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Limitations Of Administrative Databases In Orthopaedic Surgery Research: A Study In Obesity And Anemia

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LIMITATIONS OF ADMINISTRATIVE DATABASES IN ORTHOPAEDIC SURGERY RESEARCH: A STUDY IN OBESITY AND ANEMIA.

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Abstract

The use of national inpatient databases for orthopaedic surgery research has been increasing. However, large databases that rely on administrative data, such as International Classification of Diseases Ninth Revision (ICD-9) codes, may misrepresent patient information, thus affecting the results of studies using this data.

The present study uses easily quantified and objective variables of obesity and anemia as example comorbidities to assess the accuracy of ICD-9 codes in the setting of their continued use in orthopaedic surgery database studies.

For each study arm, a large inpatient population was obtained from the Yale-New Haven hospital. Each patient's medical record was reviewed, and the presence of ICD-9 discharge codes for obesity and anemia was directly compared to documented body mass index (BMI) and preoperative hematocrit, respectively.

ICD-9 discharge codes for both non-morbid obesity and anemia had a sensitivity of just 0.19. The sensitivity of the ICD-9 code for morbid obesity was 0.48.

Using obesity and anemia as examples, this study highlights the potential errors inherent to ICD-9 codes. This calls into serious question the utility of administrative databases for research purposes. Moreover, it is likely that these inaccuracies apply to additional variables as well. As database research continues to increase within orthopaedic surgery, it is important to realize that study outcomes can be skewed by data accuracy, and thus should not be blindly accepted simply by virtue of large sample sizes.

Acknowledgments

I have many people to thank and acknowledge. First and foremost is Dr. Grauer, who over the past two years has given me nothing but the most selfless guidance and mentorship. I would not be where I am today without him. I would also like to thank my co-authors, who have worked tirelessly with me over the past two years on a multitude of projects. I am thrilled and honored that we will all soon be colleagues in the field of orthopaedic surgery. I would also like to thank Donna Carranzo, Mae Geter, and Dr. John Forrest in the Office of Student Research, as well as the staff and faculty of the Yale Orthopaedics and Rehabilitation Department and the Yale School of Medicine who have laid the foundation for me to succeed and to reach this point in my medical education. Finally, though certainly not least, I owe everything to my eternally supportive family, and my loving fiancée Molly.

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Introduction

Recently, the use of large national inpatient databases for orthopaedic surgery research has increased significantly. While databases differ in their methods of data collection and verification, many such databases are constructed upon hospital reimbursement claims data such as the International Classification of Diseases, Ninth Revision (ICD-9) codes. Unfortunately, due to the wide variety of styles, without a working knowledge of each major database, it can be difficult for the practicing physician to discern whether a given study presents valid results to the specific questions being asked.

Many ICD-9-coded databases are currently available, including the Nationwide Inpatient Sample (NIS), the Nationwide Emergency Department Sample (NEDS), the National Hospital Discharge Survey (NHDS), and several additional private insurance databases available through for-profit distributors. Several have reached tremendous size. The NIS reports that each year of data consists of approximately 8 million hospital stays from over 1,000 hospitals.[1] Similarly, the NEDS contains approximately 130 million total emergency department visits.[2]

Other databases, including the National Surgical Quality Improvement Program database maintained by the American College of Surgeons (ACS-NSQIP), are instead built from direct chart data acquisition rather than from administrative ICD-9 coding; however, this method is currently used less often for assembling national databases due to increased costs and logistical barriers. In such patient data registry databases, patient information is abstracted in real time by trained clinical staff from the patient chart directly into the database. In the case of the ACS-NSQIP database, this process is

carefully regulated and continually monitored with an Inter-Rater Reliability (IRR) Audit of randomly selected sites. These IRR Audits exist to ensure high quality data that consistently exhibits an inter-rater disagreement of less than 2%, with an absolute upper limit of 5% disagreement.[3]

The relatively recent widespread availability of databases has generated a new avenue by which to address a multitude of research questions in medicine, and more specifically, in orthopaedic surgery. The large sample sizes dwarf what could otherwise be obtained by any single hospital system or study group, creating an attractive resource for estimating disease prevalence, healthcare utilization, and outcomes from across the nation. Additionally, these tremendous sample sizes permit, for the first time, a method by which to evaluate rare conditions, uncommon treatments, and subset populations at a large scale.[1]

However, it is important to understand the many established limitations to using patient databases in medical research. First, the majority of these databases are assembled solely from inpatient data. This method samples an inherently sicker proportion of the population, which puts substantial limits on the applicability of any findings to the general population. Moreover, and crucial to the understanding of administrative database limitations, is the fact that ICD-9 data is generally abstracted from medical provider notes for reimbursement purposes. Because this relies on both the input of the provider and the careful extraction of data by the coding professional, this system is prone to omission of details and thus may not accurately represent the entire patient.[4,5] Furthermore, it has been demonstrated previously that significant heterogeneity can exist among large databases due to variations in unknown patient variables. A recent meta-analysis found

that because of this heterogeneity, 20-40% of all observational database studies could swing from being statistically significant in one direction to being statistically significant in the opposite direction, purely based on choice of database.[6] This finding highlights the particular importance of carefully choosing a database most suitable for the research question at hand.

To follow up on these past results, our research group conducted two studies comparing the NIS, an administratively-coded database, with the ACS-NSQIP, a patient registry database. In the first study, we extracted an analogous group of lumbar fusion patients during the years 2009-2011 from each of the two databases.[7] We then proceeded to compare the demographics, length of stay, comorbidities, and inpatient adverse events between these two groups. The purpose was to get a sense of the overall relationship between ICD-9 codes and clinical reality.

With regards to patient demographics and length of stay, we found that these factors were quite similar between the two databases.[7] However, with regards to adverse events, we found that the rates of sepsis and cardiac arrest in lumbar fusion patients were more than two-fold higher in the ACS-NSQIP compared to the NIS, while conversely, the rates of acute kidney injury (AKI) and urinary tract infection (UTI) were more than two-fold higher in the NIS compared to the ACS-NSQIP. Furthermore, in terms of the comorbidity variables examined, obesity was more than twice as common in NSQIP patients than it was in NIS patients, with the reverse holding true for the incidence of peripheral vascular disease.

