the diagnoses provided in the hospital records both for 'index' admissions and for the 'lookback' period admissions. [28] The 'index' admission was the overnight hospital stay with admission date closest to the survey completion date and no longer than a year prior. Morbidity was coded as 'yes' if any of the diagnoses during that stay contained a mention of that morbidity. The 'lookback' admissions included all overnight stays in the 365-day period that preceded and included the 'index' admission. Morbidity was coded as 'yes' if any of the diagnoses from any lookback admissions contained a mention of that morbidity.

Agreement between the two data sources (yes/no) was measured using Cohen's kappa statistic (κ). Kappa values above 0.75 denote excellent agreement, 0.40 to 0.75 fair to good agreement and below 0.45 poor agreement. [29] Agreement was computed for all 313 hospitals in the state, regardless of size, as well as for the 82 largest public hospitals, for which performance metrics are publicly reported.

Multilevel logistic regression was used to estimate odds ratios (OR) with 95% confidence intervals (CI) for patient- and hospital-level factors that predicted positive agreement between the two data sources. Multilevel models were chosen because of the clustering of patients

within hospitals. Models were run for each of the six morbidities separately. These analyses were constrained to only those participants who self-reported the morbidity of interest, and the outcome was whether the index hospital record contained a mention of the morbidity or not. Addition of the hospital-level characteristics was done one at a time, due to the collinearity between variables. All ORs presented are adjusted for all other demographic variables in the model.

Variation at the hospital level was expressed as a median odds ratio (MOR), which is the median of the odds ratios of pair-wise comparisons of patients taken from randomly chosen hospitals, calculated as $exp^{0.954\times\sqrt{variance}}$;[30] and the intraclass correlation coefficient (ICC), which is the percentage of the total variance attributable to the hospital level. [31] Large ICCs indicate that differences among hospitals account for a considerable part of the variation in the outcome, whereas a small ICC means that the hospital effect on the overall variation is minimal. The relative influence of the hospital on reporting of morbidity was calculated using a variance partitioning coefficient expressed as a percentage of the total variance using the Snijders and Bosker latent variable approach. [31]

All data management was done using SAS 9.2 [32] and multilevel modeling using MLwiN 2.24. [33]

The conduct of the 45 and Up Study was approved by the University of New South Wales Human Research Ethics Committee (HREC), while ethical approval for this particular study was provided by the NSW Population and Health Services Research Ethics Committee and the University of Western Sydney HREC.

Results

Descriptive characteristics

A total of 32,832 study participants were admitted to 313 hospitals up to a year prior to completing the 45 and Up Study baseline survey. Just over half of the index admissions (53%) were planned stays in hospital, and 57% were to a public hospital. Around one-third of the index admissions occurred within the three months before study entry, and the mean length of stay was 4.8 days (median = 3 days). Just under half of the sample (47%) reported having hypertension, with heart disease or obesity reported by 25%, and current smoking by 6.1% of the sample. One-third (34%) of participants had two or more morbidities (data not shown). Other characteristics of the sample at their index admission are shown in Table 1.

Table 1 about here

Concordance between self-report and hospital records

Overall, reporting of morbidity differed between the two data sources with 23,257 (71%) participants having at least one of the six self-reported morbidities, and 11,977 (36.5%) and 14,335 (43.7%) of the sample having at least one morbidity recorded on their index or lookback hospital admissions, respectively.

Table 2 gives the summary concordance measures for each morbidity and two-way morbidity combination. For the index admission, good agreement was found for diabetes (κ=0.79), moderate agreement for smoking (κ=0.59), fair agreement for heart disease (κ=0.40), and poor agreement for stroke (κ=0.30), hypertension (κ=0.24) and obesity (κ=0.09). In two-way combinations, moderate levels of agreement were found only for diabetes combinations (with smoking, hypertension and heart disease).

Table 2 about here

Incorporating a one-year lookback period increased the numbers of participants with a morbidity recorded in a hospital record, with average relative increases in the kappa values of 20% (ranging from 2% increase for smoking, to 41% increase for obesity). Good to excellent level of agreements were still found only for diabetes (κ =0.83) and smoking (κ =0.60).

Agreement was only slightly higher among the 82 large public hospitals (see Supplementary Table 1) with relative kappa values higher by 4%, on average.

Patient- and hospital-level predictors of positive agreement

The patient factors which predicted positive agreement between the two data sources differed between morbidities (Table 3). Male sex was associated with better agreement for diabetes (OR=1.37, 95% CI 1.19 – 1.58), heart disease (OR=1.30, 95% CI 1.17 – 1.44) and hypertension (OR=1.28, 95% CI 1.18 – 1.38) (Supplementary Table 2).

Older patients were significantly less likely to have smoking (80+ years OR=0.48, 95% CI 0.31 – 0.74) and obesity (OR=0.14, 95% CI 0.08 – 0.26) recorded in their hospital records, and significantly more likely to have hypertension recorded (OR=1.32, 95% CI 1.16 – 1.49), compared to younger patients (45 – 59 years). People with higher levels of functional limitation were significantly more likely to have hypertension, diabetes and obesity recorded on their most recent hospital stay. Planned admissions to hospital had lower odds of having any of the six conditions recorded, as did medical admissions (for diabetes, smoking and obesity only). Agreement did not vary significantly for any other patient factors.

Table 3 about here

The four hospital-level covariates (hospital type, hospital peer group, hospital remoteness and depth of coding) were added to multilevel models (including a random intercept for hospital) one at a time, separately. Positive agreement between self-report and hospital records was significantly lower for hospitals with lower depth of coding across all morbidities. The odds of recording were also lower among private hospitals for all six morbidities, with this difference being statistically significant for hypertension, heart disease and stroke only. Records from smaller hospitals (district and community peer groups) were significantly less likely to agree with self-reported data on hypertension, diabetes and heart disease. Positive agreement did not vary significantly with remoteness of hospital, with the exceptions of diabetes (lower agreement for outer regional, remote and very remote hospitals) and smoking (lower agreement for remote and very remote hospitals) (Supplementary Table 3).

Quantifying variation between hospitals

Before any hospital-level variables were added into the multilevel model, the intraclass correlation coefficient indicated that between 8% (diabetes) and 22% (heart disease) of the residual (unexplained) variation in agreement was attributable to the hospital, after adjustment for the patient-level factors (Table 4). This equated to median odds ratios (MORs) of 1.64 and 2.48, respectively, indicating that a patient in one hospital had an average of between 64% and 148% higher odds of having a particular morbidity recorded than a patient in a hospital with lower levels of recording. Less variation at the hospital level was found for the recording of diabetes, smoking and stroke, while more variation at the hospital level was found for the recording of hypertension, heart disease and obesity. When the analyses were

restricted to 82 large public hospitals only, the between-hospital variation decreased to between 2% (stroke) and 13% (hypertension), or MOR of 1.24 and 1.94 (Figure 1). This between-hospital variation was still significant for all morbidities except for stroke. Between-hospital variation was further reduced once lookback admissions were used to identify morbidities.

Figure 1 about here

The addition of hospital-level variables to multilevel models, one at the time, separately, helped ascertain which factors explained the variation between hospitals (Table 4). The addition of at least one of the four hospital-level factors contributed to explaining the residual variation between hospitals for all conditions, except obesity. For the other morbidities, differences in the depth of coding explained from 16% (smoking) to 42% (hypertension) of residual variation between hospitals, while hospital type (public/private) explained from 0% (smoking) to 59% (stroke), and hospital peer group explained from 10% (hypertension) to 27% (diabetes) residual variation between hospitals.

Table 4 about here

Discussion

Our study found that the concordance of administrative hospital and self-reported data varied between the six morbidities examined, with agreement ranging from good for diabetes, moderate for smoking, through to fair for heart disease, and poor for hypertension, stroke and

obesity. We demonstrated considerable between-hospital variation in the recording of these common health conditions. Smaller, but still significant, between-hospital variation was found when restricting the analyses to the largest public hospitals in the state.

Previous studies have validated information recorded in NSW administrative hospital data for demographic factors, [34 35] and recording of perinatal conditions, [36-39] but there have been limited studies of the accuracy of the recording of health conditions commonly used for case-mix or risk-adjustment. Our findings regarding agreement for the recording of diabetes (κ=0.83) were similar to previous Australian studies [3 10], while agreement for hypertension (κ=0.30) and heart disease (κ=0.47) was considerably lower in our study. These differences may be due to the fact that both previous studies used medical records as a 'gold standard', while we used self-report. Higher sensitivities reported in a study from the state of Victoria [10] could also be attributable to the differences in public hospital funding models between the two states. Specifically, Victoria has used activity- based funding since 1993, while this method of funding was introduced in NSW and other Australian states only subsequent to our study period. [40] Introduction of activity-based funding has been shown to increase recording of additional diagnoses and procedures in Europe. [41]

Some of the apparent discrepancies in the levels of coding between conditions can be attributed to the coding rules that govern whether or not a diagnosis is recorded in administrative hospital data. Additional diagnoses are coded only if they affect the patient's treatments received, investigations required and/or resources used during the hospital stay. Thus, diagnoses that relate to an earlier episode, and which have no bearing on the current hospital stay, are excluded. Therefore, it is not surprising that (managed) hypertension, in particular, might not be recorded in hospital data relating to, for example, elective surgery. On the other hand, we found that diabetes is well recorded, suggesting that it is considered to affect patient management in most hospital stays.

As well as looking at single morbidities, ours is the first study to our knowledge to explore the variations of recording of multiple conditions in hospital data. Concordance of two-way condition combinations was very low, with best results found for combinations of diseases involving diabetes, which had the highest single-condition level of agreement with self-reported data (κ =0.83). Agreement measures for two-way combinations were found to be fair to good at best, with agreement on three-way condition combinations (not investigated here) expected to be even lower. These findings have implications for research into multimorbidity (the co-occurrence of multiple chronic or acute diseases and medical conditions within one person [42]). We suggest that researchers who use administrative data for research into multimorbidity should use linked data to increase ascertainment, and, if possible, supplement this information from other data sources, such as physician claims data or self-reported data.

We identified considerable between-hospital variability in the levels of recording of common health conditions, with between 8% and 22% of the variation attributable to hospital-level factors, after adjustment for patient factors. This was similar in magnitude to the variability previously reported for performance measures (varying from patient satisfaction, mortality, length of stay to quality of care) clustered at the facility level (0-51%) [43] and hospital-level variations in the use of services. [44-46] Significant between-hospital variation was still present after constraining the analyses to the 82 largest public hospitals in the state.

The recording of hypertension and heart disease was particularly variable between hospitals, those with better reporting having on average 2.3 and 2.5 times, respectively, the odds of recording these conditions than those with lower levels of reporting. The corresponding figures were 1.9 and 1.6 times for the 82 largest hospitals in the state. These findings indicate the potential for reporting bias to influence comparisons of health performance indicators between hospitals, especially for indicators that use conditions such as heart disease or hypertension for case-mix adjustment. To our knowledge, no previous studies have provided

detailed information about how the validity of morbidity reporting varies among hospitals after accounting for patient factors.

Further, we have shown that variations in the accuracy of morbidity reporting between hospitals are predominantly driven by the hospital's depth of coding – concordance between self-reported and hospital data is lower in hospitals with a lower average number of additional diagnoses recorded. Up to 42% of the variation in recording at the hospital level could be attributed to differences in hospital depth of coding. Even though the measure of depth of coding we used was crude, and related to hospital size, it still helps in highlighting the impact of coding practices on variations among hospitals. Other research using the same depth of coding measure has shown that the lower depth of coding can disproportionately disadvantage hospitals' standardised mortality ratios, one of the commonly reported measures of hospital performance. [2] It will be important to track changes in the levels of the depth of coding across Australian states, and to consider the implications of these for state-based performance comparisons, following the national rollout of activity-based funding and comparative performance reporting.

Several factors might explain variation in depth of coding between hospitals. Clinical coders can code only information that has been recorded in the patient's medical record, so varying level of details recorded by clinicians will influence what gets coded. The training and professional development opportunities for coding staff might also influence the depth of coding. Also, casemix funding systems, such as the Diagnosis Related Group (DRG) classification, are prone to 'upcoding' in order for services to receive higher reimbursement costs. [14]

We found that the reporting of conditions varied with hospital size, larger metropolitan hospitals having higher concordance, with kappa values higher by 7% on average when comparing large tertiary with smaller urban hospitals. This finding echoes those of Powell et

al. [3] in NSW, Australia during 1996 – 1998 and Rangachari et al. [16] in the US, during 2000 – 2004. Our study showed that large tertiary hospitals had better concordance for the recording of hypertension and heart disease than smaller urban hospitals, but the reverse was true for stroke and smoking. Our finding that between-hospital variation in the recording of morbidities was up to two times higher when all hospitals, rather than just the largest ones, were included has implications for further research using data from smaller hospitals. This high variability in concordance among smaller hospitals may mean that morbidity-adjusted comparisons are not as valid as for larger hospitals. Researchers using information from these hospitals are encouraged to supplement their data with either self-report information and/or data linkage. The value-add of incorporating previous hospitalizations was also highlighted in our results for stroke and obesity, with 43% – 47% more patients identified using lookback admissions than from a single admission only.

A particular strength of our study lies in the use of linked data from a large-scale cohort study to comprehensively evaluate the recording of common conditions in hospital data, and explore the variation in recording among hospitals. The 45 and Up Study contains records for one in every 10 persons aged 45 and over in NSW, so it provides a rich resource to answer research questions. Additionally, we used advanced multilevel modeling methods to quantify the amount of between-hospital variation in the level of recording of common health conditions, a finding which is of importance for both research and policy paradigms due to its impact on adjusted comparisons among hospitals and the highlighted need to improve consistency of recording in hospitals across the State. To date, hospital-level variation has only been explored with a set outcome (e.g. mortality, readmission) in mind.

A potential limitation of our study was its use of self-reported information to explore concordance, in the absence of another 'gold standard', such as medical records. Access to medical records was not possible given the de-identified nature of our data, and the large

number of records in the dataset. Moreover, studies that have examined accuracy of self-reported conditions against medical records have found high levels of agreement, ranging from 81% [47] to 87% [48] for hypertension, 66% [49] to 96% [47 48] for diabetes and 60% [47] to 98% [50] for acute myocardial infarction. Validation studies in the 45 and Up Study cohort have reported strong correlations and excellent levels of agreement between self-reported and measured height and weight, and derived BMI [51] as well as self-reported diabetes. [52]

Conclusion

The recording of common comorbid conditions in routine hospital data is highly variable, and, for some conditions, very poor. Recording varies considerably among hospitals, presenting the potential to introduce bias into risk-adjusted comparisons of hospital performance, especially for indicators that use heart disease or hypertension for risk adjustment. Furthermore, between-hospital variation is amplified when smaller and private hospitals are included in the analyses. Stratification of analyses according to factors that predict the completeness of recording, including hospital depth of coding and hospital type and size, supplementing morbidity information with linked data from previous hospitalizations and increases in efforts to standardize recording across hospitals, all offer potential for increasing the validity of risk-adjusted comparisons.

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Contributorship

SL had overall responsibility for the design of this study, data management, statistical analysis and drafting this paper. DW and LJ contributed to the conception and design of the study. LJ helped with data acquisition, and provided oversight for all analyses. DR and JS provided oversight and advice for the design and interpretation of the statistical analyses. All

authors contributed to the interpretation of the findings, the writing of the paper and approved the final draft.

Data sharing

This study used the data from the Assessing Preventable Hospitalisation InDicators (APHID) project. The data has been constructed with the permission of each of the custodians of the respective source datasets and with specific ethical approval. These data are available to researchers on request and subject to approval from the relevant data custodians and ethics committees, as outlined on the 45 and Up Study website (https://www.saxinstitute.org.au/our-work/45-up-study/for-researchers/#application-forms) as well as the NSW Centre for Health Record Linkage website (www.cherel.org.au). More information about these approvals is available from the authors on request.

