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Agreement between medical record and administrative coding of common comorbidities in orthopaedic trauma patients

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ABSTRACT

Objective: To i) quantify the agreement between comorbidities documented within medical records and an orthopaedic trauma dataset; and ii) compare agreement between these sources before and after the introduction of new comorbidity coding rules in Australian hospitals.
Study design and setting: A random sample of adult ($\geq$ 16 years) orthopaedic trauma patients (n = 400) were extracted from the Victorian Orthopaedic Trauma Outcomes Registry (VOTOR). Diagnoses of obesity, arthritis, diabetes and cardiac conditions documented within patients' medical records were compared to ICD-10-AM comorbidity codes (provided by hospitals) for the same admission. Agreement was calculated (Cohen's kappa) before and after the introduction of new coding rules.
Results: All comorbidities had the same or higher prevalence in medical record data compared to coded data. Kappa values ranged from <0.001 (poor agreement) for coronary artery disease to 0.94 (excellent agreement) for type 2 diabetes. There was improvement in agreement between sources for most conditions following the introduction of new coding rules.
Conclusion: There has been improvement in the coding of certain comorbidities since the introduction of new coding rules, suggesting that, since 2015, administrative data has improved capacity to capture patients' comorbidity profiles. Consideration must be taken when using the ICD-10-AM data due to its limitations.

Introduction

Understanding the extent of comorbid conditions in injury populations is important from a health service planning and policy perspective, and can influence health care expenditure [1]. Specifically, health outcomes and costs can be better estimated through performing risk adjustment analyses based on patients' comorbidity profiles [2]. Previous studies have used a variety of data sources to characterise comorbidities in injured populations [3]. Traditionally, the gold standard for capturing information about pre-existing comorbidities is through clinical interviews. However, in large epidemiological studies, this is not feasible nor time efficient [4]. An alternative is to review medical records, which provide extensive detailed clinical information, but this can be tedious, time-consuming and labour-intensive [5]. Therefore, administrative hospital datasets are more commonly used for large studies and in clinical registries. Previous studies have shown that coding of comorbidities within administrative datasets has varying levels of agreement with medical records [6,7].

In Australia, injury is a major cause of disease burden and is increasing as a cause of mortality and morbidity internationally [8,9]. Orthopaedic trauma ranks as the most common type of injury requiring hospitalisation [10,11]. For people with orthopaedic trauma, comorbidities can increase the risk of morbidity and mortality [12–14]. Obesity, osteoarthritis, diabetes and cardiac conditions have been shown to increase the complexity of patient care and prolong the recovery time for trauma patients [15,16]. In particular, the prevalence of obesity has risen significantly in the last 20 years and has been linked with an increased risk of injury overall, and higher mortality following a traumatic injury [16–18]. Furthermore, obesity is commonly associated with other comorbidities such as osteoarthritis, diabetes and cardiac conditions [18].

The introduction of new comorbidity coding rules to Australian hospitals in 2015 reflects increasing recognition of the need to accurately estimate comorbidity prevalence in hospitalised

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populations. However, there has been little evaluation of the effect of these coding changes on comorbidity data within administrative datasets. Therefore, the aims of this study were to: i) quantify the agreement between documentation of comorbidities (obesity, osteoarthritis, diabetes and cardiac conditions) within patients' medical records, and comorbidities coded within an administrative dataset (via the International Classification of Diseases, Tenth Revision, Australian Modification, ICD-10-AM) in a sample of orthopaedic trauma patients; and ii) compare agreement between these sources before and after the introduction of new comorbidity coding rules in Australian hospitals.

Patients and methods

Setting and participants

All patients registered by the Victorian Orthopaedic Trauma Outcomes Registry (VOTOR) with a date of injury from 1 July 2013 to 30 June 2017 and receiving their definitive care from a single major trauma centre in Melbourne, Australia, were eligible for inclusion. The VOTOR is a comprehensive and robust monitoring system for orthopaedic patients in Victoria. The VOTOR has been collecting data from hospitals since 2003 and captures approximately 5800 patients per year. The registry collects data about adult patients ($\geq$16 years) who have an orthopaedic injury (bone or soft tissue) with an emergency admission greater than 24 h at one of four hospitals: one regional trauma centre, one metropolitan trauma centre and two adult major trauma services [19]. Patients are excluded if they have an isolated soft tissue injury managed non-operatively or a pathological fracture [20]. The full methodology has been published previously [21]. Patients (or next of kin if deceased) can request to opt-out of the VOTOR and the opt-out rate is less than 1% [22]. The registry has approval from the Human Research Ethics Committees of the Department of Health and Human Services Human Research and each participating hospital. This study was approved by the Human Research Ethics Committees of the Alfred Hospital and Monash University.