This study was then performed again, only this time comparing two analogous populations of patients undergoing operative stabilization of transcervical and

intertrochanteric hip fractures from the NSQIP and NIS databases.[8] We again found that demographics and length of stay were similar between groups. Additional findings continued to be strikingly similar to our previous study in lumbar fusion patients, as the incidences of AKI and UTI were again two-fold higher in NIS compared to NSQIP. Similarly, the rate of obesity was more than two-fold higher in NSQIP compared to NIS, only this time obesity was accompanied by anemia and coagulopathy in this finding.

By comparing one national database constructed purely on ICD-9 codes to a different national database built from direct chart data, these studies shed important light on the overall landscape of ICD-9 coding accuracy. While the populations were found to be nearly demographically identical, it is worrisome to note how divergent many of the rates of inpatient adverse events and comorbidities were between groups. From this advantageous vantage point generated by these initial studies, we endeavor to direct our focus to a more granular examination of the specifics of ICD-9 coding and its potential flaws.

Several previous studies have noted the inaccuracies of ICD-9 discharge codes in various different medical and surgical populations.[9-19] One such study sought to evaluate the ability of ICD-9 codes to identify cardiovascular and stroke risk factors in Medicare patients with atrial fibrillation, such as arterial peripheral embolus, heart failure, stroke/TIA, coronary heart disease, diabetes, and hypertension.[14] Of the nine conditions evaluated, no condition had a sensitivity of greater than 76%, with the lowest sensitivity at 20%, and a mean sensitivity of 54%. A similar study evaluated ICD-9 codes related to stroke and stroke risk factors, finding sensitivities ranging from 7% for tobacco use, to 28% for history of cerebrovascular accident, to 91% for diabetes.[16] Finally, a third

previous study looked at the ability of ICD-9 codes to accurately identify thirty-two different conditions. These results varied from a sensitivity of just 1% for postural hypotension, to 27.6% for peptic ulcers, to 68.7% for hypertension.[19] While these prior investigations cover a wide breadth of subject matter, a common thread among these studies is the tremendous variability in ICD-9 coding accuracies, as well as the unpredictable nature of which conditions will be well coded versus those that will be poorly coded.

More specifically, some previous studies have examined the relationship between ICD-9 codes and obesity. A 2012 study in obstetric patients compared multiple ICD-9 codes to patient chart data and found widely variable coding accuracies among comorbidities such as hemorrhage, infection, and obesity.[20] For obesity, ICD-9 codes correctly identified just 15% of obese patients. Similarly, three studies have examined the difficulties of diagnosing obesity in a pediatric population that include, but are not limited to, body mass index (BMI) cutoffs that change both with age and gender.[21-23] These studies found ICD-9 codes for pediatric obesity to be only 7.0-8.3% accurate.

While these prior works provide much thought-provoking groundwork about the potentially poor sensitivity of various ICD-9 codes, the current study endeavors to build upon this foundation and further delineate how ICD-9 codes reflect clinical reality for a given diagnosis in orthopaedic surgery patients. Prior investigations were conducted in specialized patient populations that may have their own inherent considerations not readily generalizable to adult orthopaedic surgery populations. Moreover, ICD-9 coding issues were largely examined either as secondary outcomes or as one of many other questions being addressed.

With previous investigations as a valuable foundation, there remains a clear need to directly analyze how ICD-9 codes relate to clinical reality. The current study uses the variables of obesity and anemia to present individual illustrative examples that we anticipate will be widely applicable to many further comorbidities and patient factors that are commonly documented in national administrative inpatient databases. Obesity and anemia were chosen because they are easily quantifiable, continuous variables with well-established BMI and hematocrit designations, respectively. Moreover, each of these variables was recently found to be undercoded in the ICD-9-coded NIS database compared to the specifically abstracted patient registry ACS-NSQIP database.[7,8] Finally, obesity and anemia are used ubiquitously in large orthopaedic surgery database research, both as comorbidities in multivariable analyses and predictors of clinical outcomes.[24-27]

The current study consists of two separate, but related, arms. In each case, we employed a large inpatient population to explore the accuracy of ICD-9 coding. This was done by comparing the chart documentation of a specific patient entity to whether or not that variable was captured via the ICD-9 codes assigned to the patient upon discharge. For obesity, the specific patient entity used in this study was BMI, while for anemia the specific patient entity was preoperative hematocrit. These are the very codes that are used to construct large national administrative databases, such as the NIS and NEDS. We hypothesize that ICD-9 codes underestimate true rates of obesity and anemia, potentially to such a degree that they may sway the results of studies using ICD-9 coded databases for research purposes.

Methods

In each arm of this investigation, we conducted a cross-sectional study comparing each patient's ICD-9 discharge codes to chart-documented patient variables. This variable was obesity (based on BMI) in the first arm and anemia (based on hematocrit) in the second arm. All chart data acquisition and analysis was performed by myself.

Obesity

For the portion of this work that focused on obesity, we obtained a sixteen-day inpatient cohort from the Yale-New Haven Hospital. This included all patients over 18 years of age who spent at least one night in the hospital between April 1 and April 16, 2013. Patients from Obstetrics & Gynecology, Psychiatry, and Pediatrics were excluded, as it was reasoned that these patients can be subject to irregular or inaccurate weights, whether due to physiology or pharmaceuticals.

Following approval from the Yale University Human Investigations Committee, patient data was collected from the electronic medical record. Beyond demographic data, the patients' discharge height (inches) and weight (pounds) were collected, along with all assigned primary and secondary ICD-9 diagnosis codes. For patients without a recorded discharge height and weight, the values recorded closest to discharge were used.

BMI was calculated using the formula BMI = 703 x (weight (lb) / [height (in)*height (in)]).[28] Standard BMI classifications were used, with a BMI of less than 30 kg/m^2 as non-obese, a BMI of 30-39.9 kg/m^2 as obese, and a BMI of 40 kg/m^2 and above as morbidly obese.[29] For ease of terminology, the rest of the paper refers to a BMI of 30-

39.9 kg/m^2 as "non-morbid obesity" and a BMI at or above 40 kg/m^2 as "morbid obesity."