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List of tables and figures

Table 1. Characteristics of the study sample at their index admission

Characteristics	All participants (N = 32,832)		All hospitals[a] (N = 313)	
	N	%	N	%
Demographic characteristics				
Sex				
Male	16,812	51.2		
Female	16,020	48.8		
Age				
45-59	9,666	29.4		
60-79	16,624	50.6		
80+	6,540	19.9		
Country of birth				
Australia	25,001	76.2		
Other	7,448	22.7		
Unknown	383	1.2		
Highest education level				
No school	5,196	15.8		
Year 10 or equivalent	7,894	24.0		
Year 12 or equivalent	2,975	9.1		
Trade	4,270	13.0		
Certificate	6,109	18.6		
University degree	5,662	17.3		
Unknown	726	2.2		
Household income ($, per annum)				
<20,000	9,077	27.7		
20,000 - <50,000	8,223	25.1		
50,0000 - <70,000	2,560	7.8		
70,000+	5,042	15.4		
Not disclosed	6,003	18.3		
Missing	1,927	5.9		
Functional status				
No limitation	4,915	15.0		
Mild limitation	6,011	18.3		
Moderate limitation	8,701	26.5		
Severe limitation	10,121	30.8		
Missing	3,084	9.4		
Admission characteristics				
Admission type				
Surgical	15,464	47.1		
Other	1,439	4.4		
Medical	15,929	48.5		
Emergency status				
Emergency	13,484	41.1		

Planned	17,544	53.4		
Other	1,803	5.5		
Hospital characteristics				
Hospital type				
Public	18,734	57.1	224	71.6
Private	14,096	42.9	88	28.1
Hospital remoteness				
Major city	19,754	60.2	124	39.6
Inner regional	8,424	25.7	72	23.0
Outer regional	4,137	12.6	94	30.0
Remote/very remote	363	1.1	20	6.4
Hospital depth of coding				
1 - least comprehensive	1,629	5.0	48	15.3
2	8,803	26.8	91	29.1
3	11,543	35.2	89	28.4
4 - most comprehensive	10,857	33.1	85	27.2
Hospital peer group				
Principal referral	6,329	19.3	14	4.5
Major	11,052	33.7	33	10.5
District	6,862	20.8	51	16.3
Community	7,018	21.4	121	38.7
Other	1,571	4.8	94	30.0

[a] for comparisons of hospital characteristics

Table 2. Agreement measures between self-report and hospital data, index and lookback admissions, all public and private hospitals in New South Wales, Australia (n=313)

Morbidities[a]	Index admission						Lookback admissions					
	45 and Up Yes:		45 and Up No:		Kappa		45 and Up Yes:		45 and Up No:		Kappa	
	APDC yes	APDC no	APDC yes	APDC no	%	95% CI	APDC yes	APDC no	APDC yes	APDC no	%	95% CI
Hypertension	4,767	10,512	1,434	16,119	**24.0**	(22.9-25.0)	6,260	9,019	2,051	15,502	**30.2**	(29.1-31.2)
Heart disease	3,639	4,668	1,942	22,583	**40.3**	(39.0-41.5)	4,673	3,634	2,697	21,828	**47.0**	(45.8-48.2)
Diabetes	3,560	1,234	347	27,691	**79.1**	(78.1-80.1)	3,928	866	479	27,559	**83.0**	(82.1-83.9)
Stroke	541	1939	306	30,046	**29.8**	(27.0-32.6)	776	1,704	488	29,864	**38.3**	(35.8-40.8)
Smoking	1,205	804	727	30,096	**58.7**	(56.7-60.7)	1,411	598	1,076	29,747	**60.1**	(58.2-61.9)
Obesity	551	7,611	114	24,556	**9.1**	(7.3-10.9)	810	7,352	209	24,461	**12.8**	(11.1-14.6)
Hypertension + heart disease	1,172	3,481	1,270	26,909	**25.8**	(23.8-27.7)	1,807	2,846	2,008	26,171	**34.3**	(32.6-36.0)
Hypertension + diabetes	1,819	1,238	759	29,016	**61.3**	(59.6-62.9)	2,186	871	1,021	28,754	**66.6**	(65.2-68.1)
Hypertension + stroke	203	1,317	189	31,123	**19.7**	(15.7-23.7)	329	1,191	340	30,972	**28.0**	(24.5-31.5)
Hypertension + smoking	133	598	180	31,921	**24.5**	(19.2-29.7)	199	532	319	31,782	**30.6**	(26.0-35.2)
Hypertension + obesity	234	4,574	93	27,931	**7.4**	(4.9-9.8)	383	4,425	183	27,841	**11.5**	(9.2-13.9)
Heart disease + diabetes	646	1,154	404	30,628	**43.0**	(40.3-45.8)	904	896	661	30,371	**51.2**	(48.9-53.6)
Heart disease + stroke	76	973	126	31,657	**11.2**	(6.1-16.4)	149	900	261	31,522	**19.0**	(14.4-23.5)
Heart disease + smoking	76	294	222	32,240	**22.0**	(15.3-28.6)	118	252	373	32,089	**26.5**	(20.8-32.2)
Heart disease + obesity	79	1,938	79	30,736	**6.4**	(2.5-10.4)	151	1,866	169	30,646	**11.4**	(7.7-15.2)
Diabetes + stroke	85	555	58	32,134	**21.1**	(15.0-27.3)	140	500	119	32,073	**30.4**	(24.9-35.8)
Diabetes + smoking	143	161	108	32,420	**51.1**	(45.3-56.9)	171	133	176	32,352	**52.1**	(46.7-57.4)
Diabetes + obesity	232	1,701	65	30,834	**19.5**	(15.9-23.2)	351	1,582	120	30,779	**27.5**	(24.2-30.9)
Stroke + smoking	13	142	28	32,649	**13.1**	(0.1-26.1)	23	132	57	32,620	**19.3**	(7.8-30.8)
Stroke + obesity	6	558	9	32,259	**2.0**	(0.0-10.0)	13	551	21	32,247	**4.2**	(0.0-11.9)
Smoking + obesity	27	447	29	32,329	**9.9**	(1.9-17.9)	38	436	47	32,311	**13.2**	(5.5-20.9)

[a] ICD-10-AM codes: hypertension (I10-I15, R03.0), heart disease (I20-I25, I26-I28, I30-I52), diabetes (E10-E14), stroke (I60-I69, G45, G46), smoking (F17.2, Z72.0), obesity (E66)

Table 3. Factors that predict positive agreement between self-report and hospital data, using multilevel modelling, all public and private hospitals in New South Wales, Australia (n=313)

	Hypertension (N = 15,279)	Diabetes (N = 4,794)	Heart disease (N = 8,307)	Stroke (N = 2,480)	Smoking (N = 2,099)	Obesity (N = 8,162)
Person-level variables						
Sex[1]	**	**	**			
Age[1]	**				**	**
Education[1]			*	**	**	
Country of birth[1]						
Functional limitation[1]	**	**				**
Income[1]						
Admission type[2]	**	**	**	**	**	**
Emergency status[2]	**	**	**	**		**
Hospital-level variables						
Hospital type (public/private)[3]	**		**	**		
Hospital remoteness[3]					*	
Hospital depth of coding[3]	**	**	**	**	**	**
Hospital peer group[3]	**	**	**		**	

* Significant at 5% level
** Significant at 1% level

1 – Model 0: adjusted for demographic factors + random intercept for hospital
2 – Model 0 + admission type + emergency status
3 – Model 0 + hospital-level variables (entered one at a time)

Table 4. Variance and intraclass correlation coefficient for hospital-level random effects from multilevel logistic regression, all public and private hospitals in New South Wales, Australia (n=313)

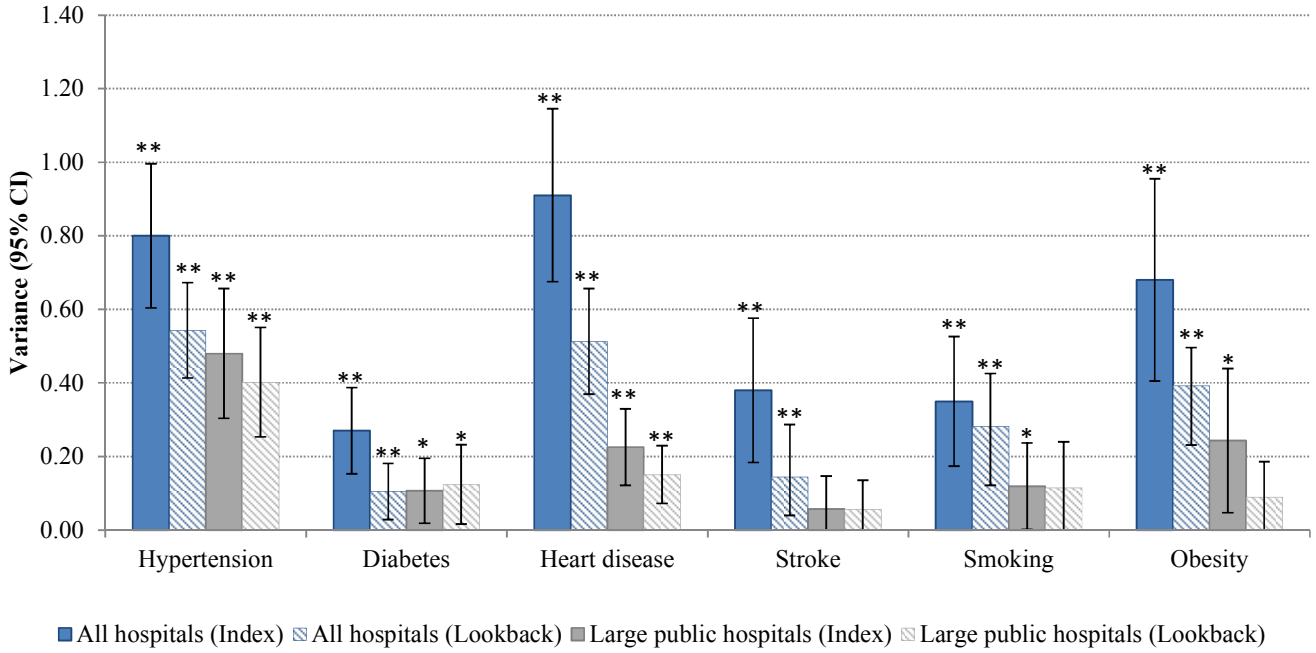
		Hypertension (N† = 15,279)	Diabetes (N† = 4,794)	Heart disease (N† = 8,307)	Stroke (N† = 2,480)	Smoking (N† = 2,099)	Obesity (N† = 8,162)
Hospital-level variance (SE)*							
Model 0.	Patient factors	0.80 (0.10)	0.27 (0.06)	0.91 (0.12)	0.38 (0.10)	0.35 (0.09)	0.68 (0.14)
Model 1.	Model 0 + hospital type (public/private)	0.65 (0.08)	0.27 (0.06)	0.71 (0.10)	0.16 (0.06)	0.35 (0.09)	0.69 (0.14)
Model 2.	Model 0 + hospital remoteness	0.77 (0.09)	0.25 (0.05)	0.92 (0.12)	0.37 (0.10)	0.33 (0.08)	0.68 (0.14)
Model 3.	Model 0 + hospital depth of coding	0.46 (0.06)	0.20 (0.05)	0.56 (0.08)	0.26 (0.08)	0.29 (0.08)	0.68 (0.14)
Model 4.	Model 0 + hospital peer group	0.72 (0.09)	0.21 (0.05)	0.75 (0.10)	0.34 (0.09)	0.31 (0.08)	0.67 (0.14)
Intraclass correlation coefficient (ICC)**		19.5%	7.6%	21.6%	10.4%	9.6%	17.1%
Median odds ratio (MOR)**		2.34	1.64	2.48	1.80	1.76	2.19

† N = number of patients who self-reported condition

* Patient-level variance in a logistic regression is set at $\pi^2/3=3.29$ [31]

** ICC and MOR calculated from Model 0 [ICC = hospital-level variance divided by total variance (hospital-level + patient-level); MOR is calculated as $exp^{0.954\times\sqrt{variance}}$] [30]

Figure 1. Variance for hospital-level random effects from multilevel logistic regression, for index and lookback admissions, by hospital size



* Significantly different from 0 at 5% level
** Significantly different from 0 at 1% level

Supplementary Table 1. Agreement measures between self-report and hospital data, index and lookback admissions, large public hospitals in New South Wales, Australia (n=82)

Supplementary Table 2. Adjusted ORs for patient-level variables from the multilevel logistic regression with random intercept for hospital of admission, all public and private hospitals in New South Wales, Australia (n=313)

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	45 and Up Yes:		45 and Up No:		Kappa		45 and Up Yes:		45 and Up No:		Kappa	
	APDC yes	APDC no	APDC yes	APDC no	%	95% CI	APDC yes	APDC no	APDC yes	APDC no	%	95% CI
Hypertension	3,061	4,803	983	7,634	**28.1**	(26.6-29.6)	3,829	4,035	1,339	7,278	**33.7**	(32.2-35.1)
Heart disease	2,306	2,455	1,309	10,411	**40.1**	(38.5-41.8)	2,910	1,851	1,710	10,010	**46.9**	(45.4-48.5)
Diabetes	2,168	661	214	13,438	**80.1**	(78.8-81.4)	2,355	474	289	13,363	**83.3**	(82.1-84.4)
Stroke	414	1,210	213	14,644	**33.1**	(29.8-36.4)	563	1,061	311	14,546	**41**	(38.0-44.0)
Smoking	820	507	468	14,686	**59.5**	(57.0-62.0)	948	379	692	14,462	**60.4**	(58.1-62.7)
Obesity	265	3,857	61	12,298	**8.6**	(6.1-11.1)	414	3,708	114	12,245	**12.9**	(10.4-15.3)
Hypertension + heart disease	799	1,878	893	12,911	**27.4**	(25.0-29.9)	1,159	1,518	1,327	12,477	**34.7**	(32.5-36.9)
Hypertension + diabetes	1,129	670	518	14,164	**61.5**	(59.4-63.6)	1,317	482	662	14,020	**65.8**	(63.9-67.7)
Hypertension + stroke	160	825	145	15,351	**22.6**	(17.9-27.3)	238	747	237	15,259	**29.9**	(25.6-34.1)
Hypertension + smoking	106	399	135	15,841	**27**	(20.9-33.1)	154	351	237	15,739	**32.6**	(27.2-37.9)
Hypertension + obesity	157	2,291	62	13,971	**9.6**	(6.2-13.0)	251	2,197	117	13,916	**14.5**	(11.3-17.7)
Heart disease + diabetes	452	686	293	15,050	**45**	(41.7-48.3)	620	518	442	14,901	**53.2**	(50.4-56.1)
Heart disease + stroke	61	641	93	15,686	**12.9**	(6.8-19.1)	107	595	171	15,608	**19.9**	(14.4-25.4)
Heart disease + smoking	65	209	163	16,044	**24.8**	(17.2-32.3)	98	176	280	15,927	**28.7**	(22.2-35.1)
Heart disease + obesity	63	1,145	62	15,211	**8.2**	(3.2-13.2)	117	1,091	119	15,154	**14.1**	(9.5-18.8)
Diabetes + stroke	66	374	38	16,003	**23.5**	(16.2-30.8)	110	330	69	15,972	**34.5**	(28.2-40.9)
Diabetes + smoking	107	112	83	16,179	**51.7**	(45.0-58.5)	130	89	132	16,130	**53.4**	(47.3-59.5)
Diabetes + obesity	150	994	39	15,298	**20.9**	(16.3-25.6)	229	915	76	15,261	**29.5**	(25.3-33.8)
Stroke + smoking	13	106	23	16,339	**16.5**	(2.1-30.8)	19	100	41	16,321	**20.8**	(7.8-33.9)
Stroke + obesity	4	368	7	16,102	**2**	(0.0-11.8)	9	363	13	16,096	**4.3**	(0.0-13.9)
Smoking + obesity	17	292	18	16,154	**9.5**	(0.0-19.5)	25	284	29	16,143	**13.3**	(3.8-22.8)

[a] ICD-10-AM codes: hypertension (I10-I15, R03.0), heart disease (I20-I25, I26-I28, I30-I52), diabetes (E10-E14), smoking (F17.2, Z72.0), obesity (E66)

Supplementary Table 2. Adjusted ORs[a] for patient-level variables from the multilevel logistic regression with random intercept for hospital of admission, all public and private hospitals in New South Wales, Australia (n=313)

Patient characteristics	Hypertension (N = 15,279)		Diabetes (N = 4,794)		Heart disease (N = 8,307)		Stroke (N = 2,480)		Smoking (N = 2,099)		Obesity (N = 8,162)	
	OR[a]	(95%CI)[b]	OR[a]	(95%CI)[b]	OR[a]	(95%CI)[b]	OR[a]	(95%CI)[b]	OR[a]	(95%CI)[b]	OR[a]	(95%CI)[b]
Sex												
Female	1		1		1		1		1		1	
Male	1.28	(1.18,1.38)	1.37	(1.19,1.58)	1.30	(1.17,1.44)	1.13	(0.91,1.40)	1.14	(0.94,1.40)	0.85	(0.70,1.04)
Age												
45-59	1		1		1		1		1		1	
60-79	1.27	(1.15,1.41)	0.97	(0.81,1.16)	0.94	(0.82,1.09)	1.08	(0.78,1.52)	0.80	(0.65,0.99)	0.57	(0.47,0.70)
80+	1.32	(1.16,1.49)	1.00	(0.80,1.25)	1.01	(0.86,1.19)	1.02	(0.72,1.46)	0.48	(0.31,0.74)	0.14	(0.08,0.26)
Education												
None	1		1		1		1		1		1	
Trade	0.90	(0.79,1.03)	0.93	(0.73,1.18)	0.80	(0.68,0.94)	1.08	(0.76,1.54)	0.67	(0.48,0.94)	1.42	(1.01,2.02)
School certificate	0.96	(0.86,1.07)	1.00	(0.82,1.23)	0.90	(0.78,1.05)	1.22	(0.90,1.66)	0.87	(0.66,1.16)	1.04	(0.77,1.41)
HSC	0.99	(0.85,1.15)	0.89	(0.68,1.17)	0.91	(0.75,1.11)	2.23	(1.51,3.30)	0.53	(0.37,0.76)	1.24	(0.84,1.83)
Diploma	0.96	(0.84,1.09)	0.90	(0.72,1.14)	0.87	(0.74,1.03)	1.08	(0.75,1.56)	1.00	(0.73,1.37)	1.15	(0.83,1.59)
University	0.85	(0.74,0.98)	0.90	(0.70,1.16)	0.72	(0.60,0.86)	1.23	(0.83,1.81)	0.54	(0.37,0.80)	1.25	(0.88,1.79)
County of birth												
Australia	1		1		1		1		1		1	
Overseas	1.00	(0.91,1.09)	0.95	(0.81,1.11)	1.10	(0.98,1.23)	1.19	(0.94,1.51)	1.17	(0.92,1.48)	0.89	(0.69,1.14)
Functional limitation												
No limitation	1		1		1		1		1		1	
Mild	1.07	(0.91,1.25)	0.91	(0.68,1.23)	1.02	(0.82,1.28)	0.82	(0.48,1.42)	0.92	(0.65,1.30)	1.07	(0.72,1.60)
Moderate	1.23	(1.07,1.42)	1.14	(0.87,1.50)	0.92	(0.75,1.13)	0.68	(0.42,1.11)	0.79	(0.57,1.09)	1.06	(0.73,1.53)
Severe	1.53	(1.33,1.76)	1.54	(1.18,2.01)	0.97	(0.79,1.19)	0.84	(0.53,1.33)	0.82	(0.60,1.12)	2.27	(1.59,3.24)
Income												
<20,000	1		1		1		1		1		1	
20-50,000	0.89	(0.81,0.99)	0.95	(0.79,1.14)	1.03	(0.91,1.17)	1.14	(0.87,1.49)	1.17	(0.90,1.53)	0.76	(0.57,1.00)