ICD-10-AM coding

In Australian hospitals, patients' diagnoses relating to their admission are recorded and coded using the ICD-10-AM. Clinical coders are employed by the hospital and must undergo specific training and be accredited via specific courses. Previous admissions are not reviewed by coders, with only comorbidities from the current admission coded. The Australian Coding Standards (ACS) assist clinical coders to assign codes to patient diagnoses. Previously, the ACS required conditions to be coded as comorbidities only if they required an investigation, increased clinical care or monitoring, altered treatment or used resources during the admission [23]. On 1 July 2015, an update to the ACS coding was created, which aimed to address the under-coding of certain chronic conditions in administrative datasets. A supplementary 'U' coding system was generated to be used for conditions that are a part of the patient's current health status during an episode of admitted patient care, but where the condition has not met the criteria for coding [24].

Procedures

From a possible 10,351 cases eligible for inclusion, 400 were selected for the study using random sampling without replacement within Stata 13.0 (StataCorp, College Station, TX). An even number of patients (n = 200) were selected prior to the ACS changes (admission 01 July 2013 to 30 June 2015) and after (admission 01 July 2015 to 30 June 2017). Sample size calculations were based on an expected change in agreement on U-codes from $\kappa = 0.0$ (pre-ACS) to $\kappa = 0.2$ (post-ACS). At 80% power, 95% confidence and using a dichotomous rating scale (i.e. yes/no), a minimum of 194 participants were required [25]. Therefore, we included 200 cases with a date of admission pre-ACS and 200 post-ACS, for a total of 400 cases.

Following case selection, the following data were extracted from the VOTOR dataset: patient demographics (age, gender), date, type and cause of injury, and all ICD-10-AM diagnoses for the admission of interest, including comorbidities. The key comorbidities of interest were obesity, osteoarthritis, diabetes and cardiac disease (Box 1).

Medical record review

An electronic medical record (EMR) review was performed for each included patient to identify any record of the comorbidities listed in Box 1. For all patients, medical records examined were a combination of paper-based forms scanned into electronic form and EMR into one computer system. Medical records were obtained through the EMR program, permission for which was granted by the hospital for this study. No patient was replaced due to insufficient data such as missing paper-based records. Information regarding previous admissions was not examined. Data on comorbidities were collected systematically using a standardised data collection form piloted in a previous study [26]. The patient's

Box 1. The comorbidities examined with their corresponding ICD-10-AM codes.

Conditions		ICD-10-AM codes	Supplementary codes for chronic conditions
Obesity		E66	U78.1
Osteoarthritis		M15-M19, M47	U86.2
Diabetes	Type 1 diabetes	E10	None
	Type 2 diabetes	E11	None
Cardiac conditions	Congestive heart failure	I50	U82.2
	Ischaemic heart disease	I24 (except I24.1), I25.8, I25.9	U82.1
	Coronary artery disease	I25.1, I70	U82.1
	Hypertension	I10-I15	U82.3
	Angina	I20	None
	Arrhythmia	I47, I48, I49	None
	Myocardial infarction history	I21, I22, I24.1, I25.2, I46	None

progress notes, discharge summary, admission notes, ambulance report, clinician correspondence (letters, transfers, referrals), pharmacist notes and trauma and resuscitation records were examined. Overall, data were collected via entries from a variety of health professionals: doctors, nurses, paramedics, pharmacists, allied health professionals and social workers. The reviewer was blinded to the ICD-10-AM codes that had been assigned to the patient admissions to decrease any preconceived agreement between data sources and reduce potential bias. The reviewer was medically trained, was taught how to use the standardised data collection form, and had six months of experience using the hospital's EMR system before the study. No intra-rater reliability evaluation was undertaken.