ICD-9 codes were then evaluated, with the code of 278.00 designated for "Obesity, unspecified" and the code of 278.01 for "Morbid obesity."[30] The presence of ICD-9 code 278.00 was compared to patients with a calculated BMI between 30 and 39.9, while 278.01 was compared to patients with a BMI that was greater than 40. These comparisons are consistent with prior studies utilizing ICD-9-based databases. On occasion, comorbidities such as obesity are captured using secondary ICD-9 codes. The secondary ICD-9 codes of V85.3 (BMI 30-39.9) and V85.4 (BMI 40 and above) exist to attempt to capture a patient's specific BMI, rather than a BMI range. These secondary codes were included in a separate analysis.

Anemia

In the portion of this research investigating anemia, we used a large population of patients who had undergone cervical or lumbar fusion surgery. This population was chosen because these patients are universally required to obtain a preoperative hemoglobin and hematocrit level due to the risk of blood loss associated with spine surgery. This population was retrospectively collected from Yale-New Haven Hospital and included all patients who underwent either cervical or lumbar fusion between February 1, 2013 and December 31, 2013. Patients either without a documented preoperative complete blood count (CBC) or who underwent fusion as a result of trauma were excluded.

This anemia arm of the study was also approved by the Yale University Human Investigations Committee. Patient data was abstracted from the electronic medical record and included demographics, preoperative hematocrit, and all assigned primary and secondary ICD-9 diagnosis codes. Standard classifications of anemia were used to determine the prevalence of preoperative anemia in the current study population: anemia in a female was defined as a hematocrit of less than 36.0%, and anemia in a male was defined as a hematocrit of less than 41.0%.[31]

ICD-9 codes were then evaluated based on the batch of ICD-9 codes that are grouped together to be used for the NIS database definition of the comorbidity "deficiency anemia." These codes, determined by the NIS, are as follows: 280.1 (Iron Deficiency Anemia Secondary to Inadequate Dietary Iron Intake), 280.8 (Other Specified Iron Deficiency Anemias), 280.9 (Iron Deficiency Anemia Unspecified), 281.0 (Pernicious Anemia), 281.1 (Other Vitamin B12 Deficiency Anemia), 281.2 (Folate-Deficiency Anemia), 281.3 (Other Specified Megaloblastic Anemias Not Elsewhere Classified), 281.4 (Protein-Deficiency Anemia), 281.8 (Anemia Associated with Other Specified Nutritional Deficiency, 281.8 (Anemia Associated with Other Specified Nutritional Deficiency), 281.9 (Unspecified Deficiency Anemia), 285.21 (Anemia in Chronic Kidney Disease), 285.22 (Anemia in Neoplastic Disease), 285.29 (Anemia of Other Chronic Disease), and 285.9 (Anemia Unspecified).[32,33]

Because this NIS variable is designed to capture anemia as a comorbidity upon entry to the hospital, this designation excludes patients who experienced any sort of acute blood loss as a result of their surgery or hospital stay. For similar reasons, we compared the presence of these codes to a given patient's preoperative hematocrit, rather than a

hematocrit taken during the hospital stay, so as to most closely approximate the anemia status of the patient upon entry to the hospital. This is consistent with the manner in which current studies investigating the relationship between spinal pathologies and anemia in the NIS use the "deficiency anemia" variable.[34-42]

Statistical Methods

Data analyses and organization were performed by the study authors using Stata® version 13.0 (StataCorp, LP, College Station, Texas, USA).

Results

Obesity

During the sixteen-day study period, there were 2,115 adult patients identified who spent at least one inpatient night in the hospital. 40 (1.9%) were excluded for missing either a height or weight in the medical record, leaving 2,075 patients for analysis.

Patient demographics can be found in Table 1. The average patient age was 59.6 ± 18.5 years (mean ± standard deviation [SD]) and 50.2% of patients in this cohort were female.

Table 1: Demographics of the patient population for the obesity arm of the present study

	Number	Percent
Overall	2,075	100%
Sex		
Female	1,043	50.3%
Male	1,032	49.7%
Age		
18-39	297	14.3%
40-49	295	14.2%
50-59	415	20.0%
60-69	407	19.6%
70-79	340	16.4%
80+	321	15.5%
Body Mass Index		
10-19.9 [Not Obese]	169	8.1%
20-29.9 [Not Obese]	1,159	55.9%
30-39.9 [Non-Morbid Obesity]	573	27.6%
40-49.9 [Morbid Obesity]	130	6.3%
50-59.9 [Morbid Obesity]	29	1.4%
60-69.9 [Morbid Obesity]	11	0.5%
70-80.0 [Morbid Obesity]	4	0.2%

The calculated BMI distribution is shown by BMI decile in Table 1 and by total column height in Figure 1a. The average calculated BMI was 28.9 ± 7.9 kg/m^2. Overall, 1,328 patients (64.0%) had a BMI less than 30 (non-obese), 573 patients (27.6%) had a BMI between 30 and 39.9 (non-morbid obesity), and 174 patients (8.4%) had a BMI of 40 or above (morbid obesity). When non-morbid and morbid obesity patients were combined, a total of 747 (36.0%) were categorized as being obese in some fashion (BMI $\geq$ 30).

Patients were then subdivided based on ICD-9 coding data. They are shown matched to chart-documented BMI calculations as sections of columns for each BMI decile in Figure 1a and subsequently by percent of patients for a given BMI decile in Figure 1b.

From 156 patients who received the “obesity” ICD-9 code of 278.00, 109 had a true BMI between 30 and 39.9, while 47 had miscoded BMIs outside of this range (Figure 1). 15 miscoded patients had a BMI below 30, and 32 had a BMI above 40. Thus, only 109 of the 573 patients (19.0%) with BMIs between 30 and 39.9 received the correct “obesity” designation by ICD-9 code (Figure 2). This equates to an ICD-9 code sensitivity of 0.19, with specificity and positive and negative predictive values of 0.97, 0.70, and 0.76, respectively (Figure 3). Only 14 patients were assigned the more specific ICD-9 code V85.3 without code 278.00. When V85.3 was included with 278.00, sensitivity, specificity, and positive and negative predictive values were 0.21, 0.97, 0.72, and 0.76, respectively.