50-70,000	0.89	(0.75,1.05)	0.87	(0.64,1.19)	1.11	(0.89,1.38)	1.16	(0.68,1.99)	1.37	(0.93,2.02)	0.89	(0.60,1.30)
>70,000	0.86	(0.74,1.00)	1.03	(0.77,1.38)	1.24	(1.02,1.50)	1.07	(0.63,1.82)	0.95	(0.66,1.36)	1.15	(0.83,1.59)
Not disclosed	1.00	(0.90,1.12)	1.04	(0.86,1.27)	1.14	(0.99,1.31)	1.18	(0.89,1.56)	1.36	(1.02,1.80)	1.07	(0.81,1.41)
Admission type[c]												
Surgical	1		1		1		1		1		1	
Other	1.45	(1.23,1.72)	1.01	(0.72,1.42)	2.34	(1.91,2.87)	0.47	(0.16,1.37)	0.69	(0.41,1.14)	0.62	(0.36,1.09)
Medical	1.14	(1.03,1.27)	0.66	(0.55,0.80)	0.97	(0.84,1.11)	4.36	(3.02,6.29)	0.50	(0.38,0.65)	0.64	(0.50,0.84)
Emergency status[c]												
Emergency	1		1		1		1		1		1	
Planned	0.63	(0.56,0.71)	0.64	(0.52,0.77)	0.42	(0.36,0.49)	0.65	(0.48,0.88)	0.86	(0.65,1.13)	0.58	(0.44,0.78)
Other	0.96	(0.80,1.15)	0.98	(0.72,1.33)	1.02	(0.81,1.28)	1.19	(0.80,1.76)	1.03	(0.65,1.62)	0.80	(0.50,1.28)

[a] Odds ratio of a hospital record of a condition, among those that self-reported having a condition. Adjusted for age, sex, income, education, country of birth and functional limitation
[b] Confidence interval
[c] Model included both admission type and emergency status together with other listed patient characteristics

Supplementary Table 3. Adjusted ORs[a] for hospital-level variables from the multilevel logistic regression with random intercept for hospital of admission, all public and private hospitals in New South Wales, Australia (n=313)

Hospital characteristics	Hypertension (N = 15,279)		Diabetes (N = 4,794)		Heart disease (N = 8,307)		Stroke (N = 2,480)		Smoking (N = 2,099)		Obesity (N = 8,162)	
	OR[a]	(95%CI)[b]	OR[a]	(95%CI)[b]	OR[a]	(95%CI)[b]	OR[a]	(95%CI)[b]	OR[a]	(95%CI)[b]	OR[a]	(95%CI)[b]
Hospital type[c]												
Public	1		1		1		1		1		1	
Private	0.49	(0.38,0.63)	0.98	(0.78,1.23)	0.35	(0.26,0.47)	0.31	(0.22,0.43)	0.99	(0.72,1.35)	0.91	(0.64,1.31)
Hospital remoteness[c]												
Major city	1		1		1		1		1		1	
Inner regional	0.89	(0.64,1.23)	0.86	(0.67,1.11)	1.01	(0.70,1.47)	1.29	(0.91,1.83)	1.04	(0.75,1.45)	0.91	(0.60,1.38)
Outer regional	0.75	(0.55,1.02)	0.69	(0.52,0.91)	0.97	(0.67,1.41)	1.09	(0.72,1.67)	0.82	(0.57,1.18)	0.91	(0.58,1.44)
Remote/very remote	1.05	(0.57,1.94)	0.53	(0.28,1.00)	1.70	(0.81,3.59)	0.66	(0.22,1.98)	0.33	(0.15,0.71)	0.52	(0.16,1.68)
Hospital size[c]												
Principal referral	1		1		1		1		1		1	
Major	0.59	(0.34,1.01)	0.89	(0.62,1.27)	0.76	(0.44,1.34)	0.93	(0.58,1.47)	1.03	(0.66,1.61)	1.10	(0.59,2.05)
District	0.45	(0.27,0.76)	0.83	(0.58,1.19)	0.45	(0.26,0.78)	0.97	(0.60,1.55)	0.73	(0.47,1.15)	1.02	(0.55,1.91)
Community	0.41	(0.25,0.68)	0.61	(0.43,0.87)	0.35	(0.20,0.59)	0.57	(0.35,0.94)	0.89	(0.56,1.39)	0.88	(0.47,1.62)
Other	0.52	(0.30,0.89)	0.44	(0.29,0.68)	0.35	(0.19,0.65)	1.19	(0.66,2.14)	0.39	(0.22,0.68)	1.22	(0.59,2.53)
Depth of coding[c]												
1 - least comprehensive	0.17	(0.11,0.27)	0.26	(0.17,0.40)	0.09	(0.04,0.17)	0.38	(0.17,0.82)	0.22	(0.12,0.42)	0.28	(0.12,0.65)
2	0.29	(0.22,0.38)	0.66	(0.52,0.85)	0.41	(0.29,0.56)	0.31	(0.21,0.48)	0.74	(0.52,1.06)	0.59	(0.38,0.92)
3	0.58	(0.45,0.76)	0.85	(0.66,1.08)	0.75	(0.55,1.02)	0.66	(0.48,0.91)	0.89	(0.65,1.24)	0.65	(0.43,0.99)
4 - most comprehensive	1		1		1		1		1		1	

[a] Odds ratio of a hospital record of a condition, among those that self-reported having a condition. Adjusted for age, sex, income, education, country of birth and functional limitation

[b] Confidence interval

[c] Hospital-level covariates added one at a time, separately

STROBE 2007 (v4) Statement—Checklist of items that should be included in reports of *cross-sectional studies*

Section/Topic	Item #	Recommendation	Reported on page #
Title and abstract	1	(*a*) Indicate the study's design with a commonly used term in the title or the abstract	2
		(*b*) Provide in the abstract an informative and balanced summary of what was done and what was found	2
Introduction			
Background/rationale	2	Explain the scientific background and rationale for the investigation being reported	4-5
Objectives	3	State specific objectives, including any prespecified hypotheses	5
Methods			
Study design	4	Present key elements of study design early in the paper	6
Setting	5	Describe the setting, locations, and relevant dates, including periods of recruitment, exposure, follow-up, and data collection	6-7
Participants	6	(*a*) Give the eligibility criteria, and the sources and methods of selection of participants	6
Variables	7	Clearly define all outcomes, exposures, predictors, potential confounders, and effect modifiers. Give diagnostic criteria, if applicable	7-8
Data sources/ measurement	8*	For each variable of interest, give sources of data and details of methods of assessment (measurement). Describe comparability of assessment methods if there is more than one group	6-8
Bias	9	Describe any efforts to address potential sources of bias	9
Study size	10	Explain how the study size was arrived at	7, 10
Quantitative variables	11	Explain how quantitative variables were handled in the analyses. If applicable, describe which groupings were chosen and why	8
Statistical methods	12	(*a*) Describe all statistical methods, including those used to control for confounding	9-10
		(*b*) Describe any methods used to examine subgroups and interactions	9
		(*c*) Explain how missing data were addressed	8
		(*d*) If applicable, describe analytical methods taking account of sampling strategy	n/a
		(*e*) Describe any sensitivity analyses	9
Results			

Participants	13*	(a) Report numbers of individuals at each stage of study—eg numbers potentially eligible, examined for eligibility, confirmed eligible, included in the study, completing follow-up, and analysed	10
		(b) Give reasons for non-participation at each stage	n/a
		(c) Consider use of a flow diagram	n/a
Descriptive data	14*	(a) Give characteristics of study participants (eg demographic, clinical, social) and information on exposures and potential confounders	10-11, 25-26
		(b) Indicate number of participants with missing data for each variable of interest	25-26
Outcome data	15*	Report numbers of outcome events or summary measures	11, 27,28,29,31-34
Main results	16	(*a*) Give unadjusted estimates and, if applicable, confounder-adjusted estimates and their precision (eg, 95% confidence interval). Make clear which confounders were adjusted for and why they were included	10, 12-13, 32-34
		(*b*) Report category boundaries when continuous variables were categorized	30,32-34
		(*c*) If relevant, consider translating estimates of relative risk into absolute risk for a meaningful time period	n/a
Other analyses	17	Report other analyses done—eg analyses of subgroups and interactions, and sensitivity analyses	11-13,30
Discussion			
Key results	18	Summarise key results with reference to study objectives	14
Limitations	19	Discuss limitations of the study, taking into account sources of potential bias or imprecision. Discuss both direction and magnitude of any potential bias	18-19
Interpretation	20	Give a cautious overall interpretation of results considering objectives, limitations, multiplicity of analyses, results from similar studies, and other relevant evidence	15-19
Generalisability	21	Discuss the generalisability (external validity) of the study results	18-19
Other information			
Funding	22	Give the source of funding and the role of the funders for the present study and, if applicable, for the original study on which the present article is based	20

*Give information separately for cases and controls in case-control studies and, if applicable, for exposed and unexposed groups in cohort and cross-sectional studies.

Note: An Explanation and Elaboration article discusses each checklist item and gives methodological background and published examples of transparent reporting. The STROBE checklist is best used in conjunction with this article (freely available on the Web sites of PLoS Medicine at http://www.plosmedicine.org/, Annals of Internal Medicine at http://www.annals.org/, and Epidemiology at http://www.epidem.com/). Information on the STROBE Initiative is available at www.strobe-statement.org.

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Variation in the recording of common health conditions in routine hospital data: study using linked survey and administrative data in New South Wales, Australia

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Variation in the recording of common health conditions in routine hospital data: study using linked survey and administrative data in New South Wales, Australia

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Word count: 4,625 words

Keywords: hospital data, morbidity, multilevel modeling, agreement

Abstract

Objectives: To investigate the nature and potential implications of underreporting of morbidity information in administrative hospital data.

Setting and participants: Retrospective analysis of linked self-report and administrative hospital data for 32,832 participants in the large-scale cohort study (45 and Up Study), who joined the study from 2006-2009 and who were admitted to 313 hospitals in New South Wales, Australia, for at least an overnight stay, up to a year prior to study entry.

Outcome measures: Agreement between self-report and recording of six morbidities in administrative hospital data, and between-hospital variation and predictors of positive agreement between the two data sources.

Results: Agreement between data sources was good for diabetes (κ=0.79), moderate for smoking (κ=0.59), fair for heart disease, stroke and hypertension (κ=0.40, κ =0.30, κ =0.24, respectively) and poor for obesity (κ=0.09), indicating that a large number of individuals with self-reported morbidities did not have a corresponding diagnosis coded in their hospital records. Significant between-hospital variation was found (ranging from 8% of unexplained variation for diabetes to 22% for heart disease), with higher agreement in public and large hospitals, and hospitals with greater depth of coding.

Conclusions: The recording of six common health conditions in administrative hospital data is highly variable, and for some conditions, very poor. To support more valid performance comparisons, it is important to stratify or control for factors that predict the completeness of recording, including hospital depth of coding and hospital type (public/private), and to increase efforts to standardize recording across hospitals. Studies using these conditions for risk adjustment should also be cautious of their use in smaller hospitals.

Keywords: hospital data, morbidity, multilevel modeling, agreement

Article summary

Article focus

- Explore the agreement between administrative hospital data and self-report information for four clinical conditions, as well as smoking and obesity.
- Quantify the between-hospital variation in the level of recording of these conditions.

Key messages

- Good levels of agreement found only for diabetes, with other conditions exhibiting moderate to poor agreement.
- Better recording was found in public and large hospitals, and hospitals with greater depth of coding.
- Significant between-hospital variation in the levels of agreement, amplified when smaller and private hospitals are included.

Strengths and limitations

- Use of linked data from a large-scale cohort study and advanced multilevel modeling methods to comprehensively evaluate the recording of common health conditions in hospital data, and explore between-hospital variation.
- Limitations include the absence of 'gold standard' such as medical records.

Introduction

Most nations with advanced economies publicly report on the comparative performance of hospitals with a view to accelerating and informing efforts to improve quality and allowing patients to make informed choices. Diagnoses recorded in administrative hospital data are commonly used in the construction and case-mix adjustment of hospital performance metrics, as well as for risk adjustment in epidemiological studies.

The construction of reliable health metrics relies on statistical methods that take into account the degree to which patients treated in different facilities have different morbidity and risk profiles that predispose them to requiring different interventions or to achieving different outcomes. These statistical methods, known as case-mix or risk adjustment, account for patient-related factors that are above and beyond the immediate control of health care professionals.

Thus, properly constructed performance metrics fairly reflect differences in health care experiences, patient outcomes and risks of adverse events. There has been some criticism of case-mix adjustments because they are subject to measurement error, [1] but case-mix adjustment is still considered to be less biased than unadjusted comparisons. [2]

Most methods of case-mix adjustment rely principally on demographic and diagnostic information that is captured in administrative hospital data collections. The hospital data is collected and recorded in a database for administrative purposes, with clinical coders coding diagnostic information based on the patient's medical records. [3] This approach may be sub-optimal [4 5] because evidence from many countries suggests that administrative hospital data underreport the morbidity information needed to fully account for differences between hospitals in patient-related factors that predispose them to differences in measured outcomes. [6-13] However, the impact of this underreporting on comparative measures of hospital

performance depends on whether it varies systematically among hospitals, because of differences in factors such as training or practice among coding staff, the comprehensiveness of clinicians' notes, or "upcoding" relating to funding models or incentives. [14]

This issue is relatively unexplored, aside from the work by Mohammed et al. [2] which reported a non-constant relationship between case-mix variables and mortality among hospitals in the UK, explained by differences in clinical coding and admission practices across hospitals. These variations in coding accuracy were shown to be related to geographic location and bed size, with small rural facilities performing better than large urban hospitals. [15 16] In Australia, variations in the reporting and coding of secondary diagnoses in administrative hospital data have been shown to exist in public hospitals among Australian states, [17] and also among hospitals within the state of New South Wales (NSW), with greater underreporting in private and rural hospitals. [3] However, the relative contributions of patient and hospital factors to these variations have not been identified, nor has this variation been formally quantified.

This study, using data-linkage of survey and administrative data, aimed to further investigate the nature and potential implications of underreporting of morbidity information in administrative hospital data by: 1) measuring the agreement between self-reported morbidity information and coded diagnoses; 2) quantifying the amount of between-hospital variation in this agreement; and 3) identifying patient and hospital characteristics that predict higher or lower levels of agreement. We focused on clinical conditions common to case-mix and risk-adjustment models – diabetes, heart disease, hypertension and stroke. We also focus on smoking and obesity, due to their impact on health trajectories, rapid shifts in prevalence, substantial geographic variation in rates [18] and paucity of international evidence on completeness of coding.

Methods

Data sources

The 45 and Up Study

The 45 and Up Study is a large-scale cohort study involving 267,153 men and women aged 45 years and over from the general population of NSW, Australia. The study is described in detail elsewhere. [19] Briefly, participants in the 45 and Up Study were randomly sampled from the database of Australia's universal health insurance provider, Medicare Australia, which provides near complete coverage of the population. People 80+ years of age and residents of rural and remote areas were oversampled. Participants joined the Study by completing a baseline questionnaire (available at https://www.saxinstitute.org.au/our-work/45-up-study/questionnaires/) between January 2006 and December 2009 and giving signed consent for follow-up and linkage of their information to routine health databases. About 18% of those invited participated and participants included about 11% of the NSW population aged 45 years and over. [19]

The NSW Admitted Patient Data Collection (APDC)

The APDC includes records of all public and private hospital admissions ending in a separation, i.e. discharge, transfer, type-change or death. Each separation is referred to as an episode of care. Diagnoses are coded according to the Australian modification of the International Statistical Classification of Diseases and Health Related Problems 10th Revision, ICD-10-AM. [20] Up to 55 diagnoses codes are recorded on the APDC, including the principal diagnosis and up to 54 additional diagnoses. Additional diagnoses are defined as 'a condition or complaint either coexisting with the principal diagnosis or arising during the episode of care' in the Australian Coding Standards and should be interpreted as

conditions that affect patient management. [21] Assignment of diagnosis codes is done by trained clinical coders, using information from the patient's medical records.

The APDC from 1 July 2000 to 31 December 2010 was linked probabilistically to survey information from the 45 and Up Study by the NSW Centre for Health Record Linkage (www.cherel.org.au) using the 'best practice' protocol for preserving privacy. [22]

Study population

The study population comprised patients aged 45 years and above who participated in the 45 and Up Study and who had a hospitalization lasting at least one night in the period up to 365 days prior to filling out the baseline 45 and Up Study survey. Day stay patients were excluded from the analysis to make the study more robust and generalizable beyond NSW and Australia, as there are differences in admission practices for same day patients between Australia and most other comparable countries.[23] NSW is home to 7.4 million people or one-third of the population of Australia.