Data analysis

Comorbidity data extracted from patients' medical records were compared to the ICD-10-AM codes provided to VOTOR. Calculations of the prevalence of comorbidities, percentage agreement, Cohen's Kappa, prevalence-adjusted bias-adjusted kappa (PABAK), and positive and negative percentage agreement were performed to compare data sources with regards to obesity, osteoarthritis, diabetes and cardiac conditions. These statistics were calculated for the whole sample and then compared pre- and post-ACS.

Kappa (κ) is a standardized value that represents chance-adjusted agreement, with 1 representing perfect agreement and zero indicating no agreement [27]. The PABAK reduces bias as it allows adjustment for high or low prevalence within conditions, taking into account a high or low proportion of responses in a single category [28]. A kappa coefficient of greater than 0.80 was considered excellent agreement, between 0.61 and 0.80 substantial agreement, between 0.41 and 0.60 moderate agreement, 0.20–0.40 fair agreement and <0.20 as poor agreement [29]. To calculate the 95% confidence interval for kappa and PABAK, 200 bootstrap replications were used.

Positive and negative percentage agreements (proportions of specific agreement) were calculated for each comorbidity. These statistics address potential inflation of agreement when the condition under study is rare. Positive percentage agreement estimates the proportion of positive agreement (i.e. presence of comorbidity in both sources) out of the average number of positive readings (i.e. average number of comorbidities from both sources), while negative percentage agreement estimates the proportion of negative agreement (i.e. no comorbidity in either source) out of the average number of negative readings (i.e. average number of patients with no comorbidities from both sources) [28]. All analyses were conducted using Stata 13.0

Results

Patient characteristics

Patients were evenly spread across age groups, except for a slight increase in older age groups, which is consistent with the wider VOTOR population. Moreover half (56.8%) of the sample were male and over a third were injured via a low fall (36.5%). The most prevalent injuries sustained were isolated lower extremity (29.8%), spinal (22.8%) and isolated upper extremity injury (15.8%). Most patients (68.8%) sustained only orthopaedic injuries (Table 1).

Prevalence pre-mandatory coding changes

Before mandatory coding changes were introduced prevalence of all conditions was higher in the medical record compared to ICD-10-AM data, except for type 2 diabetes (equal). There was a substantial difference in prevalence between the two data sources for obesity (9.5% to 0.5%), osteoarthritis (9.5% to 0%), ischaemic heart disease (8.0% to 0%) and hypertension (28.0%–2.5%). There was no osteoarthritis, type 1 diabetes, angina or ischaemic heart disease recorded pre-ACS when using ICD-10-AM data. (Table 2). Coronary artery disease was recorded via ICD-10-AM coding (0.0–2.8%) but was absent from medical records.

Table 1
Clinical and demographic characteristics of study sample.

Demographic characteristics n (%)		Total n = 400
Age (years)	16-24	45 (11.3)
	25-34	54 (13.5)
	35-44	45 (11.3)
	45-54	54 (13.5)
	55-64	42 (10.5)
	65-74	46 (11.5)
	75-84	56 (14.0)
	>85	58 (14.5)
Sex	Male	227 (56.8)
	Female	173 (43.4)
Mechanism of injury	Low fall	146 (36.5)
	Motor vehicle crash	68 (17.0)
	High fall	53 (13.3)
	Motorcycle/pedal cyclist crash	39 (9.8)
	Struck by object or person	15 (3.8)
	Pedestrian collision	13 (3.3)
	Other	33 (8.3)
Type of injury	Isolated lower extremity	119 (29.8)
	Spinal injuries only	91 (22.8)
	Isolated upper extremity	63 (15.8)
	Multiple lower extremity	28 (7.0)
	Upper and lower extremity	26 (6.5)
	Spine and lower extremity	19 (4.8)
	Multiple upper extremity	16 (4.0)
	Spine and upper extremity	16 (4.0)
	Soft tissue only	16 (4.0)
	Spine and upper and lower extremities	6 (1.5)
Associated non-orthopaedic injury*	None	275 (68.8)
	Yes	125 (31.2)

* Including head, chest, abdominal injuries and burns.