Figure 1a

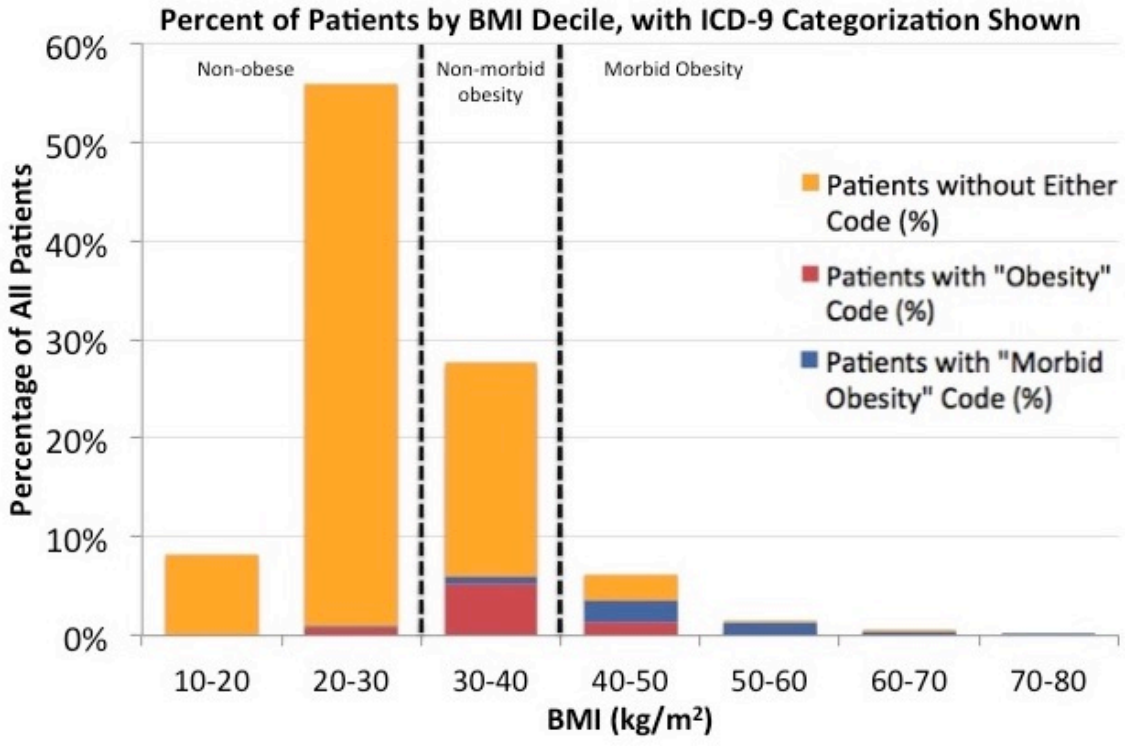

Figure 1b

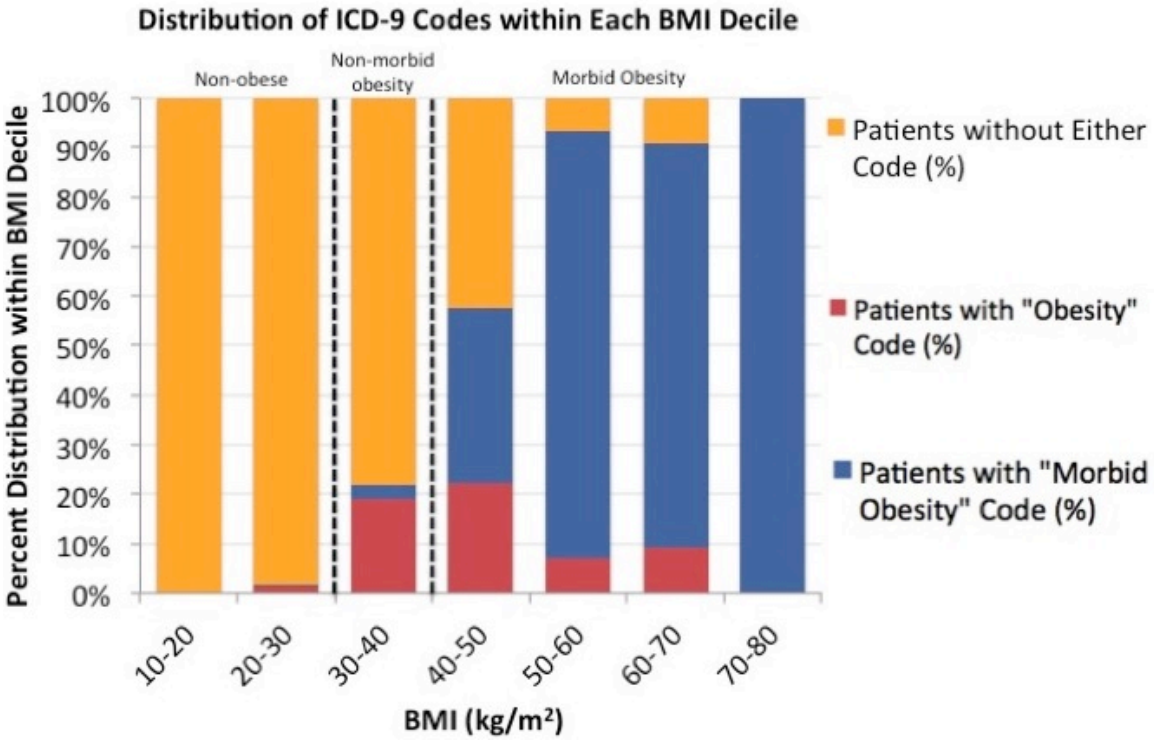

Figure 1: Bar graph depicting patients by BMI decile, based on calculated BMI. These bars are broken down to indicate the coding associated with the patients in each bar (no obesity ICD-9 code, "obesity" ICD-9 code (278.00), or "morbid obesity" ICD-9 code (278.01)). Figure 1a uses percent of the population studied as the y axis. Figure 1b uses percent of patients for a given BMI decile as the y axis (to allow better visualization of the components of the smaller bars in figure 1a).