Measuring morbidity

We examined four health conditions (diabetes, heart disease, hypertension and stroke) and two health risk factors (obesity and smoking), referred to hereafter collectively as "morbidities". For each participant, these health conditions were measured using self-report and administrative hospital data.

Self-reported morbidities were ascertained on the basis of responses to questions in the baseline 45 and Up Study survey. Diabetes, hypertension, stroke and heart disease were identified using the question "Has a doctor ever told you that you have [name of condition]?". Participants who did not answer the question were excluded from analyses (n=1,242).

Smoking was classified on the basis of answering "yes" to both of the questions "Have you ever been a regular smoker?" and "Are you a regular smoker now?". Participants' responses to the questions "How tall are you without shoes?" and "About how much do you weigh?" were used to derive body mass index (BMI), defined as body weight divided by height squared (kg/m^2). The World Health Organization's [24] classification system was used to categorize individuals as obese (BMI $\geq 30 kg/m^2$).

Morbidity information in administrative hospital data was ascertained using all 55 diagnosis codes in the APDC records (ICD-10-AM: E10-E14 for diabetes, I20-I52 for heart disease, I60-I69, G45, G46 for stroke, I10-I15 and R03.0 for hypertension, F17.2 or Z72.0 for smoking and E66 for obesity). The inclusion of broader ICD-10-AM codes for heart disease and stroke was chosen because of the broad definition of disease type in the self-reported data. Thus, heart disease codes were inclusive of coronary heart disease, pulmonary heart disease, and other forms of heart diseases including heart failure and arrhythmias. Stroke codes included cerebrovascular diseases without infarction among others.

Predictors of agreement

We explored both patient- and hospital-level factors as predictors of agreement between the two data sources.

Patient-level factors were self-reported in the 45 and Up Study baseline survey and included age, sex, education, country of birth, income and functional limitation. Functional limitation was measured using the Medical Outcomes Study – Physical Functioning scale, [25] and classified into 5 groups: no limitation (score of 100), minor limitation (score 95-99), mild limitation (score 85-94), moderate limitation (60-84) and severe limitation (score 0-59).

Facility-level factors were type of hospital (public/private), hospital peer group (akin to hospital size defined by number of case-mix weighted separations, [26] which includes hospital remoteness in the classification), remoteness of hospital and depth of coding. Remoteness of the Statistical Local Area in which the hospital was located was classified according to the Accessibility/Remoteness Index of Australia (ARIA+), grouped into four categories (major city, inner regional, outer regional, remote/very remote). [27] Depth of hospital coding was the mean number of additional diagnoses coded per episode of care for each hospital, calculated using all overnight hospitalizations for the full 45 and Up Study cohort from 2000 to 2010, and divided into four groups at the 25th, 50th and 75th percentile. Hospital peer groups were divided into 5 categories: principal referral (≥25,000 separations per year), major (10,000-24,999 separations per year), district (2,000-9,999 separations per year), community (up to 2,000 separations per year) and other (non-acute, un-peered hospitals). Missing information was treated as a separate category for any variables with missing data.

Statistical methods

We examined patient-level agreement between data sources for each of the six morbidities individually, as well as for their 15 two-way combinations. We compared the self-reported responses (yes/no) with all the diagnoses provided in the hospital records both for 'index' admissions and for the 'lookback' period admissions. [28] The 'index' admission was the overnight hospital stay with admission date closest to the survey completion date and no longer than a year prior. Morbidity was coded as 'yes' if any of the diagnoses during that stay contained a mention of that morbidity. The 'lookback' admissions included all overnight stays in the 365-day period that preceded and included the 'index' admission. Morbidity was

coded as 'yes' if any of the diagnoses from any lookback admissions contained a mention of that morbidity.

Agreement between the two data sources (yes/no) was measured using Cohen's kappa statistic (κ). Kappa values above 0.75 denote excellent agreement, 0.40 to 0.75 fair to good agreement and below 0.45 poor agreement. [29] Agreement was computed for all 313 hospitals in the state, regardless of size, as well as for the 82 largest public hospitals, for which performance metrics are publicly reported.

Multilevel logistic regression was used to estimate odds ratios (OR) with 95% confidence intervals (CI) for patient- and hospital-level factors that predicted positive agreement between the two data sources. Multilevel models were chosen because of the clustering of patients within hospitals. Models were run for each of the six morbidities separately. These analyses were constrained to only those participants who self-reported the morbidity of interest, and the outcome was whether the index hospital record contained a mention of the morbidity or not. Addition of the hospital-level characteristics was done one at a time, due to the collinearity between variables. All ORs presented are adjusted for all other demographic variables in the model.

Variation at the hospital level was expressed as a median odds ratio (MOR), which is the median of the odds ratios of pair-wise comparisons of patients taken from randomly chosen hospitals, calculated as $exp^{0.954\times\sqrt{variance}}$;[30] and the intraclass correlation coefficient (ICC), which is the percentage of the total variance attributable to the hospital level. [31] Large ICCs indicate that differences among hospitals account for a considerable part of the variation in the outcome, whereas a small ICC means that the hospital effect on the overall variation is minimal. The relative influence of the hospital on reporting of morbidity was calculated using a variance partitioning coefficient expressed as a percentage of the total variance using the Snijders and Bosker latent variable approach. [31]

All data management was done using SAS 9.2 [32] and multilevel modeling using MLwiN 2.24. [33]

The conduct of the 45 and Up Study was approved by the University of New South Wales Human Research Ethics Committee (HREC), while ethical approval for this particular study was provided by the NSW Population and Health Services Research Ethics Committee and the University of Western Sydney HREC.

Results

Descriptive characteristics

A total of 32,832 study participants were admitted to 313 hospitals up to a year prior to completing the 45 and Up Study baseline survey. Just over half of the index admissions (53%) were planned stays in hospital, and 57% were to a public hospital. Around one-third of the index admissions occurred within the three months before study entry, and the mean length of stay was 4.8 days (median = 3 days). Just under half of the sample (47%) reported having hypertension, with heart disease or obesity reported by 25%, and current smoking by 6.1% of the sample. One-third (34%) of participants had two or more morbidities (data not shown). Other characteristics of the sample at their index admission are shown in Table 1. Characteristics of hospitals are summarized in Table 2.

Table 1 about here

Table 2 about here

Concordance between self-report and hospital records

Overall, reporting of morbidity differed between the two data sources with 23,257 (71%) participants having at least one of the six self-reported morbidities, and 11,977 (36.5%) and 14,335 (43.7%) of the sample having at least one morbidity recorded on their index or lookback hospital admissions, respectively.

Table 3 gives the summary concordance measures for each morbidity and two-way morbidity combination. For the index admission, good agreement was found for diabetes (κ=0.79), moderate agreement for smoking (κ=0.59), fair agreement for heart disease (κ=0.40), and poor agreement for stroke (κ=0.30), hypertension (κ=0.24) and obesity (κ=0.09). In two-way combinations, moderate levels of agreement were found only for diabetes combinations (with smoking, hypertension and heart disease).

Table 3 about here

Incorporating a one-year lookback period increased the numbers of participants with a morbidity recorded in a hospital record, with average relative increases in the kappa values of 20% (ranging from 2% increase for smoking, to 41% increase for obesity). Good to excellent level of agreements were still found only for diabetes (κ =0.83) and smoking (κ =0.60).

Agreement was only slightly higher among the 82 large public hospitals (see Supplementary Table 1) with relative kappa values higher by 4%, on average.

Patient- and hospital-level predictors of positive agreement

The patient factors which predicted positive agreement between the two data sources differed between morbidities (Table 4). Male sex was associated with better agreement for diabetes (OR=1.37, 95% CI 1.19 – 1.58), heart disease (OR=1.30, 95% CI 1.17 – 1.44) and hypertension (OR=1.28, 95% CI 1.18 – 1.38) (Supplementary Table 2).

Older patients were significantly less likely to have smoking (80+ years OR=0.48, 95% CI 0.31 – 0.74) and obesity (OR=0.14, 95% CI 0.08 – 0.26) recorded in their hospital records, and significantly more likely to have hypertension recorded (OR=1.32, 95% CI 1.16 – 1.49), compared to younger patients (45 – 59 years). People with higher levels of functional limitation were significantly more likely to have hypertension, diabetes and obesity recorded on their most recent hospital stay. Planned admissions to hospital had lower odds of having any of the six conditions recorded, as did medical admissions (for diabetes, smoking and obesity only). Agreement did not vary significantly for any other patient factors.

Table 4 about here

The four hospital-level covariates (hospital type, hospital peer group, hospital remoteness and depth of coding) were added to multilevel models (including a random intercept for hospital) one at a time, separately. Positive agreement between self-report and hospital records was significantly lower for hospitals with lower depth of coding across all morbidities. The odds of recording were also lower among private hospitals for all six morbidities, with this difference being statistically significant for hypertension, heart disease and stroke only. Records from smaller hospitals (district and community peer groups) were significantly less likely to agree with self-reported data on hypertension, diabetes and heart disease. Positive agreement did not vary significantly with remoteness of hospital, with the exceptions of

diabetes (lower agreement for outer regional, remote and very remote hospitals) and smoking (lower agreement for remote and very remote hospitals) (Supplementary Table 3).

Quantifying variation between hospitals

Before any hospital-level variables were added into the multilevel model, the intraclass correlation coefficient indicated that between 8% (diabetes) and 22% (heart disease) of the residual (unexplained) variation in agreement was attributable to the hospital, after adjustment for the patient-level factors (Table 5). This equated to median odds ratios (MORs) of 1.64 and 2.48, respectively, indicating that a patient in one hospital had an average of between 64% and 148% higher odds of having a particular morbidity recorded than a patient in a hospital with lower levels of recording. Less variation at the hospital level was found for the recording of diabetes, smoking and stroke, while more variation at the hospital level was found for the recording of hypertension, heart disease and obesity. When the analyses were restricted to 82 large public hospitals only, the between-hospital variation decreased to between 2% (stroke) and 13% (hypertension), or MOR of 1.24 and 1.94 (Figure 1). This between-hospital variation was still significant for all morbidities except for stroke. Between-hospital variation was further reduced once lookback admissions were used to identify morbidities.

Figure 1 about here

The addition of hospital-level variables to multilevel models, one at the time, separately, helped ascertain which factors explained the variation between hospitals (Table 5). The addition of hospital-level factors contributed to explaining (i.e. decreasing) the residual

variation for all conditions, except obesity. For the other morbidities, differences in the depth of coding explained from 16% (smoking) to 42% (hypertension) of residual variation between hospitals, while hospital type (public/private) explained from 0% (smoking) to 59% (stroke), and hospital peer group explained from 10% (hypertension) to 27% (diabetes) residual variation between hospitals.

Table 5 about here

Discussion

Our study found that the concordance of administrative hospital and self-reported data varied between the six morbidities examined, with agreement ranging from good for diabetes, moderate for smoking, through to fair for heart disease, and poor for hypertension, stroke and obesity. We demonstrated considerable between-hospital variation in the recording of these common health conditions. Smaller, but still significant, between-hospital variation was found when restricting the analyses to the largest public hospitals in the state.

Previous studies have validated information recorded in NSW administrative hospital data for demographic factors, [34 35] and recording of perinatal conditions, [36-39] but there have been limited studies of the accuracy of the recording of health conditions commonly used for case-mix or risk-adjustment. Our findings regarding agreement for the recording of diabetes (κ=0.83) were similar to previous Australian studies [3 10], while agreement for hypertension (κ=0.30) and heart disease (κ=0.47) was considerably lower in our study. These differences may be due to the fact that both previous studies used medical records as a 'gold standard', while we used self-report. Lower agreement rates for heart disease could be due to the broader range of heart disease types included in our study, with known lower levels of

agreement for heart failure compared to myocardial infarction.[9],[40] Higher sensitivities reported in a study from the state of Victoria [10] could also be attributable to the differences in public hospital funding models between the two states. Specifically, Victoria has used activity- based funding since 1993, while this method of funding was introduced in NSW and other Australian states only subsequent to our study period. [41] Introduction of activity-based funding has been shown to increase recording of additional diagnoses and procedures in Europe. [42]

Some of the apparent discrepancies in the levels of coding between conditions can be attributed to the coding rules that govern whether or not a diagnosis is recorded in administrative hospital data. Additional diagnoses, recorded on administrative hospital data, are coded only if they affect the patient's treatments received, investigations required and/or resources used during the hospital stay. Thus, diagnoses that relate to an earlier episode, and which have no bearing on the current hospital stay, are not coded for that particular stay. Therefore, it is not surprising that (managed) hypertension, in particular, might not be recorded in hospital data relating to, for example, elective surgery. On the other hand, we found that diabetes is well recorded, suggesting that it is considered to affect patient management in most hospital stays, and possibly reflecting the impact of changes to the Australian Coding Standards for diabetes such that between 2008 and 2010 diabetes with complications could be coded even where there was no established cause and effect relationship between diabetes and the complication. [43] It is for these reasons that researchers using administrative datasets are encouraged to incorporate information from previous hospitalizations, to increase the likelihood of capturing morbidity, as demonstrated in this as well as other Australian studies.[44]As well as looking at single morbidities, ours is the first study to our knowledge to explore the variations of recording of multiple conditions in hospital data. Concordance of two-way condition combinations was very low, with best

results found for combinations of diseases involving diabetes, which had the highest single-condition level of agreement with self-reported data (κ =0.83). Agreement measures for two-way combinations were found to be fair to good at best, with agreement on three-way condition combinations (not investigated here) expected to be even lower. These findings have implications for research into multimorbidity (the co-occurrence of multiple chronic or acute diseases and medical conditions within one person [45]). We suggest that researchers who use administrative data for research into multimorbidity should use linked data to increase ascertainment, and, if possible, supplement this information from other data sources, such as physician claims data or self-reported data.

We identified considerable between-hospital variability in the levels of recording of common health conditions, with between 8% and 22% of the variation attributable to hospital-level factors, after adjustment for patient factors. This was similar in magnitude to the variability previously reported for performance measures (varying from patient satisfaction, mortality, length of stay to quality of care) clustered at the facility level (0-51%) [46] and hospital-level variations in the use of services. [47-49] Significant between-hospital variation was still present after constraining the analyses to the 82 largest public hospitals in the state.

The recording of hypertension and heart disease was particularly variable between hospitals, those with better reporting having on average 2.3 and 2.5 times, respectively, the odds of recording these conditions than those with lower levels of reporting. The corresponding figures were 1.9 and 1.6 times for the 82 largest hospitals in the state. These findings indicate the potential for reporting bias to influence comparisons of health performance indicators between hospitals, especially for indicators that use conditions such as heart disease or hypertension for case-mix adjustment. To our knowledge, no previous studies have provided detailed information about how the validity of morbidity reporting varies among hospitals after accounting for patient factors.

Further, we have shown that variations in the accuracy of morbidity reporting between hospitals are predominantly driven by the hospital's depth of coding – concordance between self-reported and hospital data is lower in hospitals with a lower average number of additional diagnoses recorded. Up to 42% of the variation in recording at the hospital level could be attributed to differences in hospital depth of coding. Even though the measure of depth of coding we used was crude, and related to hospital size, it still helps in highlighting the impact of coding practices on variations among hospitals. Other research using the same depth of coding measure has shown that the lower depth of coding can disproportionately disadvantage hospitals' standardised mortality ratios, one of the commonly reported measures of hospital performance. [2] It will be important to track changes in the levels of the depth of coding across Australian states, and to consider the implications of these for state-based performance comparisons, following the national rollout of activity-based funding and comparative performance reporting.

Several factors might explain variation in depth of coding between hospitals. Clinical coders can code only information that has been recorded in the patient's medical record, so varying level of details recorded by clinicians will influence what gets coded. The training and professional development opportunities for coding staff might also influence the depth of coding. Also, casemix funding systems, such as the Diagnosis Related Group (DRG) classification, are prone to 'upcoding' in order for services to receive higher reimbursement costs. [14]

We found that the reporting of conditions varied with hospital size, larger metropolitan hospitals having higher concordance, with kappa values higher by 7% on average when comparing large tertiary with smaller urban hospitals. This finding echoes those of Powell et al. [3] in NSW, Australia during 1996 – 1998 and Rangachari et al. [16] in the US, during 2000 – 2004. Our study showed that large tertiary hospitals had better concordance for the

recording of hypertension and heart disease than smaller urban hospitals, but the reverse was true for stroke and smoking. Our finding that between-hospital variation in the recording of morbidities was up to two times higher when all hospitals, rather than just the largest ones, were included has implications for further research using data from smaller hospitals. This high variability in concordance among smaller hospitals may mean that morbidity-adjusted comparisons are not as valid as for larger hospitals. Researchers using information from these hospitals are encouraged to supplement their data with either self-report information and/or data linkage. The value-add of incorporating previous hospitalizations was also highlighted in our results for stroke and obesity, with 43% – 47% more patients identified using lookback admissions than from a single admission only.

A particular strength of our study lies in the use of linked data from a large-scale cohort study to comprehensively evaluate the recording of common conditions in hospital data, and explore the variation in recording among hospitals. The 45 and Up Study contains records for one in every 10 persons aged 45 and over in NSW, so it provides a rich resource to answer research questions. Additionally, we used advanced multilevel modeling methods to quantify the amount of between-hospital variation in the level of recording of common health conditions, a finding which is of importance for both research and policy paradigms due to its impact on adjusted comparisons among hospitals and the highlighted need to improve consistency of recording in hospitals across the State. To date, hospital-level variation has only been explored with a set outcome (e.g. mortality, readmission) in mind.