Prevalence post-mandatory coding changes

The prevalence of obesity, osteoarthritis and all cardiac conditions remained higher in the medical records compared to the ICD-10-AM coding data post-mandatory coding changes. Both type 1 and type 2 diabetes had the same prevalence when compared to the ICD-10-AM data. Only coronary artery disease showed an increase in prevalence in medical record data post-ACS. There were no other substantial differences in the prevalence of conditions in medical record data after the coding rule change. By comparison, ICD-10-AM data noted a substantial increase in prevalence after mandatory coding changes in osteoarthritis, type I diabetes, ischaemic heart disease and hypertension (Table 2).

Agreement between medical record and ICD-10-AM (Table 3)

Overall, there was poor agreement between medical record and ICD-10-AM data for obesity (kappa = 0.16) but excellent agreement when adjusting for prevalence and bias (PABAK = 0.83). Similarly, osteoarthritis coding rose from moderate (kappa = 0.42) to excellent agreement (PABAK = 0.82). There was excellent agreement between sources for diabetes as a condition and its subtypes with regards to both kappa and PABAK.

There was moderate agreement between sources for cardiac conditions and adjustment for prevalence and bias increased agreement to excellent for congestive heart failure, ischaemic heart disease, coronary artery disease and, angina. Agreement for

Table 2
Prevalence in medical records and ICD-10-AM coded data of pre-existing obesity, osteoarthritis, diabetes and cardiac conditions.

Condition	Pre-ACS (n = 200)		Post-ACS (n = 200)		Total (n = 400)	
	Medical record prevalence (%) (95% CI)	ICD-10-AM prevalence (%) (95% CI)	Medical record prevalence (%) (95% CI)	ICD-10-AM prevalence (%) (95% CI)	Medical record prevalence (%) (95% CI)	ICD-10-AM prevalence (%) (95% CI)
Obesity	9.5 (5.8, 14.4)	0.5 (0.0, 2.8)	9.0 (5.4, 13.9)	2.5 (0.8, 5.7)	9.3 (6.6, 12.5)	1.5 (0.6, 3.2)
Osteoarthritis	9.5 (5.8, 14.4)	0	15.5 (10.8, 21.3)	9.5 (5.4, 13.9)	12.5 (9.4, 16.1)	4.8 (2.9, 7.3)
Diabetes						
Type 1 diabetes	0.5 (0.0, 2.8)	0	1.5 (0.3, 4.3)	1.5 (0.3, 4.3)	1.0 (0.3, 2.5)	0.8 (0.2, 2.2)
Type 2 diabetes	11.0 (7.0, 16.2)	11.0 (7.0, 16.2)	9.0 (5.4, 13.9)	9.0 (5.4, 13.9)	10.0 (7.2, 13.4)	10.0 (7.2, 13.4)
Cardiac conditions						
Congestive heart failure	4.0 (1.7, 7.7)	0.5 (0.0, 2.8)	7.5 (4.3, 12.1)	5.0 (2.4, 9.0)	5.8 (3.7, 8.5)	2.8 (1.4, 4.9)
Ischaemic heart disease	8.0 (4.6, 12.7)	0	11.5 (7.4, 16.8)	10.5 (6.6, 15.6)	9.8 (7.0, 13.1)	5.3 (3.3, 7.9)
Coronary artery disease	0	0.5 (0.0, 2.8)	1.0 (0.1, 3.6)	0	0.5 (0.0, 1.8)	0.3 (0.0, 1.4)
Hypertension	28.0 (22.0, 34.8)	2.5 (0.8, 5.7)	35.0 (28.4, 42.0)	30.0 (23.7, 36.9)	31.5 (27.0, 36.3)	16.3 (12.8, 20.2)
Angina	3.5 (1.4, 7.1)	0	4.5 (2.1, 8.4)	0.5 (0.0, 2.8)	4.0 (2.3, 6.4)	0.3 (0.0, 1.4)
Arrhythmia	11.5 (7.4, 16.8)	6.0 (0.3, 10.2)	17.0 (12.1, 23.0)	9.5 (5.4, 13.9)	14.3 (11.0, 18.1)	7.8 (5.3, 10.8)
Myocardial infarction history	6.5 (3.5, 10.9)	2.0 (0.5, 5.0)	7.0 (3.9, 11.5)	2.0 (0.5, 5.0)	6.8 (4.5, 9.7)	2.0 (0.9, 3.9)

ICD-10-AM, International Classification of Diseases, Tenth Revision, Australian Modification; ACS, Australian Coding Standards.

hypertension and arrhythmia rose as well but only to substantial agreement.