Figure 2

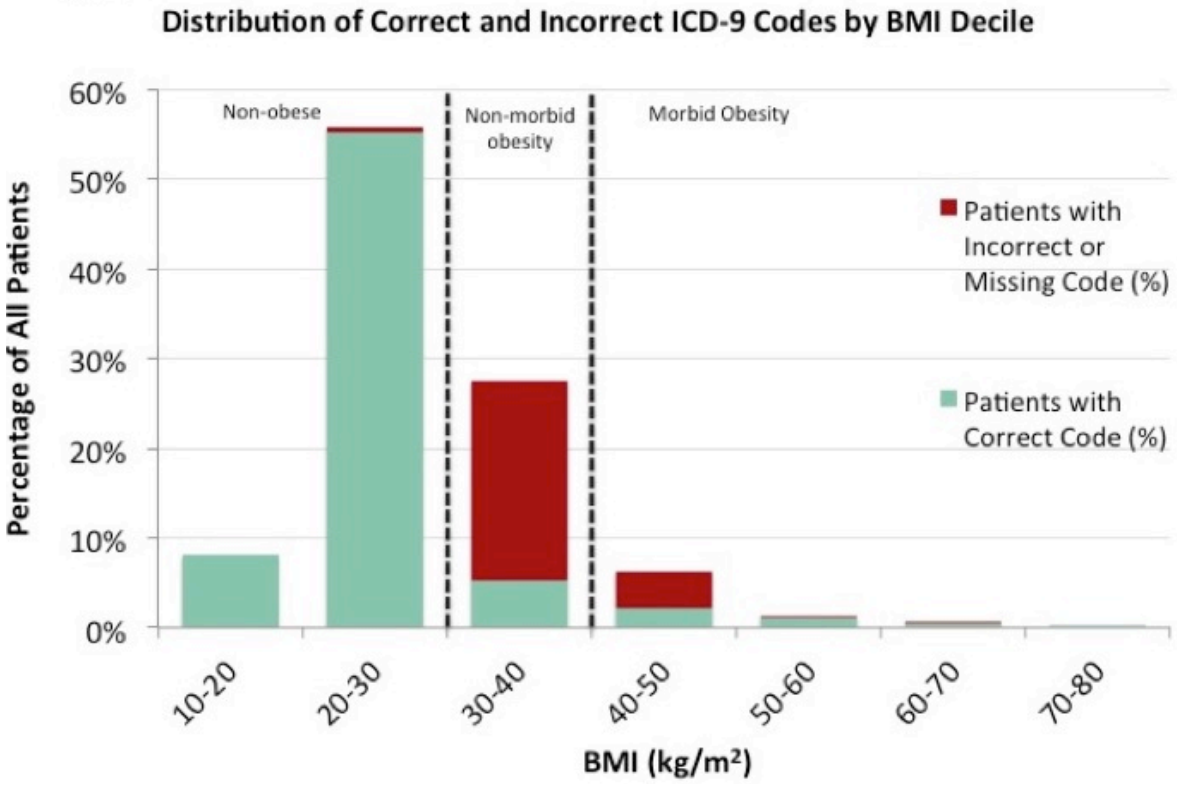

Figure 2: Bar graph depicting the percent of all patients by specific BMI decile, based on calculated BMI. Included within each bar is the portion of patients who received a correct obesity-related ICD-9 code (no code for those with a BMI < 30; 278.00 for those with a BMI of 30-40; 278.01 for those with a BMI >40) or an incorrect or missing obesity-related ICD-9 code.

Of the 104 patients who received ICD-9 code 278.01 ("morbid obesity"), 84 had a true BMI of 40 or greater, while 20 of these patients had miscoded BMIs outside of this range (Figure 1). 4 miscoded patients had a BMI below 30, and 16 had a BMI between 30-39.9. Thus, only 84 of the 174 patients (48.2%) with BMIs over 40 received the correct "morbid obesity" designation by ICD-9 code (Figure 2). This equates to ICD-9 code sensitivity, specificity, and positive and negative predictive values of 0.48, 0.99, 0.81, and 0.96, respectively (Figure 4). Only 11 patients were assigned the more specific ICD-9 code V85.4 without code 278.01. When V85.4 was included with 278.01,

sensitivity, specificity, and positive and negative predictive values were 0.54, 0.99, 0.82, and 0.96, respectively.

Figure 3

		True Calculated BMI		
		BMI 30 - 39.9	BMI < 30 or ≥ 40	
ICD-9 Codes	Patients Coded as "Obese"	True Positive 109	False Positive 47	Positive Predictive Value 0.70
	Patients Not Coded as "Obese"	False Negative 464	True Negative 1,455	Negative Predictive Value 0.76
		Sensitivity 0.19	Specificity 0.97	

Figure 3: Chart showing the sensitivity, specificity, positive predictive value, and negative predictive value of ICD-9 Code 278.00 ("Obesity, unspecified") compared to calculated BMI.

Figure 4

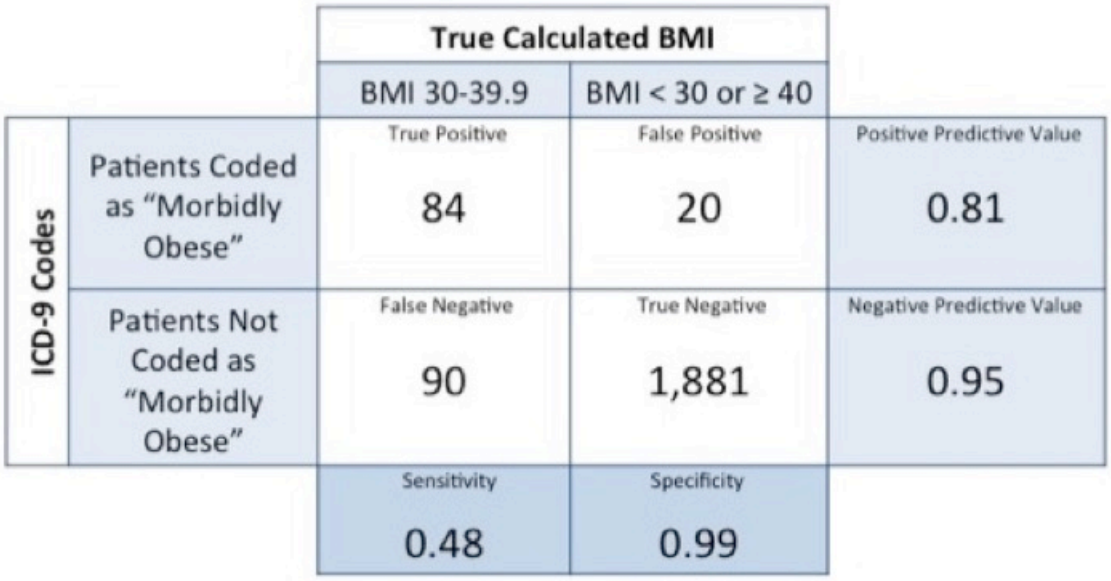

Figure 4: Chart showing the sensitivity, specificity, positive predictive value, and negative predictive value of ICD-9 Code 278.01 ("Morbid Obesity") compared to calculated BMI.