A potential limitation of our study was its use of self-reported information to explore concordance, in the absence of another 'gold standard', such as medical records. Access to medical records was not possible given the de-identified nature of our data, and the large number of records in the dataset. Moreover, studies that have examined accuracy of self-reported conditions against medical records have found high levels of agreement, ranging

from 81% [50] to 87% [51] for hypertension, 66% [40] to 96% [50 51] for diabetes and 60% [50] to 98% [52] for acute myocardial infarction. Validation studies in the 45 and Up Study cohort have reported strong correlations and excellent levels of agreement between self-reported and measured height and weight, and derived BMI [53] as well as self-reported diabetes. [54] Although the 45 and Up Study had a response rate of 18%, the study sample is very large and has excellent heterogeneity. Furthermore, exposure-outcome relationships estimated from the 45 and Up Study data have been shown to be consistent with a large 'representative' population survey of the same population.[55]

Conclusion

The recording of common comorbid conditions in routine hospital data is highly variable, and, for some conditions, very poor. Recording varies considerably among hospitals, presenting the potential to introduce bias into risk-adjusted comparisons of hospital performance, especially for indicators that use heart disease or hypertension for risk adjustment. Furthermore, between-hospital variation is amplified when smaller and private hospitals are included in the analyses. Stratification of analyses according to factors that predict the completeness of recording, including hospital depth of coding and hospital type and size, supplementing morbidity information with linked data from previous hospitalizations and increases in efforts to standardize recording across hospitals, all offer potential for increasing the validity of risk-adjusted comparisons.

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Contributorship

SL had overall responsibility for the design of this study, data management, statistical analysis and drafting this paper. DW and LJ contributed to the conception and design of the study. LJ helped with data acquisition, and provided oversight for all analyses. DR and JS

provided oversight and advice for the design and interpretation of the statistical analyses. All authors contributed to the interpretation of the findings, the writing of the paper and approved the final draft.

Competing interests: None

Data sharing statement

No additional data are available.

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List of tables and figures

Figure 1 Legend:
* Significantly different from 0 at 5% level
** Significantly different from 0 at 1% level

Table 1. Characteristics of the study sample at their index admission

	All participants (N = 32,832)	
	N	%
Demographic characteristics		
Sex		
Male	16,812	51.2
Female	16,020	48.8
Age		
45-59	9,666	29.4
60-79	16,624	50.6
80+	6,540	19.9
Country of birth		
Australia	25,001	76.2
Other	7,448	22.7
Unknown	383	1.2
Highest education level		
No school	5,196	15.8
Year 10 or equivalent	7,894	24.0
Year 12 or equivalent	2,975	9.1
Trade	4,270	13.0
Certificate	6,109	18.6
University degree	5,662	17.3
Unknown	726	2.2
Household income ($, per annum)		
<20,000	9,077	27.7
20,000 - <50,000	8,223	25.1
50,0000 - <70,000	2,560	7.8
70,000+	5,042	15.4
Not disclosed	6,003	18.3
Missing	1,927	5.9
Functional status		
No limitation	4,915	15.0
Mild limitation	6,011	18.3
Moderate limitation	8,701	26.5
Severe limitation	10,121	30.8
Missing	3,084	9.4
Admission characteristics		
Admission type		
Surgical	15,464	47.1
Other	1,439	4.4
Medical	15,929	48.5
Emergency status		
Emergency	13,484	41.1

Planned	17,544	53.4
Other	1,803	5.5
Hospital of admission		
Hospital type		
Public	18,734	57.1
Private	14,096	42.9
Hospital remoteness		
Major city	19,754	60.2
Inner regional	8,424	25.7
Outer regional	4,137	12.6
Remote/very remote	363	1.1
Hospital depth of coding		
1 - least comprehensive	1,629	5.0
2	8,803	26.8
3	11,543	35.2
4 - most comprehensive	10,857	33.1
Hospital peer group		
Principal referral	6,329	19.3
Major	11,052	33.7
District	6,862	20.8
Community	7,018	21.4
Other	1,571	4.8

Table 2. Characteristics of the hospital of admission

	All hospitals[a] (N = 313)	
	N	%
Hospital type		
Public	224	71.6
Private	88	28.1
Hospital remoteness		
Major city	124	39.6
Inner regional	72	23.0
Outer regional	94	30.0
Remote/very remote	20	6.4
Hospital depth of coding		
1 - least comprehensive	48	15.3
2	91	29.1
3	89	28.4
4 - most comprehensive	85	27.2
Hospital peer group		
Principal referral	14	4.5
Major	33	10.5
District	51	16.3
Community	121	38.7
Other	94	30.0

Table 3. Agreement measures between self-report and hospital data, index and lookback admissions, all public and private hospitals in New South Wales, Australia (n=313)

Morbidities[a]	Index admission						Lookback admissions					
	45 and Up Yes:		45 and Up No:		Kappa		45 and Up Yes:		45 and Up No:		Kappa	
	APDC yes	APDC no	APDC yes	APDC no	%	95% CI	APDC yes	APDC no	APDC yes	APDC no	%	95% CI
Hypertension	4,767	10,512	1,434	16,119	**24.0**	(22.9-25.0)	6,260	9,019	2,051	15,502	**30.2**	(29.1-31.2)
Heart disease	3,639	4,668	1,942	22,583	**40.3**	(39.0-41.5)	4,673	3,634	2,697	21,828	**47.0**	(45.8-48.2)
Diabetes	3,560	1,234	347	27,691	**79.1**	(78.1-80.1)	3,928	866	479	27,559	**83.0**	(82.1-83.9)
Stroke	541	1939	306	30,046	**29.8**	(27.0-32.6)	776	1,704	488	29,864	**38.3**	(35.8-40.8)
Smoking	1,205	804	727	30,096	**58.7**	(56.7-60.7)	1,411	598	1,076	29,747	**60.1**	(58.2-61.9)
Obesity	551	7,611	114	24,556	**9.1**	(7.3-10.9)	810	7,352	209	24,461	**12.8**	(11.1-14.6)
Hypertension + heart disease	1,172	3,481	1,270	26,909	**25.8**	(23.8-27.7)	1,807	2,846	2,008	26,171	**34.3**	(32.6-36.0)
Hypertension + diabetes	1,819	1,238	759	29,016	**61.3**	(59.6-62.9)	2,186	871	1,021	28,754	**66.6**	(65.2-68.1)
Hypertension + stroke	203	1,317	189	31,123	**19.7**	(15.7-23.7)	329	1,191	340	30,972	**28.0**	(24.5-31.5)
Hypertension + smoking	133	598	180	31,921	**24.5**	(19.2-29.7)	199	532	319	31,782	**30.6**	(26.0-35.2)
Hypertension + obesity	234	4,574	93	27,931	**7.4**	(4.9-9.8)	383	4,425	183	27,841	**11.5**	(9.2-13.9)
Heart disease + diabetes	646	1,154	404	30,628	**43.0**	(40.3-45.8)	904	896	661	30,371	**51.2**	(48.9-53.6)
Heart disease + stroke	76	973	126	31,657	**11.2**	(6.1-16.4)	149	900	261	31,522	**19.0**	(14.4-23.5)
Heart disease + smoking	76	294	222	32,240	**22.0**	(15.3-28.6)	118	252	373	32,089	**26.5**	(20.8-32.2)
Heart disease + obesity	79	1,938	79	30,736	**6.4**	(2.5-10.4)	151	1,866	169	30,646	**11.4**	(7.7-15.2)
Diabetes + stroke	85	555	58	32,134	**21.1**	(15.0-27.3)	140	500	119	32,073	**30.4**	(24.9-35.8)
Diabetes + smoking	143	161	108	32,420	**51.1**	(45.3-56.9)	171	133	176	32,352	**52.1**	(46.7-57.4)
Diabetes + obesity	232	1,701	65	30,834	**19.5**	(15.9-23.2)	351	1,582	120	30,779	**27.5**	(24.2-30.9)
Stroke + smoking	13	142	28	32,649	**13.1**	(0.1-26.1)	23	132	57	32,620	**19.3**	(7.8-30.8)
Stroke + obesity	6	558	9	32,259	**2.0**	(0.0-10.0)	13	551	21	32,247	**4.2**	(0.0-11.9)
Smoking + obesity	27	447	29	32,329	**9.9**	(1.9-17.9)	38	436	47	32,311	**13.2**	(5.5-20.9)

[a] ICD-10-AM codes: hypertension (I10-I15, R03.0), heart disease (I20-I52), diabetes (E10-E14), stroke (I60-I69, G45, G46), smoking (F17.2, Z72.0), obesity (E66)

Table4. Factors that predict positive agreement between self-report and hospital data, using multilevel modelling, all public and private hospitals in New South Wales, Australia (n=313)

	Hypertension (N = 15,279)	Diabetes (N = 4,794)	Heart disease (N = 8,307)	Stroke (N = 2,480)	Smoking (N = 2,099)	Obesity (N = 8,162)
Person-level variables						
Sex[1]	**	**	**			
Age[1]	**				**	**
Education[1]			*	**	**	
Country of birth[1]						
Functional limitation[1]	**	**				**
Income[1]						
Admission type[2]	**	**	**	**	**	**
Emergency status[2]	**	**	**	**		**
Hospital-level variables						
Hospital type (public/private)[3]	**		**	**		
Hospital remoteness[3]					*	
Hospital depth of coding[3]	**	**	**	**	**	**
Hospital peer group[3]	**	**	**		**	

* Significant at 5% level
** Significant at 1% level

1 – Model 0: adjusted for demographic factors + random intercept for hospital
2 – Model 0 + admission type + emergency status
3 – Model 0 + hospital-level variables (entered one at a time)

Table 5. Variance and intraclass correlation coefficient for hospital-level random effects from multilevel logistic regression, all public and private hospitals in New South Wales, Australia (n=313)

		Hypertension (N† = 15,279)	Diabetes (N† = 4,794)	Heart disease (N† = 8,307)	Stroke (N† = 2,480)	Smoking (N† = 2,099)	Obesity (N† = 8,162)
Hospital-level variance (SE)*							
Model 0.	Patient factors	0.80 (0.10)	0.27 (0.06)	0.91 (0.12)	0.38 (0.10)	0.35 (0.09)	0.68 (0.14)
Model 1.	Model 0 + hospital type (public/private)	0.65 (0.08)	0.27 (0.06)	0.71 (0.10)	0.16 (0.06)	0.35 (0.09)	0.69 (0.14)
Model 2.	Model 0 + hospital remoteness	0.77 (0.09)	0.25 (0.05)	0.92 (0.12)	0.37 (0.10)	0.33 (0.08)	0.68 (0.14)
Model 3.	Model 0 + hospital depth of coding	0.46 (0.06)	0.20 (0.05)	0.56 (0.08)	0.26 (0.08)	0.29 (0.08)	0.68 (0.14)
Model 4.	Model 0 + hospital peer group	0.72 (0.09)	0.21 (0.05)	0.75 (0.10)	0.34 (0.09)	0.31 (0.08)	0.67 (0.14)
Intraclass correlation coefficient (ICC)**		19.5%	7.6%	21.6%	10.4%	9.6%	17.1%
Median odds ratio (MOR)**		2.34	1.64	2.48	1.80	1.76	2.19

† N = number of patients who self-reported condition

* Patient-level variance in a logistic regression is set at $\pi^2/3=3.29$ [31]

** ICC and MOR calculated from Model 0 [ICC = hospital-level variance divided by total variance (hospital-level + patient-level); MOR is calculated as $exp^{0.954\times\sqrt{variance}}$] [30]

Variations in the recording of common health conditions in ~~Australian~~ routine hospital datas: study using linked survey and administrative data in New South Wales, Australia

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Abstract

Objectives: To investigate the nature and potential implications of underreporting of morbidity information in administrative hospital data. ~~To investigate the agreement between self-report and recording of six morbidities in administrative hospital data, quantify the between-hospital variation and identify predictors of positive agreement between the two data sources.~~

Setting and participants: Retrospective analysis of linked self-report and administrative hospital data for 32,832 participants in the large-scale cohort study (45 and Up Study), who joined the study from 2006-2009 and who were admitted to 313 hospitals in New South Wales, Australia, for at least an overnight stay, up to a year prior to study entry.

Outcome measures: Agreement between self-report and recording of six morbidities in administrative hospital data, and between-hospital variation and predictors of ~~and~~ positive agreement ~~among participants who self-reported any of the six morbidities~~between the two data sources.

Results: Agreement between data sources was good for diabetes (κ=0.79), moderate for smoking (κ=0.59), fair for heart disease, stroke and hypertension (κ=0.40, κ =0.30, κ =0.24, respectively) and poor for obesity (κ=0.09), indicating that a large number of individuals with self-reported morbidities did not have a corresponding diagnosis coded in their hospital records. Significant between-hospital variation was found (ranging from 8% of unexplained variation for diabetes to 22% for heart disease), with higher agreement in public and large hospitals, and hospitals with greater depth of coding.

Conclusions: The recording of six common health conditions in administrative hospital data is highly variable, and for some conditions, very poor. To support more valid performance comparisons, it is important to stratify or control for factors that predict the completeness of

recording, including hospital depth of coding and hospital type (public/private), and to increase efforts to standardize recording across hospitals. Studies using these conditions for risk adjustment should also be cautious of their use in smaller hospitals.

Keywords: hospital data, morbidity, multilevel modeling, agreement

Article summary

Article focus

- Explore the agreement between administrative hospital data and self-report information for four clinical conditions, as well as smoking and obesity.
- Quantify the between-hospital variation in the level of recording of these conditions.

Key messages

- Good levels of agreement found only for diabetes, with other conditions exhibiting moderate to poor agreement.
- Better recording was found in public and large hospitals, and hospitals with greater depth of coding.
- Significant between-hospital variation in the levels of agreement, amplified when smaller and private hospitals are included.

Strengths and limitations

- Use of linked data from a large-scale cohort study and advanced multilevel modeling methods to comprehensively evaluate the recording of common health conditions in hospital data, and explore between-hospital variation.
- Limitations include the absence of 'gold standard' such as medical records.

Introduction

Most nations with advanced economies publicly report on the comparative performance of hospitals with a view to accelerating and informing efforts to improve quality and allowing patients to make informed choices. Diagnoses recorded in administrative hospital data are commonly used in the construction and case-mix adjustment of hospital performance metrics, as well as for risk adjustment in epidemiological studies.

The construction of reliable health metrics relies on statistical methods that take into account the degree to which patients treated in different facilities have different morbidity and risk profiles that predispose them to requiring different interventions or to achieving different outcomes. These statistical methods, known as case-mix or risk adjustment, account for patient-related factors that are above and beyond the immediate control of health care professionals.

Thus, properly constructed performance metrics fairly reflect differences in health care experiences, patient outcomes and risks of adverse events. There has been some criticism of case-mix adjustments because they are subject to measurement error, [1] but case-mix adjustment is still considered to be less biased than unadjusted comparisons. [2]

Most methods of case-mix adjustment rely principally on demographic and diagnostic information that is captured in administrative hospital data collections. The hospital data is collected and recorded in a database for administrative purposes, with clinical coders coding diagnostic information based on the patient's medical records. [3] This approach may be sub-optimal [4 5] because evidence from many countries suggests that administrative hospital data underreport the morbidity information needed to fully account for differences between hospitals in patient-related factors that predispose them to differences in measured outcomes. [6-13] However, the impact of this underreporting on comparative measures of hospital

performance depends on whether it varies systematically among hospitals, because of differences in factors such as training or practice among coding staff, the comprehensiveness of clinicians' notes, or "upcoding" relating to funding models or incentives. [14]

This issue is relatively unexplored, aside from the work by Mohammed et al. [2] which reported a non-constant relationship between case-mix variables and mortality among hospitals in the UK, explained by differences in clinical coding and admission practices across hospitals. These variations in coding accuracy were shown to be related to geographic location and bed size, with small rural facilities performing better than large urban hospitals. [15 16] In Australia, variations in the reporting and coding of secondary diagnoses in administrative hospital data have been shown to exist in public hospitals among Australian states, [17] and also among hospitals within the state of New South Wales (NSW), with ~~worse~~ greater underreporting in private and rural hospitals. [3] However, the relative contributions of patient and hospital factors to these variations have not been identified, nor has this variation been formally quantified.

This study, using data-linkage of survey and administrative data, aimed to further investigate the nature and potential implications of underreporting of morbidity information in administrative hospital data by: 1) measuring the agreement between self-reported morbidity information and coded diagnoses; 2) quantifying the amount of between-hospital variation in this agreement; and 3) identifying patient and hospital characteristics that predict higher or lower levels of agreement. We focused on clinical conditions common to case-mix and risk-adjustment models – diabetes, heart disease, hypertension and stroke. We also focus on smoking and obesity, due to their impact on health trajectories, rapid shifts in prevalence, substantial geographic variation in rates [18] and paucity of international evidence on completeness of coding.