All comorbidities had a very good negative agreement of above 85%, indicating excellent agreement when there was no comorbidity diagnosis from either source. Diabetes subtypes were the only comorbidities that had very good positive agreement (above 80%). The other positive agreements ranged from 0% for coronary artery disease to 63% for hypertension. This indicates poor to moderate agreement when the comorbidity is present in the medical records but not coded in ICD-10-AM data.

Kappa and PABAK pre and post coding changes (Table 4)

There were substantial increases in kappa values following the ACS rule change except for Type 2 diabetes and arrhythmias. The introduction of mandatory coding made a difference for patients with hypertension, ischaemic heart disease and congestive heart failure, with poor/fair agreement before mandatory coding rising to substantial agreement.

After adjusting for bias and prevalence, the PABAK demonstrated excellent agreement for most comorbidities: obesity, osteoarthritis, diabetes (any subtypes), congestive heart failure, coronary artery disease, angina, arrhythmia and myocardial infarction. There was no difference between pre- and post-ACS.

Discussion

In this study of randomly sampled orthopaedic trauma registry patients, we have shown that the introduction of supplementary 'U codes' improved the capture of ICD-10-AM hospital-coded comorbidity data at a large major trauma centre in Victoria, suggesting better capacity of administrative datasets to evaluate comorbidity in trauma populations in Australian hospitals. Consistent with previous studies, we also found that the prevalence of comorbid conditions obtained from administrative data was lower than that obtained from medical records [30–32].

As this is the first study to our knowledge to compare obesity, osteoarthritis or cardiac comorbidities in hospital administrative data with medical record documentation in trauma patients, it is difficult to make direct comparisons with previous research. In other populations, obesity, diabetes, arrhythmia, angina and cardiac failure have been demonstrated to be underestimated in electronic health records [33,34]. Only one study identified substantial agreement ($\kappa = 0.69$) between coding and medical

Table 3
Agreement between medical record and ICD-10-AM coded data for presence of obesity, osteoarthritis, diabetes and cardiac conditions, all patients (n = 400).

Comorbidity	Agreement (%)	κ coefficient (95% CI)	PABAK (95% CI)	Negative agreement[1] (%)	Positive agreement[2](%)
Obesity	91.3	0.16 (0.04, 0.31)	0.83 (0.77, 0.87)	95.4	18.6
Osteoarthritis	90.8	0.42 (0.27, 0.57)	0.82 (0.76, 0.87)	94.9	46.4
Diabetes					
Type 1 diabetes	99.8	0.86 (0.50, 1.0)	1.00 (0.98, 1.01)	99.9	85.7
Type 2 diabetes	99.0	0.94 (0.88, 0.99)	0.98 (0.96, 1.00)	99.4	95.0
Cardiac conditions					
Congestive heart failure	96.5	0.57 (0.39, 0.75)	0.93 (0.89, 0.97)	98.2	58.8
Ischaemic heart disease	94.5	0.61 (0.44, 0.75)	0.89 (0.84, 0.94)	97.0	63.3
Coronary artery disease	99.3	0.00 (-0.01, 0.00)	0.99 (0.97, 1.00)	99.6	0.0
Hypertension	82.3	0.53 (0.44, 0.62)	0.65 (0.57, 0.72)	88.3	62.8
Angina	96.3	0.11 (0.00, 0.37)	0.93 (0.89, 0.96)	98.1	11.2
Arrhythmia	87.5	0.37 (0.25, 0.49)	0.75 (0.68, 0.82)	93.0	43.2
Myocardial infarction history	94.3	0.32 (0.13, 0. 51)	0.89 (0.84, 0.93)	97.0	34.3

PABAK: Prevalence-adjusted bias-adjusted kappa.
[1] Negative agreement: proportion of agreement when there is no comorbidity diagnosis from either source.
[2] Positive agreement: proportion of agreement when there is a comorbidity diagnosis from both source.