Anemia

In total, 286 patients were initially identified as part of this cohort. Of these, 24 (8.3%) were excluded due to trauma, and 2 (0.7%) were excluded for lack of a preoperative CBC. This left 260 spine surgery patients, of which 151 (58.1%) were female and 109 (41.9%) were male. The cohort included 120 (46.2%) cervical fusion patients and 140 (53.8%) lumbar fusion patients. Patient demographics can be found in Table 2.

Table 2: Demographics of the patient population for the anemia arm of the present study

	Number	Percent
Overall	260	100%
Sex		
Female	151	58.1%
Male	109	41.9%
Age (years)		
< 39	38	14.6%
40-49	55	21.5%
50-59	69	27.0%
60-69	62	24.2%
70-79	26	10.2%
> 80	10	3.9%
Spine Fusion		
Cervical	120	46.2%
Lumbar	140	53.9%

The average hematocrit of all patients was 41.6 ± 4.2%. Overall, 37 patients (14.2%) were anemic by definition. That is, 16 female patients (6.2% of the study population) had a preoperative hematocrit that was lower than 36.0%, and 21 male patients (8.1% of the study population) had a preoperative hematocrit that was lower than 41.0%.

Ten of the 260 total patients (3.8%) received an "anemia" ICD-9 code. Figures 5 and 6 show the distribution of preoperative hematocrits in the coded versus not-coded groups, relative to the normal hematocrit range for each gender. Of patients receiving an "anemia" ICD-9 code, 7 patients truly had anemia by definition, while 3 had normal hematocrits, and thus were miscoded. Thus, only 7 of the 37 patients (18.9%) with true anemia received the correct "anemic" designation by ICD-9 code. This equates to an ICD-9 code sensitivity of 19% (95% confidence interval [CI] = 6.3% to 31.5%), with specificity and positive and negative predictive values of 99% (95% CI = 97.1% to

100.0%), 70% (95% CI = 41.6% to 98.4%), and 88% (95% CI = 84.0% to 92.0%), respectively (Figure 7).

Figure 5

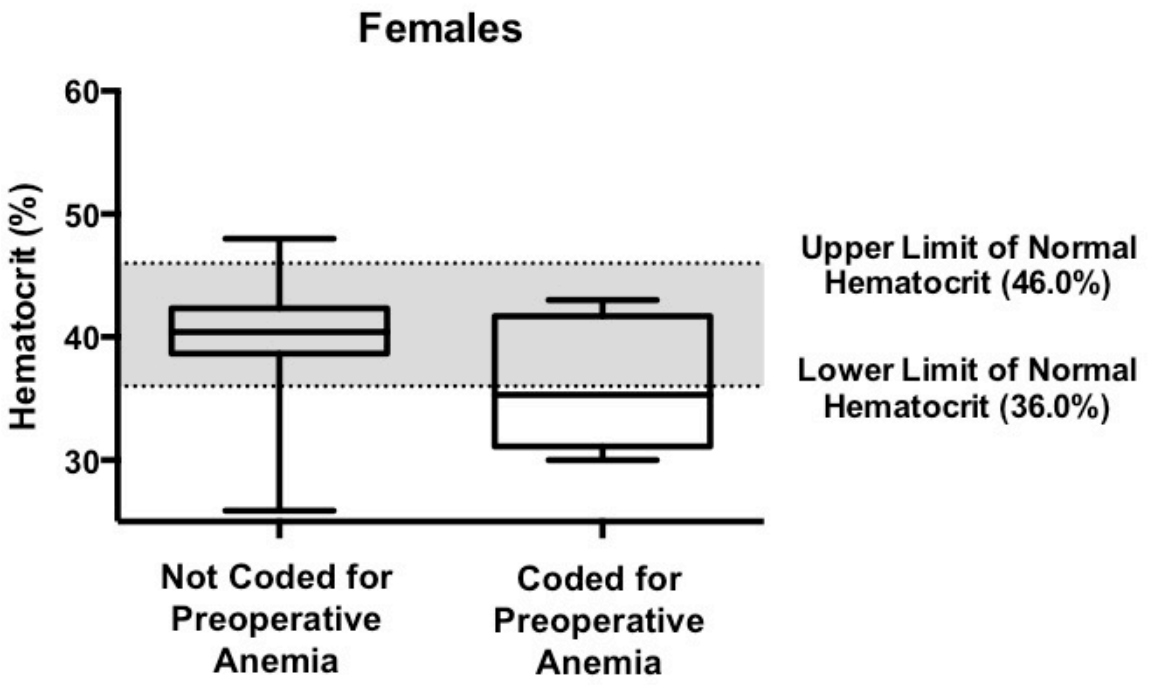

Figure 5: Box and whisker plot depicting the preoperative hematocrits of female patients. The x-axis shows female patients who were not assigned an anemia ICD-9 code upon discharge versus those who were assigned an anemia ICD-9 code. The three horizontal lines of the box represent the first quartile, median, and third quartile, respectively, while the whiskers of the plot extend to the minimum and maximum values of the cohort.