Methods

Data sources

The 45 and Up Study

The 45 and Up Study is a large-scale cohort study involving 267,153 men and women aged 45 years and over from the general population of NSW, Australia. The study is described in detail elsewhere. [19] Briefly, participants in the 45 and Up Study were randomly sampled from the database of Australia's universal health insurance provider, Medicare Australia, which provides near complete coverage of the population. People 80+ years of age and residents of rural and remote areas were oversampled. Participants joined the Study by completing a baseline questionnaire (available at https://www.saxinstitute.org.au/our-work/45-up-study/questionnaires/) between January 2006 and December 2009 and giving signed consent for follow-up and linkage of their information to routine health databases. About 18% of those invited participated and participants included about 11% of the NSW population aged 45 years and over. [19] ~~Exposure-outcome relationships estimated from the 45 and Up Study data have been shown to be consistent with a large random survey of the same population. [20]~~

The NSW Admitted Patient Data Collection (APDC)

The APDC includes records of all public and private hospital admissions ending in a separation, i.e. discharge, transfer, type-change or death. Each separation is referred to as an episode of care. Diagnoses are coded according to the Australian modification of the International Statistical Classification of Diseases and Health Related Problems 10th Revision, ICD-10-AM. [20] Up to 55 diagnoses codes are recorded on the APDC, including the principal diagnosis and up to 54 additional diagnoses. Additional diagnoses are defined

as 'a condition or complaint either coexisting with the principal diagnosis or arising during the episode of care' in the Australian Coding Standards and should be interpreted as conditions that affect patient management. [21] Assignment of diagnosis codes is done by trained clinical coders, using information from the patient's medical records.

The APDC from 1 July 2000 to 31 December 2010 was linked probabilistically to survey information from the 45 and Up Study by the NSW Centre for Health Record Linkage (www.cherel.org.au) using the 'best practice' protocol for preserving privacy. [22]

Study population

The study population comprised patients aged 45 years and above who participated in the 45 and Up Study and who had a~~n overnight hospitalisation~~hospitalization lasting at least one night in the period up to 365 days prior to filling out the baseline 45 and Up Study survey. Day stay patients were excluded from the analysis to make the study more robust and generalizable beyond NSW and Australia, as there are differences in admission practices for same day patients between Australia and most other comparable countries.[23] NSW is home to 7.4 million people or one-third of the population of Australia.

Measuring morbidity

We examined four health conditions (diabetes, heart disease, hypertension and stroke) and two health risk factors (obesity and smoking), referred to hereafter collectively as "morbidities". For each participant, these health conditions were measured using self-report and administrative hospital data.

Self-reported morbidities were ascertained on the basis of responses to questions in the baseline 45 and Up Study survey. Diabetes, hypertension, stroke and heart disease were

identified using the question "Has a doctor ever told you that you have [name of condition]?". Participants who did not answer the question were excluded from analyses (n=1,242).

Smoking was classified on the basis of answering "yes" to both of the questions "Have you ever been a regular smoker?" and "Are you a regular smoker now?". Participants' responses to the questions "How tall are you without shoes?" and "About how much do you weigh?" were used to derive body mass index (BMI), defined as body weight divided by height squared (kg/m^2). The World Health Organization's [24] classification system was used to categorize individuals as obese (BMI $\geq 30 kg/m^2$).

Morbidity information in administrative hospital data was ascertained using all 55 diagnosis codes in the APDC records (ICD-10-AM: E10-~~E16~~ E14 for diabetes, I20-I52 for heart disease, I60-I69, G45, G46 for stroke, I10-I15 and R03.0 for hypertension, F17.2 or Z72.0 for smoking and E66 for obesity). The inclusion of broader ICD-10-AM codes for heart disease and stroke was chosen because of the broad definition of disease type in the self-reported data. Thus, heart disease codes were inclusive of coronary heart disease, pulmonary heart disease, and other forms of heart diseases including heart failure and arrhythmias. Stroke codes included cerebrovascular diseases without infarction among others.

Predictors of agreement

We explored both patient- and hospital-level factors as predictors of agreement between the two data sources.

Patient-level factors were self-reported in the 45 and Up Study baseline survey and included age, sex, education, country of birth, income and functional limitation. Functional limitation was measured using the Medical Outcomes Study – Physical Functioning scale, [25] and

classified into 5 groups: no limitation (score of 100), minor limitation (score 95-99), mild limitation (score 85-94), moderate limitation (60-84) and severe limitation (score 0-59).

Facility-level factors were type of hospital (public/private), hospital peer group (akin to hospital size defined by number of case-mix weighted separations, [26] which includes hospital remoteness in the classification), remoteness of hospital and depth of coding. Remoteness of the Statistical Local Area in which the hospital was located was classified according to the Accessibility/Remoteness Index of Australia (ARIA+), grouped into four categories (major city, inner regional, outer regional, remote/very remote). [27] Depth of hospital coding was the mean number of additional diagnoses coded per episode of care for each hospital, calculated using all overnight hospitalizations for the full 45 and Up Study cohort from 2000 to 2010, and divided into four groups at the 25th, 50th and 75th percentile. Hospital peer groups were divided into 5 categories: principal referral (≥25,000 separations per year), major (10,000-24,999 separations per year), district (2,000-9,999 separations per year), community (up to 2,000 separations per year) and other (non-acute, un-peered hospitals). Missing information was treated as a separate category for any variables with missing data.

Statistical methods

We examined patient-level agreement between data sources for each of the six morbidities individually, as well as for their 15 two-way combinations. We compared the self-reported responses (yes/no) with all the diagnoses provided in the hospital records both for 'index' admissions and for the 'lookback' period admissions. [28] The 'index' admission was the overnight hospital stay with admission date closest to the survey completion date and no longer than a year prior. Morbidity was coded as 'yes' if any of the diagnoses during that stay

contained a mention of that morbidity. The 'lookback' admissions included all overnight stays in the 365-day period that preceded and included the 'index' admission. Morbidity was coded as 'yes' if any of the diagnoses from any lookback admissions contained a mention of that morbidity.

Agreement between the two data sources (yes/no) was measured using Cohen's kappa statistic (κ). Kappa values above 0.75 denote excellent agreement, 0.40 to 0.75 fair to good agreement and below 0.45 poor agreement. [29] Agreement was computed for all 313 hospitals in the state, regardless of size, as well as for the 82 largest public hospitals, for which performance metrics are publicly reported.

Multilevel logistic regression was used to estimate odds ratios (OR) with 95% confidence intervals (CI) for patient- and hospital-level factors that predicted positive agreement between the two data sources. Multilevel models were chosen because of the clustering of patients within hospitals. Models were run for each of the six morbidities separately. These analyses were constrained to only those participants who self-reported the morbidity of interest, and the outcome was whether the index hospital record contained a mention of the morbidity or not. Addition of the hospital-level characteristics was done one at a time, due to the collinearity between variables. All ORs presented are adjusted for all other demographic variables in the model.

Variation at the hospital level was expressed as a median odds ratio (MOR), which is the median of the odds ratios of pair-wise comparisons of patients taken from randomly chosen hospitals, calculated as $exp^{0.954\times\sqrt{variance}}$;[30] and the intraclass correlation coefficient (ICC), which is the percentage of the total variance attributable to the hospital level. [31] Large ICCs indicate that differences among hospitals account for a considerable part of the variation in the outcome, whereas a small ICC means that the hospital effect on the overall variation is minimal. The relative influence of the hospital on reporting of morbidity was calculated using

a variance partitioning coefficient expressed as a percentage of the total variance using the Snijders and Bosker latent variable approach. [31]

All data management was done using SAS 9.2 [32] and multilevel modeling using MLwiN 2.24. [33]

The conduct of the 45 and Up Study was approved by the University of New South Wales Human Research Ethics Committee (HREC), while ethical approval for this particular study was provided by the NSW Population and Health Services Research Ethics Committee and the University of Western Sydney HREC.

Results

Descriptive characteristics

A total of 32,832 study participants were admitted to 313 hospitals up to a year prior to completing the 45 and Up Study baseline survey. Just over half of the index admissions (53%) were planned stays in hospital, and 57% were to a public hospital. Around one-third of the index admissions occurred within the three months before study entry, and the mean length of stay was 4.8 days (median = 3 days). Just under half of the sample (47%) reported having hypertension, with heart disease or obesity reported by 25%, and current smoking by 6.1% of the sample. One-third (34%) of participants had two or more morbidities (data not shown). Other characteristics of the sample at their index admission are shown in Table 1. Characteristics of hospitals are summarized in Table 2.

Table 1 about here

Table 2 about here

Concordance between self-report and hospital records

Overall, reporting of morbidity differed between the two data sources with 23,257 (71%) participants having at least one of the six self-reported morbidities, and 11,977 (36.5%) and 14,335 (43.7%) of the sample having at least one morbidity recorded on their index or lookback hospital admissions, respectively.

Table ~~2~~ 3 gives the summary concordance measures for each morbidity and two-way morbidity combination. For the index admission, good agreement was found for diabetes (κ=0.79), moderate agreement for smoking (κ=0.59), fair agreement for heart disease (κ=0.40), and poor agreement for stroke (κ=0.30), hypertension (κ=0.24) and obesity (κ=0.09). In two-way combinations, moderate levels of agreement were found only for diabetes combinations (with smoking, hypertension and heart disease).

Table ~~2~~ 3 about here

Incorporating a one-year lookback period increased the numbers of participants with a morbidity recorded in a hospital record, with average relative increases in the kappa values of 20% (ranging from 2% increase for smoking, to 41% increase for obesity). Good to excellent level of agreements were still found only for diabetes (κ =0.83) and smoking (κ =0.60).

Agreement was only slightly higher among the 82 large public hospitals (see Supplementary Table 1) with relative kappa values higher by 4%, on average.

Patient- and hospital-level predictors of positive agreement

The patient factors which predicted positive agreement between the two data sources differed between morbidities (Table ~~3~~4). Male sex was associated with better agreement for diabetes (OR=1.37, 95% CI 1.19 – 1.58), heart disease (OR=1.30, 95% CI 1.17 – 1.44) and hypertension (OR=1.28, 95% CI 1.18 – 1.38) (Supplementary Table 2).

Older patients were significantly less likely to have smoking (80+ years OR=0.48, 95% CI 0.31 – 0.74) and obesity (OR=0.14, 95% CI 0.08 – 0.26) recorded in their hospital records, and significantly more likely to have hypertension recorded (OR=1.32, 95% CI 1.16 – 1.49), compared to younger patients (45 – 59 years). People with higher levels of functional limitation were significantly more likely to have hypertension, diabetes and obesity recorded on their most recent hospital stay. Planned admissions to hospital had lower odds of having any of the six conditions recorded, as did medical admissions (for diabetes, smoking and obesity only). Agreement did not vary significantly for any other patient factors.

Table ~~3~~ 4 about here

The four hospital-level covariates (hospital type, hospital peer group, hospital remoteness and depth of coding) were added to multilevel models (including a random intercept for hospital) one at a time, separately. Positive agreement between self-report and hospital records was significantly lower for hospitals with lower depth of coding across all morbidities. The odds of recording were also lower among private hospitals for all six morbidities, with this difference being statistically significant for hypertension, heart disease and stroke only. Records from smaller hospitals (district and community peer groups) were significantly less likely to agree with self-reported data on hypertension, diabetes and heart disease. Positive

agreement did not vary significantly with remoteness of hospital, with the exceptions of diabetes (lower agreement for outer regional, remote and very remote hospitals) and smoking (lower agreement for remote and very remote hospitals) (Supplementary Table 3).

Quantifying variation between hospitals

Before any hospital-level variables were added into the multilevel model, the intraclass correlation coefficient indicated that between 8% (diabetes) and 22% (heart disease) of the residual (unexplained) variation in agreement was attributable to the hospital, after adjustment for the patient-level factors (Table 45). This equated to median odds ratios (MORs) of 1.64 and 2.48, respectively, indicating that a patient in one hospital had an average of between 64% and 148% higher odds of having a particular morbidity recorded than a patient in a hospital with lower levels of recording. Less variation at the hospital level was found for the recording of diabetes, smoking and stroke, while more variation at the hospital level was found for the recording of hypertension, heart disease and obesity. When the analyses were restricted to 82 large public hospitals only, the between-hospital variation decreased to between 2% (stroke) and 13% (hypertension), or MOR of 1.24 and 1.94 (Figure 1). This between-hospital variation was still significant for all morbidities except for stroke. Between-hospital variation was further reduced once lookback admissions were used to identify morbidities.

Figure 1 about here

The addition of hospital-level variables to multilevel models, one at the time, separately, helped ascertain which factors explained the variation between hospitals (Table 45). The

addition of ~~at least one of the four~~ hospital-level factors contributed to explaining (i.e. decreasing) the residual variation ~~between hospitals~~ for all conditions, except obesity. For the other morbidities, differences in the depth of coding explained from 16% (smoking) to 42% (hypertension) of residual variation between hospitals, while hospital type (public/private) explained from 0% (smoking) to 59% (stroke), and hospital peer group explained from 10% (hypertension) to 27% (diabetes) residual variation between hospitals.

Table ~~4~~ 5 about here

Discussion

Our study found that the concordance of administrative hospital and self-reported data varied between the six morbidities examined, with agreement ranging from good for diabetes, moderate for smoking, through to fair for heart disease, and poor for hypertension, stroke and obesity. We demonstrated considerable between-hospital variation in the recording of these common health conditions. Smaller, but still significant, between-hospital variation was found when restricting the analyses to the largest public hospitals in the state.

Previous studies have validated information recorded in NSW administrative hospital data for demographic factors, [34 35] and recording of perinatal conditions, [36-39] but there have been limited studies of the accuracy of the recording of health conditions commonly used for case-mix or risk-adjustment. Our findings regarding agreement for the recording of diabetes (κ=0.83) were similar to previous Australian studies [3 10], while agreement for hypertension (κ=0.30) and heart disease (κ=0.47) was considerably lower in our study. These differences may be due to the fact that both previous studies used medical records as a 'gold standard', while we used self-report. Lower agreement rates for heart disease could be due to the

broader range of heart disease types included in our study, with known lower levels of agreement for heart failure compared to myocardial infarction.[9],[40] ~~[3]~~ -Higher sensitivities reported in a study from the state of Victoria [10] could also be attributable to the differences in public hospital funding models between the two states. Specifically, Victoria has used activity- based funding since 1993, while this method of funding was introduced in NSW and other Australian states only subsequent to our study period. [41] Introduction of activity-based funding has been shown to increase recording of additional diagnoses and procedures in Europe. [42]

Some of the apparent discrepancies in the levels of coding between conditions can be attributed to the coding rules that govern whether or not a diagnosis is recorded in administrative hospital data. Additional diagnoses, recorded on administrative hospital data, are coded only if they affect the patient's treatments received, investigations required and/or resources used during the hospital stay. Thus, diagnoses that relate to an earlier episode, and which have no bearing on the current hospital stay, are ~~excluded~~not coded for that particular stay. Therefore, it is not surprising that (managed) hypertension, in particular, might not be recorded in hospital data relating to, for example, elective surgery. On the other hand, we found that diabetes is well recorded, suggesting that it is considered to affect patient management in most hospital stays, and possibly reflecting the impact of changes to the Australian Coding Standards for diabetes such that between 2008 and 2010 diabetes with complications could be coded even where there was no established cause and effect relationship between diabetes and the complication. –[43] It is for these reasons that researchers using administrative datasets are encouraged to incorporate information from previous hospitalizations, to increase the likelihood of capturing morbidity, as demonstrated in this as well as other Australian studies.[44]

As well as looking at single morbidities, ours is the first study to our knowledge to explore the variations of recording of multiple conditions in hospital data. Concordance of two-way condition combinations was very low, with best results found for combinations of diseases involving diabetes, which had the highest single-condition level of agreement with self-reported data (κ =0.83). Agreement measures for two-way combinations were found to be fair to good at best, with agreement on three-way condition combinations (not investigated here) expected to be even lower. These findings have implications for research into multimorbidity (the co-occurrence of multiple chronic or acute diseases and medical conditions within one person [45]). We suggest that researchers who use administrative data for research into multimorbidity should use linked data to increase ascertainment, and, if possible, supplement this information from other data sources, such as physician claims data or self-reported data.

We identified considerable between-hospital variability in the levels of recording of common health conditions, with between 8% and 22% of the variation attributable to hospital-level factors, after adjustment for patient factors. This was similar in magnitude to the variability previously reported for performance measures (varying from patient satisfaction, mortality, length of stay to quality of care) clustered at the facility level (0-51%) [46] and hospital-level variations in the use of services. [47-49] Significant between-hospital variation was still present after constraining the analyses to the 82 largest public hospitals in the state.

The recording of hypertension and heart disease was particularly variable between hospitals, those with better reporting having on average 2.3 and 2.5 times, respectively, the odds of recording these conditions than those with lower levels of reporting. The corresponding figures were 1.9 and 1.6 times for the 82 largest hospitals in the state. These findings indicate the potential for reporting bias to influence comparisons of health performance indicators between hospitals, especially for indicators that use conditions such as heart disease or hypertension for case-mix adjustment. To our knowledge, no previous studies have provided

detailed information about how the validity of morbidity reporting varies among hospitals after accounting for patient factors.

Further, we have shown that variations in the accuracy of morbidity reporting between hospitals are predominantly driven by the hospital's depth of coding – concordance between self-reported and hospital data is lower in hospitals with a lower average number of additional diagnoses recorded. Up to 42% of the variation in recording at the hospital level could be attributed to differences in hospital depth of coding. Even though the measure of depth of coding we used was crude, and related to hospital size, it still helps in highlighting the impact of coding practices on variations among hospitals. Other research using the same depth of coding measure has shown that the lower depth of coding can disproportionately disadvantage hospitals' standardised mortality ratios, one of the commonly reported measures of hospital performance. [2] It will be important to track changes in the levels of the depth of coding across Australian states, and to consider the implications of these for state-based performance comparisons, following the national rollout of activity-based funding and comparative performance reporting.