Table 4
Prevalence and agreement between medical record and ICD-10-AM coded data for presence of obesity, osteoarthritis, diabetes and cardiac conditions, before and after coding changes.

	Pre-ACS (n = 200)				Post-ACS (n = 200)			
	ICD-10-AM Prevalence (%) (95% CI)	Agreement (%)	κ coefficient (95% CI)	PABAK (95% CI)	ICD-10-AM Prevalence (%) (95% CI)	Agreement (%)	κ coefficient (95% CI)	PABAK (95% CI)
Obesity	0.5 (0.0, 2.8)	91.0	0.09 (0.00, 0.30)	0.83 (0.74, 0.91)	2.5 (0.8, 5.7)	91.5	0.23 (0.00, 0.48)	0.83 (0.75, 0.90)
Osteoarthritis	0	90.5	0.00	0.82 (0.74, 0.89)	9.5 (5.4, 13.9)	91.0	0.59 (0.39, 0.74)	0.82 (0.74, 0.89)
Diabetes								
Type 1 diabetes	0	99.5	0.00	1.00 (0.97, 1.02)	1.5 (0.3, 4.3)	100	1.0	1.00
Type 2 diabetes	11.0 (7.0,16.2)	98.0	0.90 (0.78, 0.98)	0.98 (0.94, 1.02)	9.0 (5.4, 13.9)	100	1.0	0.98
Cardiac conditions								
Congestive heart failure	0.5 (0.0, 2.8)	96.5	0.22 (0.00, 0.59)	0.93 (0.88, 0. 98)	5.0 (2.4, 9.0)	96.5	0.70 (0.45, 0.86)	0.93 (0.88, 0.98)
Ischaemic heart disease	0	92.0	0.00	0.89 (0.81, 0.97)	10.5 (6.6, 15.6)	97.0	0.85 (0.70, 0.94)	0.89 (0.84, 0.94)
Coronary artery disease	0.5 (0.0, 2.8)	99.5	0.00	0.99 (0.97, 1.00)	0	99.0	0.0	0.99 (0.96, 1.01)
Hypertension	2.5 (0.8, 5.7)	73.5	0.09 (0.00, 0.20)	0.65 (0.52, 0.77)	30.0 (23.7, 36.9)	91.0	0.80 (0.72, 0.87)	0.65 (0.56, 0.73)
Angina	0	96.5	0.00	0.93 (0.87, 0.98)	0.5 (0.0, 2.8)	96.0	0.19 (0.00, 0.59)	0.93 (0.87, 0.98)
Arrhythmia	6.0 (0.3, 10.2)	90.5	0.41 (0.17, 0.61)	0.75 (0.67, 0.83)	9.5 (5.4, 13.9)	84.5	0.33 (0.11, 0.49)	0.75 (0.65, 0.85)
Myocardial infarction history	2.0 (0.5, 5.0)	94.5	0.33 (0.09, 0.61)	0.89 (0.82, 0.95)	2.0 (0.5, 5.0)	94.0	0.31 (0.00, 0.61)	0.89 (0.82, 0.95)

PABAK: Prevalence-adjusted bias-adjusted kappa.

records in patients with cardiac failure [33], while another demonstrated moderate agreement between medical records and administrative coding for mental health, drug and alcohol comorbidities in trauma patients [26]. The variation amongst studies may reflect administrative data inconsistencies or variations in study methods, such as differences in sample sizes, settings, data collection methods (including researcher bias) and sample populations (e.g. mental health versus trauma).

This study demonstrated improvement in comorbidity data subsequent to new coding rules for most conditions; obesity, osteoarthritis, congestive heart failure, ischaemic heart disease, coronary artery disease and hypertension. For Type 2 diabetes, excellent agreement between administrative data and medical records was demonstrated both before and after ACS changes due to this condition having always been mandatory to code when documented in the medical record [24]. In general though, the introduction of the 'U' coding system to an Australian hospital improved the agreement between medical records and coding data. In a previous study, Nguyen et al. [26] (2018), observed no change in agreement pre- and post-ACS changes for mental health, drug and alcohol conditions. However, the post-ACS group consisted of 100 patients with a time frame of six months (until 31 December 2015), which may have lacked the statistical power to detect any changes in the comparison.