Figure 6

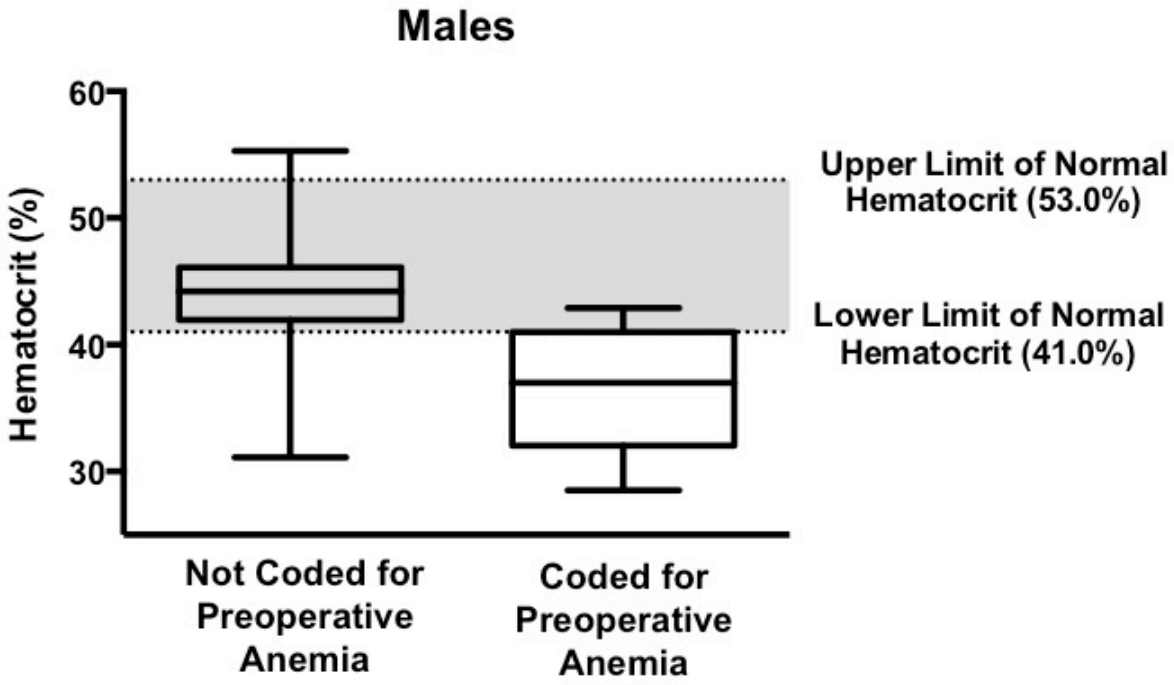

Figure 6: Box and whisker plot depicting the preoperative hematocrits of male patients. The x-axis shows male patients who were not assigned an anemia ICD-9 code upon discharge versus those who were assigned an anemia ICD-9 code. The three horizontal lines of the box represent the first quartile, median, and third quartile, respectively, while the whiskers of the plot extend to the minimum and maximum values of the cohort.

Figure 7

Preoperative Anemia in All Patients

		True Hematocrit		
		Hematocrit < Normal	Hematocrit Normal	
ICD-9 Codes	Patients Coded as Anemic	True Positive: 7	False Positive: 3	Positive Predictive Value: 0.70
	Patients Not Coded as Anemic	False Negative: 30	True Negative: 220	Negative Predictive Value: 0.88
		Sensitivity: 0.19	Specificity: 0.99	

Figure 7: The sensitivity, specificity, positive predictive value, and negative predictive value of anemia ICD-9 coding compared to chart-documented hematocrit.

Discussion

The use of administratively coded national databases for orthopaedic surgery research continues to increase. Though database use has many advantages, each dataset carries its own unique set of benefits and limitations. One pressing concern in particular is in regards to the clinical accuracy of the administrative ICD-9 diagnosis codes from which many databases are assembled.[9,10,12,13,20,21,23] Unfortunately, without close knowledge of each major database and data element, it can be difficult for the reader to determine whether a given study presents valid results to the questions being investigated. This study uses the easily quantifiable example comorbidities of obesity and anemia to clarify the relationship between administrative ICD-9 discharge codes and clinical reality, as well as to examine the ensuing possible consequences on research

studies in medicine and orthopaedic surgery that employ administrative databases as a data source.

Obesity

The results of the first segment of this study indicate that administratively coded ICD-9 diagnosis codes do not accurately represent whether a patient is obese. For patients with "non-morbid obesity" (BMI 30-39.9) just 19% of patients were correctly deemed obese by ICD-9 code. While patients with "morbid obesity" (BMI > 40) were more accurately coded, still just 48% of patients received the correct ICD-9 code. These results align with the remarkably low obesity-related coding accuracy found by the aforementioned published studies in specialized cohorts of obstetric and pediatric patients.[20-23] Though ICD-9 codes in the present study were very specific for both the non-morbid obesity and morbid obesity categories at 0.97 and 0.99, respectively, they exhibited low sensitivities of 0.19 and 0.48.

We are concerned by these results. By using obesity as an example, this study exposes a significant limitation of conducting research with national databases built upon ICD-9 coding data. While ICD-9 codes are of reasonable utility, they are coded for administrative and billing purposes and may not capture the quality of data desired for research purposes.

Numerous prior studies from the orthopaedic surgery literature have used ICD-9-coded databases like the NIS to draw conclusions about obesity and patient pathology, approximate national obesity rates, and adjust for obesity in multivariable analyses.[27,43-46]

However, the reported obesity rates in these investigational cohorts were 1.6%,[44] 3.2%,[45] 3.7%,[45] and 7%,[46] to list a few. In fact, the highest reported obesity rate we were able to find in a study using the NIS database was 15%.[47] This sharply contrasts with both the current estimate of adult obesity rates in the United States of 35.7% established by the Centers for Disease Control and Prevention (CDC),[48] as well as the 36.0% obesity rate identified by direct calculation in our study population. While many of the quoted studies analyzed specific patient subsets that could conceivably have somewhat different obesity rates compared to the general population or a hospital census, we find it unlikely that these populations would have obesity rates that so dramatically differ from national estimates.

Equally troubling, this trend of severely undercoding obesity rates with ICD-9 codes persists outside of the field of orthopaedic surgery. We discovered several published studies documenting obesity rates of 3.1%,[49] 3.8%,[25] 6.8%,[26] and 7.6%[50] in various medical fields such as cardiology, general surgery, and nephrology. While these are all specialized populations, (e.g., patients with nephrolithiasis or coronary artery disease), we believe it to be unlikely that the above-stated NIS cohorts carry obesity rates that so dramatically differ from the national average.

Is it acceptable to believe that just 12% of patients undergoing total knee arthroplasty (TKA) are obese,[51] particularly when obesity is a known contributor to early knee arthritis?[52-55] Or, similarly, that only 7.6%[50] of patients undergoing coronary artery bypass grafting are obese, again when it is well known that obesity is a risk factor for the development of coronary artery disease?[56-58] If we intend to draw meaningful clinical conclusions from database research, these significant disparities must first be taken into

account. Perhaps even more worrisome, the majority of these previous studies rarely mention their considerably discordant obesity rates and, if they do, only briefly note possible coding inaccuracies in their limitations sections. While this tremendous limitation is perhaps unknown to study authors, ongoing database publications are at risk of drawing conclusions based on fundamentally flawed source data. This is particularly concerning given the high rate at which database studies are currently being published in the literature.