Several factors might explain variation in depth of coding between hospitals. Clinical coders can code only information that has been recorded in the patient's medical record, so varying level of details recorded by clinicians will influence what gets coded. The training and professional development opportunities for coding staff might also influence the depth of coding. Also, casemix funding systems, such as the Diagnosis Related Group (DRG) classification, are prone to 'upcoding' in order for services to receive higher reimbursement costs. [14]

We found that the reporting of conditions varied with hospital size, larger metropolitan hospitals having higher concordance, with kappa values higher by 7% on average when comparing large tertiary with smaller urban hospitals. This finding echoes those of Powell et

al. [3] in NSW, Australia during 1996 – 1998 and Rangachari et al. [16] in the US, during 2000 – 2004. Our study showed that large tertiary hospitals had better concordance for the recording of hypertension and heart disease than smaller urban hospitals, but the reverse was true for stroke and smoking. Our finding that between-hospital variation in the recording of morbidities was up to two times higher when all hospitals, rather than just the largest ones, were included has implications for further research using data from smaller hospitals. This high variability in concordance among smaller hospitals may mean that morbidity-adjusted comparisons are not as valid as for larger hospitals. Researchers using information from these hospitals are encouraged to supplement their data with either self-report information and/or data linkage. The value-add of incorporating previous hospitalizations was also highlighted in our results for stroke and obesity, with 43% – 47% more patients identified using lookback admissions than from a single admission only.

A particular strength of our study lies in the use of linked data from a large-scale cohort study to comprehensively evaluate the recording of common conditions in hospital data, and explore the variation in recording among hospitals. The 45 and Up Study contains records for one in every 10 persons aged 45 and over in NSW, so it provides a rich resource to answer research questions. Additionally, we used advanced multilevel modeling methods to quantify the amount of between-hospital variation in the level of recording of common health conditions, a finding which is of importance for both research and policy paradigms due to its impact on adjusted comparisons among hospitals and the highlighted need to improve consistency of recording in hospitals across the State. To date, hospital-level variation has only been explored with a set outcome (e.g. mortality, readmission) in mind.

A potential limitation of our study was its use of self-reported information to explore concordance, in the absence of another 'gold standard', such as medical records. Access to medical records was not possible given the de-identified nature of our data, and the large

number of records in the dataset. Moreover, studies that have examined accuracy of self-reported conditions against medical records have found high levels of agreement, ranging from 81% [50] to 87% [51] for hypertension, 66% [40] to 96% [50 51] for diabetes and 60% [50] to 98% [52] for acute myocardial infarction. Validation studies in the 45 and Up Study cohort have reported strong correlations and excellent levels of agreement between self-reported and measured height and weight, and derived BMI [53] as well as self-reported diabetes. [54] Although the 45 and Up Study had a response rate of 18%, the study sample is very large and has excellent heterogeneity. Furthermore, exposure-outcome relationships estimated from the 45 and Up Study data have been shown to be consistent with a large 'representative' population survey of the same population.[55]

Conclusion

The recording of common comorbid conditions in routine hospital data is highly variable, and, for some conditions, very poor. Recording varies considerably among hospitals, presenting the potential to introduce bias into risk-adjusted comparisons of hospital performance, especially for indicators that use heart disease or hypertension for risk adjustment. Furthermore, between-hospital variation is amplified when smaller and private hospitals are included in the analyses. Stratification of analyses according to factors that predict the completeness of recording, including hospital depth of coding and hospital type and size, supplementing morbidity information with linked data from previous hospitalizations and increases in efforts to standardize recording across hospitals, all offer potential for increasing the validity of risk-adjusted comparisons.

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Contributorship

SL had overall responsibility for the design of this study, data management, statistical analysis and drafting this paper. DW and LJ contributed to the conception and design of the study. LJ helped with data acquisition, and provided oversight for all analyses. DR and JS provided oversight and advice for the design and interpretation of the statistical analyses. All authors contributed to the interpretation of the findings, the writing of the paper and approved the final draft.

Competing interests: None

Data sharing statement

This study used the data from the Assessing Preventable Hospitalisation InDicators (APHID) project. The data has been constructed with the permission of each of the custodians of the respective source datasets and with specific ethical approval. The data are available to researchers on request and subject to approval from the relevant data custodians and ethics committees. More information about these approvals is available from the authors on request.

No additional data are available.

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List of tables and figures

Figure 1 Legend:
* Significantly different from 0 at 5% level
** Significantly different from 0 at 1% level

Table 1. Characteristics of the study sample at their index admission

~~Characteristics~~	All participants (N = 32,832)	
	N	%
Demographic characteristics		
Sex		
Male	16,812	51.2
Female	16,020	48.8
Age		
45-59	9,666	29.4
60-79	16,624	50.6
80+	6,540	19.9
Country of birth		
Australia	25,001	76.2
Other	7,448	22.7
Unknown	383	1.2
Highest education level		
No school	5,196	15.8
Year 10 or equivalent	7,894	24.0
Year 12 or equivalent	2,975	9.1
Trade	4,270	13.0
Certificate	6,109	18.6
University degree	5,662	17.3
Unknown	726	2.2
Household income ($, per annum)		
<20,000	9,077	27.7
20,000 - <50,000	8,223	25.1
50,0000 - <70,000	2,560	7.8
70,000+	5,042	15.4
Not disclosed	6,003	18.3
Missing	1,927	5.9
Functional status		
No limitation	4,915	15.0
Mild limitation	6,011	18.3
Moderate limitation	8,701	26.5
Severe limitation	10,121	30.8
Missing	3,084	9.4
Admission characteristics		
Admission type		
Surgical	15,464	47.1
Other	1,439	4.4
Medical	15,929	48.5
Emergency status		
Emergency	13,484	41.1

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Planned	17,544	53.4
Other	1,803	5.5
Hospital ~~characteristics~~of admission		
Hospital type		
Public	18,734	57.1
Private	14,096	42.9
Hospital remoteness		
Major city	19,754	60.2
Inner regional	8,424	25.7
Outer regional	4,137	12.6
Remote/very remote	363	1.1
Hospital depth of coding		
1 - least comprehensive	1,629	5.0
2	8,803	26.8
3	11,543	35.2
4 - most comprehensive	10,857	33.1
Hospital peer group		
Principal referral	6,329	19.3
Major	11,052	33.7
District	6,862	20.8
Community	7,018	21.4
Other	1,571	4.8

[a] ~~for comparisons of hospital characteristics~~

Table 2. Characteristics of the hospital of admission

	All hospitals[a] (N = 313)	
	N	%
Hospital type		
Public	224	71.6
Private	88	28.1
Hospital remoteness		
Major city	124	39.6
Inner regional	72	23.0
Outer regional	94	30.0
Remote/very remote	20	6.4
Hospital depth of coding		
1 - least comprehensive	48	15.3
2	91	29.1
3	89	28.4
4 - most comprehensive	85	27.2
Hospital peer group		
Principal referral	14	4.5
Major	33	10.5
District	51	16.3
Community	121	38.7
Other	94	30.0

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Table ~~2~~3. Agreement measures between self-report and hospital data, index and lookback admissions, all public and private hospitals in New South Wales, Australia (n=313)

Morbidities[a]	Index admission						Lookback admissions					
	45 and Up Yes:		45 and Up No:		Kappa		45 and Up Yes:		45 and Up No:		Kappa	
	APDC yes	APDC no	APDC yes	APDC no	%	95% CI	APDC yes	APDC no	APDC yes	APDC no	%	95% CI
Hypertension	4,767	10,512	1,434	16,119	**24.0**	(22.9-25.0)	6,260	9,019	2,051	15,502	**30.2**	(29.1-31.2)
Heart disease	3,639	4,668	1,942	22,583	**40.3**	(39.0-41.5)	4,673	3,634	2,697	21,828	**47.0**	(45.8-48.2)
Diabetes	3,560	1,234	347	27,691	**79.1**	(78.1-80.1)	3,928	866	479	27,559	**83.0**	(82.1-83.9)
Stroke	541	1939	306	30,046	**29.8**	(27.0-32.6)	776	1,704	488	29,864	**38.3**	(35.8-40.8)
Smoking	1,205	804	727	30,096	**58.7**	(56.7-60.7)	1,411	598	1,076	29,747	**60.1**	(58.2-61.9)
Obesity	551	7,611	114	24,556	**9.1**	(7.3-10.9)	810	7,352	209	24,461	**12.8**	(11.1-14.6)
Hypertension + heart disease	1,172	3,481	1,270	26,909	**25.8**	(23.8-27.7)	1,807	2,846	2,008	26,171	**34.3**	(32.6-36.0)
Hypertension + diabetes	1,819	1,238	759	29,016	**61.3**	(59.6-62.9)	2,186	871	1,021	28,754	**66.6**	(65.2-68.1)
Hypertension + stroke	203	1,317	189	31,123	**19.7**	(15.7-23.7)	329	1,191	340	30,972	**28.0**	(24.5-31.5)
Hypertension + smoking	133	598	180	31,921	**24.5**	(19.2-29.7)	199	532	319	31,782	**30.6**	(26.0-35.2)
Hypertension + obesity	234	4,574	93	27,931	**7.4**	(4.9-9.8)	383	4,425	183	27,841	**11.5**	(9.2-13.9)
Heart disease + diabetes	646	1,154	404	30,628	**43.0**	(40.3-45.8)	904	896	661	30,371	**51.2**	(48.9-53.6)
Heart disease + stroke	76	973	126	31,657	**11.2**	(6.1-16.4)	149	900	261	31,522	**19.0**	(14.4-23.5)
Heart disease + smoking	76	294	222	32,240	**22.0**	(15.3-28.6)	118	252	373	32,089	**26.5**	(20.8-32.2)
Heart disease + obesity	79	1,938	79	30,736	**6.4**	(2.5-10.4)	151	1,866	169	30,646	**11.4**	(7.7-15.2)
Diabetes + stroke	85	555	58	32,134	**21.1**	(15.0-27.3)	140	500	119	32,073	**30.4**	(24.9-35.8)
Diabetes + smoking	143	161	108	32,420	**51.1**	(45.3-56.9)	171	133	176	32,352	**52.1**	(46.7-57.4)
Diabetes + obesity	232	1,701	65	30,834	**19.5**	(15.9-23.2)	351	1,582	120	30,779	**27.5**	(24.2-30.9)
Stroke + smoking	13	142	28	32,649	**13.1**	(0.1-26.1)	23	132	57	32,620	**19.3**	(7.8-30.8)
Stroke + obesity	6	558	9	32,259	**2.0**	(0.0-10.0)	13	551	21	32,247	**4.2**	(0.0-11.9)
Smoking + obesity	27	447	29	32,329	**9.9**	(1.9-17.9)	38	436	47	32,311	**13.2**	(5.5-20.9)

[a] ICD-10-AM codes: hypertension (I10-I15, R03.0), heart disease (~~I20-I25, I26-I28, I30-I52~~I20-I52), diabetes (E10-E14), stroke (I60-I69, G45, G46), smoking (F17.2, Z72.0), obesity (E66)

Table ~~3~~4. Factors that predict positive agreement between self-report and hospital data, using multilevel modelling, all public and private hospitals in New South Wales, Australia (n=313)

	Hypertension (N = 15,279)	Diabetes (N = 4,794)	Heart disease (N = 8,307)	Stroke (N = 2,480)	Smoking (N = 2,099)	Obesity (N = 8,162)
Person-level variables						
Sex[1]	**	**	**			
Age[1]	**				**	**
Education[1]			*	**	**	
Country of birth[1]						
Functional limitation[1]	**	**				**
Income[1]						
Admission type[2]	**	**	**	**	**	**
Emergency status[2]	**	**	**	**		**
Hospital-level variables						
Hospital type (public/private)[3]	**		**	**		
Hospital remoteness[3]					*	
Hospital depth of coding[3]	**	**	**	**	**	**
Hospital peer group[3]	**	**	**		**	

* Significant at 5% level
** Significant at 1% level

1 – Model 0: adjusted for demographic factors + random intercept for hospital
2 – Model 0 + admission type + emergency status
3 – Model 0 + hospital-level variables (entered one at a time)

Table 45. Variance and intraclass correlation coefficient for hospital-level random effects from multilevel logistic regression, all public and private hospitals in New South Wales, Australia (n=313)

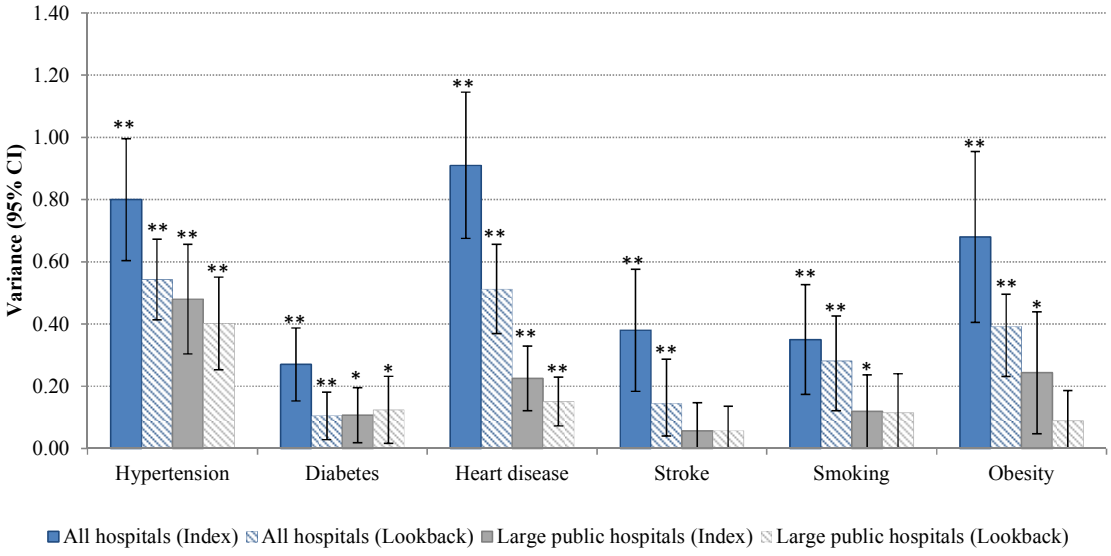
		Hypertension (N† = 15,279)	Diabetes (N† = 4,794)	Heart disease (N† = 8,307)	Stroke (N† = 2,480)	Smoking (N† = 2,099)	Obesity (N† = 8,162)
Hospital-level variance (SE)*							
Model 0.	Patient factors	0.80 (0.10)	0.27 (0.06)	0.91 (0.12)	0.38 (0.10)	0.35 (0.09)	0.68 (0.14)
Model 1.	Model 0 + hospital type (public/private)	0.65 (0.08)	0.27 (0.06)	0.71 (0.10)	0.16 (0.06)	0.35 (0.09)	0.69 (0.14)
Model 2.	Model 0 + hospital remoteness	0.77 (0.09)	0.25 (0.05)	0.92 (0.12)	0.37 (0.10)	0.33 (0.08)	0.68 (0.14)
Model 3.	Model 0 + hospital depth of coding	0.46 (0.06)	0.20 (0.05)	0.56 (0.08)	0.26 (0.08)	0.29 (0.08)	0.68 (0.14)
Model 4.	Model 0 + hospital peer group	0.72 (0.09)	0.21 (0.05)	0.75 (0.10)	0.34 (0.09)	0.31 (0.08)	0.67 (0.14)
Intraclass correlation coefficient (ICC)**		19.5%	7.6%	21.6%	10.4%	9.6%	17.1%
Median odds ratio (MOR)**		2.34	1.64	2.48	1.80	1.76	2.19

† N = number of patients who self-reported condition

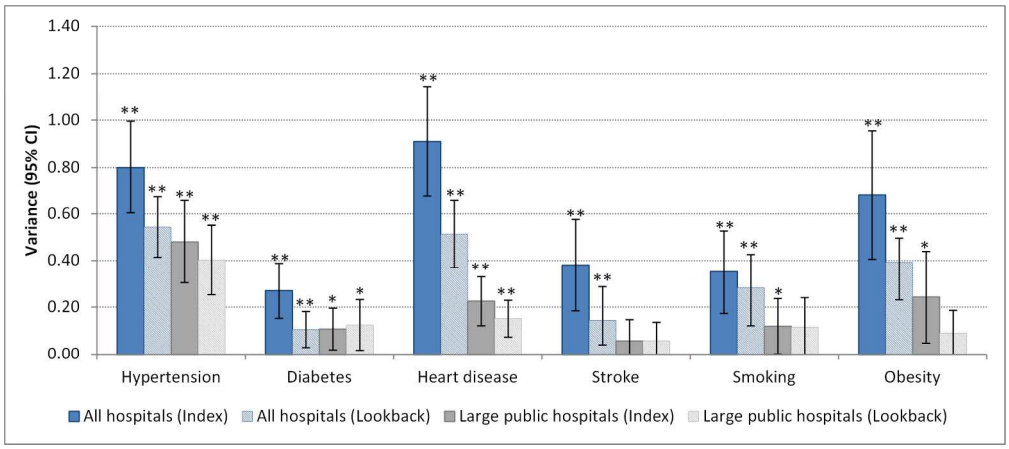
* Patient-level variance in a logistic regression is set at $\pi^2/3=3.29$ [31]

** ICC and MOR calculated from Model 0 [ICC = hospital-level variance divided by total variance (hospital-level + patient-level); MOR is calculated as $exp^{0.954\times\sqrt{variance}}$] [30]

Figure 1. Variance for hospital-level random effects from multilevel logistic regression, for index and lookback admissions, by hospital size



* Significantly different from 0 at 5% level
** Significantly different from 0 at 1% level