Certain limitations of the current study should be noted. This study used an audit of clinician documentation as the gold standard. However, it is worth noting that such documentation does not necessarily reflect the true prevalence of comorbid conditions within a population. In our study, the prevalence of comorbidities documented in the medical record was higher compared to the Australian population for certain conditions: osteoarthritis (12.5% vs 9%); type 2 diabetes (10% vs 4.5%); congestive heart failure (5.8% vs 1–2%); ischaemic heart disease (9.8% vs 5%); angina (4% vs 2.5%); and myocardial infarction history (6.8% vs 3.5%) [35,36]. The prevalence of Type 1 diabetes was the same as the Australian population (1%) [36], while marginal differences were observed for coronary artery disease (0.5% vs 1.5%) and hypertension (31.5% vs 34%) [37]. Obesity (9.3%) was considerably less prevalent within our sample compared to the Australian population (28%) [16]. These differences may reflect true differences between trauma and general populations; trauma patients have been identified to have higher preinjury physical health status compared to the general population [38]. However, it is more likely that certain conditions are not documented by clinicians in the first instance. For example, prior studies have demonstrated that obesity is significantly under-reported in medical data [39–41]. Further to this, handwritten patient medical records were sometimes difficult to read due to illegibility or poor scan quality, while electronic medical records are dependent on the clinician's skill with the technology and the system functioning at the time of input. Although the methodology for the examination of medical records was rigorous, no level of rigor can uncover what has not been clearly documented. Medical coding may potentially be improved by more legible, detailed and precise medical documentation, higher staffing levels, fewer time constraints, increased interaction between coders and clinical staff, more comprehensive data systems, and educating and reminding coders to examine both risk factors and clinical conditions [42–45]. While no intra-rater reliability evaluation was undertaken to determine the consistency of medical record reviews, data were collected using a previously piloted, standardised data collection form and the reviewer was medically trained.

The sample size of the study was relatively small which meant that particular comorbidities had a low prevalence rate, such as obesity. A larger sample may have retrieved more of the rare conditions. However, with an exploratory study such as this, an increased sample size is only likely to increase the precision of the agreement estimates. Finally, this study was conducted at a single site and therefore the findings may not be generalisable to all other Australian settings. However, the trauma centre chosen for this study is the largest and most active trauma service in Australasia, and therefore provides an adequate representation of an orthopaedic trauma population.

The implications of under-coding can lead to hospitals being under-funded due to reduced total reimbursements and can undermine hospital care [42,46]. Under-reported medical data can also lead to inaccurate epidemiological conclusions on the health status of the population and ultimately lead to misdirection of government funding. The findings of this study suggest that the introduction of coding changes has resulted in better characterisation of the comorbidities of trauma patients. Creating more codes for other **co-**morbidities could potentially lead to even more comprehensive comorbidity data within administrative datasets. However, it is important for researchers, and others using administrative coding of comorbidities, to note that a prevalence rise may be due to improvement in data collection rather than an increase in population prevalence. Future research should continue to evaluate the impact of the new ACS coding changes. Studies should also try to identify causes of under-representation for obesity in medical records given the importance of obesity as a risk factor for many conditions and comorbidities. It is unclear if obesity is not being addressed or not documented. However, if a patient's weight is not addressed in hospital, it can lead to a lost opportunity for diagnosis, education and management of the patient's weight [47].

Conclusion

This study demonstrated that despite documentation in medical records, many comorbidities of interest were not coded within an administrative dataset. There was improvement in the coding of certain comorbidities since the introduction of new coding rules, suggesting that, since 2015, administrative data has improved capacity to capture the patient's comorbidity profile. The usage of hospital coding data must be used with caution due to its limitations.

Conflict of interest statement

The authors of this manuscript certify that they have NO affiliations with or involvement in any organisation or entity with any financial interest (such as honoraria; educational grants; participation in speakers' bureaus; membership, employment, consultancies, stock ownership, or other equity interest; and expert testimony or patent-licensing arrangements), or non-financial interest (such as personal or professional relationships, affiliations, knowledge or beliefs) in the subject matter or materials discussed in this manuscript.

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