* Significantly different from 0 at 5% level
** Significantly different from 0 at 1% level

193x84mm (300 x 300 DPI)

Supplementary Table 1. Agreement measures between self-report and hospital data, index and lookback admissions, large public hospitals in New South Wales, Australia (n=82)

Supplementary Table 2. Adjusted ORs for patient-level variables from the multilevel logistic regression with random intercept for hospital of admission, all public and private hospitals in New South Wales, Australia (n=313)

Supplementary Table 3. Adjusted ORs for hospital-level variables from the multilevel logistic regression with random intercept for hospital of admission, all public and private hospitals in New South Wales, Australia (n=313)

Supplementary Table 1. Agreement measures between self-report and hospital data, index and lookback admissions, large public hospitals in New South Wales, Australia (n=82)

Morbidities[a]	Index admission						Lookback admissions					
	45 and Up Yes:		45 and Up No:		Kappa		45 and Up Yes:		45 and Up No:		Kappa	
	APDC yes	APDC no	APDC yes	APDC no	%	95% CI	APDC yes	APDC no	APDC yes	APDC no	%	95% CI
Hypertension	3,061	4,803	983	7,634	**28.1**	(26.6-29.6)	3,829	4,035	1,339	7,278	**33.7**	(32.2-35.1)
Heart disease	2,306	2,455	1,309	10,411	**40.1**	(38.5-41.8)	2,910	1,851	1,710	10,010	**46.9**	(45.4-48.5)
Diabetes	2,168	661	214	13,438	**80.1**	(78.8-81.4)	2,355	474	289	13,363	**83.3**	(82.1-84.4)
Stroke	414	1,210	213	14,644	**33.1**	(29.8-36.4)	563	1,061	311	14,546	**41**	(38.0-44.0)
Smoking	820	507	468	14,686	**59.5**	(57.0-62.0)	948	379	692	14,462	**60.4**	(58.1-62.7)
Obesity	265	3,857	61	12,298	**8.6**	(6.1-11.1)	414	3,708	114	12,245	**12.9**	(10.4-15.3)
Hypertension + heart disease	799	1,878	893	12,911	**27.4**	(25.0-29.9)	1,159	1,518	1,327	12,477	**34.7**	(32.5-36.9)
Hypertension + diabetes	1,129	670	518	14,164	**61.5**	(59.4-63.6)	1,317	482	662	14,020	**65.8**	(63.9-67.7)
Hypertension + stroke	160	825	145	15,351	**22.6**	(17.9-27.3)	238	747	237	15,259	**29.9**	(25.6-34.1)
Hypertension + smoking	106	399	135	15,841	**27**	(20.9-33.1)	154	351	237	15,739	**32.6**	(27.2-37.9)
Hypertension + obesity	157	2,291	62	13,971	**9.6**	(6.2-13.0)	251	2,197	117	13,916	**14.5**	(11.3-17.7)
Heart disease + diabetes	452	686	293	15,050	**45**	(41.7-48.3)	620	518	442	14,901	**53.2**	(50.4-56.1)
Heart disease + stroke	61	641	93	15,686	**12.9**	(6.8-19.1)	107	595	171	15,608	**19.9**	(14.4-25.4)
Heart disease + smoking	65	209	163	16,044	**24.8**	(17.2-32.3)	98	176	280	15,927	**28.7**	(22.2-35.1)
Heart disease + obesity	63	1,145	62	15,211	**8.2**	(3.2-13.2)	117	1,091	119	15,154	**14.1**	(9.5-18.8)
Diabetes + stroke	66	374	38	16,003	**23.5**	(16.2-30.8)	110	330	69	15,972	**34.5**	(28.2-40.9)
Diabetes + smoking	107	112	83	16,179	**51.7**	(45.0-58.5)	130	89	132	16,130	**53.4**	(47.3-59.5)
Diabetes + obesity	150	994	39	15,298	**20.9**	(16.3-25.6)	229	915	76	15,261	**29.5**	(25.3-33.8)
Stroke + smoking	13	106	23	16,339	**16.5**	(2.1-30.8)	19	100	41	16,321	**20.8**	(7.8-33.9)
Stroke + obesity	4	368	7	16,102	**2**	(0.0-11.8)	9	363	13	16,096	**4.3**	(0.0-13.9)
Smoking + obesity	17	292	18	16,154	**9.5**	(0.0-19.5)	25	284	29	16,143	**13.3**	(3.8-22.8)

[a] ICD-10-AM codes: hypertension (I10-I15, R03.0), heart disease (I20-I25, I26-I28, I30-I52), diabetes (E10-E14), smoking (F17.2, Z72.0), obesity (E66)

Supplementary Table 2. Adjusted ORs[a] for patient-level variables from the multilevel logistic regression with random intercept for hospital of admission, all public and private hospitals in New South Wales, Australia (n=313)

Patient characteristics	Hypertension (N = 15,279)		Diabetes (N = 4,794)		Heart disease (N = 8,307)		Stroke (N = 2,480)		Smoking (N = 2,099)		Obesity (N = 8,162)	
	OR[a]	(95%CI)[b]	OR[a]	(95%CI)[b]	OR[a]	(95%CI)[b]	OR[a]	(95%CI)[b]	OR[a]	(95%CI)[b]	OR[a]	(95%CI)[b]
Sex												
Female	1		1		1		1		1		1	
Male	1.28	(1.18,1.38)	1.37	(1.19,1.58)	1.30	(1.17,1.44)	1.13	(0.91,1.40)	1.14	(0.94,1.40)	0.85	(0.70,1.04)
Age												
45-59	1		1		1		1		1		1	
60-79	1.27	(1.15,1.41)	0.97	(0.81,1.16)	0.94	(0.82,1.09)	1.08	(0.78,1.52)	0.80	(0.65,0.99)	0.57	(0.47,0.70)
80+	1.32	(1.16,1.49)	1.00	(0.80,1.25)	1.01	(0.86,1.19)	1.02	(0.72,1.46)	0.48	(0.31,0.74)	0.14	(0.08,0.26)
Education												
None	1		1		1		1		1		1	
Trade	0.90	(0.79,1.03)	0.93	(0.73,1.18)	0.80	(0.68,0.94)	1.08	(0.76,1.54)	0.67	(0.48,0.94)	1.42	(1.01,2.02)
School certificate	0.96	(0.86,1.07)	1.00	(0.82,1.23)	0.90	(0.78,1.05)	1.22	(0.90,1.66)	0.87	(0.66,1.16)	1.04	(0.77,1.41)
HSC	0.99	(0.85,1.15)	0.89	(0.68,1.17)	0.91	(0.75,1.11)	2.23	(1.51,3.30)	0.53	(0.37,0.76)	1.24	(0.84,1.83)
Diploma	0.96	(0.84,1.09)	0.90	(0.72,1.14)	0.87	(0.74,1.03)	1.08	(0.75,1.56)	1.00	(0.73,1.37)	1.15	(0.83,1.59)
University	0.85	(0.74,0.98)	0.90	(0.70,1.16)	0.72	(0.60,0.86)	1.23	(0.83,1.81)	0.54	(0.37,0.80)	1.25	(0.88,1.79)
County of birth												
Australia	1		1		1		1		1		1	
Overseas	1.00	(0.91,1.09)	0.95	(0.81,1.11)	1.10	(0.98,1.23)	1.19	(0.94,1.51)	1.17	(0.92,1.48)	0.89	(0.69,1.14)
Functional limitation												
No limitation	1		1		1		1		1		1	
Mild	1.07	(0.91,1.25)	0.91	(0.68,1.23)	1.02	(0.82,1.28)	0.82	(0.48,1.42)	0.92	(0.65,1.30)	1.07	(0.72,1.60)
Moderate	1.23	(1.07,1.42)	1.14	(0.87,1.50)	0.92	(0.75,1.13)	0.68	(0.42,1.11)	0.79	(0.57,1.09)	1.06	(0.73,1.53)
Severe	1.53	(1.33,1.76)	1.54	(1.18,2.01)	0.97	(0.79,1.19)	0.84	(0.53,1.33)	0.82	(0.60,1.12)	2.27	(1.59,3.24)
Income												
<20,000	1		1		1		1		1		1	
20-50,000	0.89	(0.81,0.99)	0.95	(0.79,1.14)	1.03	(0.91,1.17)	1.14	(0.87,1.49)	1.17	(0.90,1.53)	0.76	(0.57,1.00)

50-70,000	0.89	(0.75,1.05)	0.87	(0.64,1.19)	1.11	(0.89,1.38)	1.16	(0.68,1.99)	1.37	(0.93,2.02)	0.89	(0.60,1.30)
>70,000	0.86	(0.74,1.00)	1.03	(0.77,1.38)	1.24	(1.02,1.50)	1.07	(0.63,1.82)	0.95	(0.66,1.36)	1.15	(0.83,1.59)
Not disclosed	1.00	(0.90,1.12)	1.04	(0.86,1.27)	1.14	(0.99,1.31)	1.18	(0.89,1.56)	1.36	(1.02,1.80)	1.07	(0.81,1.41)
Admission type[c]												
Surgical	1		1		1		1		1		1	
Other	1.45	(1.23,1.72)	1.01	(0.72,1.42)	2.34	(1.91,2.87)	0.47	(0.16,1.37)	0.69	(0.41,1.14)	0.62	(0.36,1.09)
Medical	1.14	(1.03,1.27)	0.66	(0.55,0.80)	0.97	(0.84,1.11)	4.36	(3.02,6.29)	0.50	(0.38,0.65)	0.64	(0.50,0.84)
Emergency status[c]												
Emergency	1		1		1		1		1		1	
Planned	0.63	(0.56,0.71)	0.64	(0.52,0.77)	0.42	(0.36,0.49)	0.65	(0.48,0.88)	0.86	(0.65,1.13)	0.58	(0.44,0.78)
Other	0.96	(0.80,1.15)	0.98	(0.72,1.33)	1.02	(0.81,1.28)	1.19	(0.80,1.76)	1.03	(0.65,1.62)	0.80	(0.50,1.28)

[a] Odds ratio of a hospital record of a condition, among those that self-reported having a condition. Adjusted for age, sex, income, education, country of birth and functional limitation
[b] Confidence interval
[c] Model included both admission type and emergency status together with other listed patient characteristics

Supplementary Table 3. Adjusted ORs[a] for hospital-level variables from the multilevel logistic regression with random intercept for hospital of admission, all public and private hospitals in New South Wales, Australia (n=313)

Hospital characteristics	Hypertension (N = 15,279)		Diabetes (N = 4,794)		Heart disease (N = 8,307)		Stroke (N = 2,480)		Smoking (N = 2,099)		Obesity (N = 8,162)	
	OR[a]	(95%CI)[b]	OR[a]	(95%CI)[b]	OR[a]	(95%CI)[b]	OR[a]	(95%CI)[b]	OR[a]	(95%CI)[b]	OR[a]	(95%CI)[b]
Hospital type[c]												
Public	1		1		1		1		1		1	
Private	0.49	(0.38,0.63)	0.98	(0.78,1.23)	0.35	(0.26,0.47)	0.31	(0.22,0.43)	0.99	(0.72,1.35)	0.91	(0.64,1.31)
Hospital remoteness[c]												
Major city	1		1		1		1		1		1	
Inner regional	0.89	(0.64,1.23)	0.86	(0.67,1.11)	1.01	(0.70,1.47)	1.29	(0.91,1.83)	1.04	(0.75,1.45)	0.91	(0.60,1.38)
Outer regional	0.75	(0.55,1.02)	0.69	(0.52,0.91)	0.97	(0.67,1.41)	1.09	(0.72,1.67)	0.82	(0.57,1.18)	0.91	(0.58,1.44)
Remote/very remote	1.05	(0.57,1.94)	0.53	(0.28,1.00)	1.70	(0.81,3.59)	0.66	(0.22,1.98)	0.33	(0.15,0.71)	0.52	(0.16,1.68)
Hospital size[c]												
Principal referral	1		1		1		1		1		1	
Major	0.59	(0.34,1.01)	0.89	(0.62,1.27)	0.76	(0.44,1.34)	0.93	(0.58,1.47)	1.03	(0.66,1.61)	1.10	(0.59,2.05)
District	0.45	(0.27,0.76)	0.83	(0.58,1.19)	0.45	(0.26,0.78)	0.97	(0.60,1.55)	0.73	(0.47,1.15)	1.02	(0.55,1.91)
Community	0.41	(0.25,0.68)	0.61	(0.43,0.87)	0.35	(0.20,0.59)	0.57	(0.35,0.94)	0.89	(0.56,1.39)	0.88	(0.47,1.62)
Other	0.52	(0.30,0.89)	0.44	(0.29,0.68)	0.35	(0.19,0.65)	1.19	(0.66,2.14)	0.39	(0.22,0.68)	1.22	(0.59,2.53)
Depth of coding[c]												
1 - least comprehensive	0.17	(0.11,0.27)	0.26	(0.17,0.40)	0.09	(0.04,0.17)	0.38	(0.17,0.82)	0.22	(0.12,0.42)	0.28	(0.12,0.65)
2	0.29	(0.22,0.38)	0.66	(0.52,0.85)	0.41	(0.29,0.56)	0.31	(0.21,0.48)	0.74	(0.52,1.06)	0.59	(0.38,0.92)
3	0.58	(0.45,0.76)	0.85	(0.66,1.08)	0.75	(0.55,1.02)	0.66	(0.48,0.91)	0.89	(0.65,1.24)	0.65	(0.43,0.99)
4 - most comprehensive	1		1		1		1		1		1	

[a] Odds ratio of a hospital record of a condition, among those that self-reported having a condition. Adjusted for age, sex, income, education, country of birth and functional limitation

[b] Confidence interval

[c] Hospital-level covariates added one at a time, separately

STROBE 2007 (v4) Statement—Checklist of items that should be included in reports of *cross-sectional studies*

Section/Topic	Item #	Recommendation	Reported on page #
Title and abstract	1	(*a*) Indicate the study's design with a commonly used term in the title or the abstract	2
		(*b*) Provide in the abstract an informative and balanced summary of what was done and what was found	2
Introduction			
Background/rationale	2	Explain the scientific background and rationale for the investigation being reported	4-5
Objectives	3	State specific objectives, including any prespecified hypotheses	5
Methods			
Study design	4	Present key elements of study design early in the paper	6
Setting	5	Describe the setting, locations, and relevant dates, including periods of recruitment, exposure, follow-up, and data collection	6-7
Participants	6	(*a*) Give the eligibility criteria, and the sources and methods of selection of participants	6
Variables	7	Clearly define all outcomes, exposures, predictors, potential confounders, and effect modifiers. Give diagnostic criteria, if applicable	7-8
Data sources/ measurement	8*	For each variable of interest, give sources of data and details of methods of assessment (measurement). Describe comparability of assessment methods if there is more than one group	6-8
Bias	9	Describe any efforts to address potential sources of bias	9
Study size	10	Explain how the study size was arrived at	7, 10
Quantitative variables	11	Explain how quantitative variables were handled in the analyses. If applicable, describe which groupings were chosen and why	8
Statistical methods	12	(*a*) Describe all statistical methods, including those used to control for confounding	9-10
		(*b*) Describe any methods used to examine subgroups and interactions	9
		(*c*) Explain how missing data were addressed	8
		(*d*) If applicable, describe analytical methods taking account of sampling strategy	n/a
		(*e*) Describe any sensitivity analyses	9
Results			

Participants	13*	(a) Report numbers of individuals at each stage of study—eg numbers potentially eligible, examined for eligibility, confirmed eligible, included in the study, completing follow-up, and analysed	10
		(b) Give reasons for non-participation at each stage	n/a
		(c) Consider use of a flow diagram	n/a
Descriptive data	14*	(a) Give characteristics of study participants (eg demographic, clinical, social) and information on exposures and potential confounders	10-11, 25-26
		(b) Indicate number of participants with missing data for each variable of interest	25-26
Outcome data	15*	Report numbers of outcome events or summary measures	11, 27,28,29,31-34
Main results	16	(*a*) Give unadjusted estimates and, if applicable, confounder-adjusted estimates and their precision (eg, 95% confidence interval). Make clear which confounders were adjusted for and why they were included	10, 12-13, 32-34
		(*b*) Report category boundaries when continuous variables were categorized	30,32-34
		(*c*) If relevant, consider translating estimates of relative risk into absolute risk for a meaningful time period	n/a
Other analyses	17	Report other analyses done—eg analyses of subgroups and interactions, and sensitivity analyses	11-13,30
Discussion			
Key results	18	Summarise key results with reference to study objectives	14
Limitations	19	Discuss limitations of the study, taking into account sources of potential bias or imprecision. Discuss both direction and magnitude of any potential bias	18-19
Interpretation	20	Give a cautious overall interpretation of results considering objectives, limitations, multiplicity of analyses, results from similar studies, and other relevant evidence	15-19
Generalisability	21	Discuss the generalisability (external validity) of the study results	18-19
Other information			
Funding	22	Give the source of funding and the role of the funders for the present study and, if applicable, for the original study on which the present article is based	20

*Give information separately for cases and controls in case-control studies and, if applicable, for exposed and unexposed groups in cohort and cross-sectional studies.

Note: An Explanation and Elaboration article discusses each checklist item and gives methodological background and published examples of transparent reporting. The STROBE checklist is best used in conjunction with this article (freely available on the Web sites of PLoS Medicine at http://www.plosmedicine.org/, Annals of Internal Medicine at http://www.annals.org/, and Epidemiology at http://www.epidem.com/). Information on the STROBE Initiative is available at www.strobe-statement.org.