Take the example of non-morbid obesity in our present analysis. In this case, any ICD-9-based conclusions would be drawn from a mere 19% of the intended obese population, with remaining obese patients incorrectly grouped into non-obese cohorts. This means that for every five obese patients an investigator expects to include, only one actually enters the analysis, an exclusion rate that would be unacceptable in any other study design. This raises serious concerns regarding the validity of studies conducted in this fashion.

Furthermore, there is a potential selection bias to this ICD-9 coding inaccuracy, as there may be additional unknown factors causing this 19% of obese patients to be coded as such while omitting the rest. For example, it is possible that this 19% is the sickest fraction of obese patients, whose care was so complicated by body habitus that the patient's obesity was unmistakable to those providing patient care, as well as to those assigning codes upon discharge. This is supported by the higher sensitivity of ICD-9 codes for morbidly obese patients (48%), as their morbid obesity was likely more prone to influence their hospitalization, perhaps leading to the increased accuracy of coding compared to non-morbid obesity. In light of this, researchers using ICD-9-coded

databases may be drawing conclusions about the most extreme effects of obesity, rather than developing the intended and more useful collective representation of this important cohort.

Anemia

The results of the second arm of the current study demonstrate the inability of administrative ICD-9 discharge diagnosis codes to accurately document whether a patient is anemic prior to surgery. Only 10 of the 260 patients received an ICD-9 code indicating anemia, 7 of whom were truly anemic based on preoperative hematocrit, and 3 of whom had normal hematocrits. However, 37 patients were deemed to be truly anemic based on preoperative hematocrit, meaning just 19% of anemic patients were correctly identified by ICD-9 code.

These results mirror those of the previously mentioned studies that examined the ICD-9 coding accuracy of other comorbidities,[8,20] as well as the obesity arm of the present study. Although the ICD-9 codes in the current study were very specific at 99%, the sensitivity was quite low at 19%, with a positive and negative predictive value of 70% and 88%, respectively.

These results are troubling, as they further demonstrate an important limitation of using ICD-9-coded databases for scientific research. Many published studies from the orthopaedic surgery literature have used ICD-9-coded databases, such as the NIS, to examine relationships between preoperative anemia and various surgical spinal disorders.[34-42] For example, preoperative anemia has been stated to be correlated with reintubation following anterior cervical fusion, perioperative visual loss following spinal

fusion, and a significantly increased risk of deep vein thrombosis and pulmonary embolism following lumbar spine surgery.[38,40,41] However, the current study indicates that these anemia codes, originally developed for the purposes of reimbursement and billing, may not capture the quality of data necessary for making such clinical conclusions.

As a field, orthopaedic surgery is entering an era in which it must become more aware of the limitations of administratively coded database research. As further studies continue to delineate the substantial inaccuracies of ICD-9 codes, it is becoming clear that ongoing database studies are at risk of using a flawed data source. Many publications only briefly mention this considerable limitation, an understatement that is especially concerning given the high usage of administrative databases in the field of orthopaedic surgery research.

Through the example of preoperative anemia in our present analysis, we show that any conclusions about anemia based on ICD-9 data from this single medical center would be drawn from a mere 19% of the intended anemic population, with remaining anemic patients incorrectly grouped into normal cohorts. This is similar to the 19% ICD-9 coding accuracy found previously for the comorbidity of obesity. In both examples, this would equate to an exclusion rate of 81% of patients, a percentage that would be unacceptable in any other study design. An exclusion rate of 81% subjects the remaining study cohort to tremendous bias, as there are most certainly additional unidentified characteristics causing the 19% of correctly identified anemic patients to be coded accurately.

In an attempt to determine a unifying characteristic of this cohort, the hematocrit range for those who were coded versus those who were not was plotted in both males and females (Figures 5 and 6). These figures demonstrate a slight trend indicating those with the lowest hematocrits were more frequently coded for anemia, however this trend cannot be definitively stated.

Future considerations

As introduced previously, both obesity and anemia were chosen as variables for this analysis because of their readily quantifiable and continuous nature. However, because this study suggests ICD-9 codes are unable to adequately identify obesity and anemia in hospitalized patients, we must question if other comorbidities (e.g., hypertension, diabetes, coagulopathy) fall subject, at least in part, to similar coding issues.

Additional comorbidities were not presently evaluated primarily because they lack a consistently quantifiable gold standard for comparison to ICD-9 coding data. As an example, would it be most appropriate to compare an ICD-9 discharge code for a patient with diabetes to that patient's hemoglobin A1c? Or would a better comparison be between the ICD-9 code and a fasting glucose on the day of discharge? Furthermore, how would researchers best account for any medications a patient may be taking and the way that might affect such measurements? Similar questions can be raised for comorbidities such as hypertension and hyperlipidemia.

However, a study that develops a standardized method for scrutinizing additional variables would be a logical next step for investigation. Though some previous analyses

have been conducted on additional comorbidities,[10,13] these were done retrospectively and thus rely on the same medical record review as ICD-9 data. In contrast, obesity and anemia have readily available gold standard BMI and hematocrit data that is routinely entered for each patient, allowing a retrospective review without the corresponding bias. Validation of other comorbidities that lack such an objective gold standard may require prospective studies in the future.

ICD-10

Another important consideration related to this study is the approaching nationwide implementation of the International Classification of Diseases Tenth Revision (ICD-10). In the coming months and years, hospital systems across the United States will be required to begin implementing the ICD-10 system of codes as a replacement for the ICD-9 codes. ICD-10 has already been in use across the world for several years, giving us an idea of the benefits and pitfalls that might accompany this transition in the United States.

ICD-10 is being implemented with the idea of shifting healthcare across the globe to a coding system that is both universal and more precise than previous methods. ICD-10 is far more granular and specific than its predecessor, a characteristic that is intended to decrease medical errors, enhance healthcare delivery, and improve the reporting of healthcare data. However, these lofty goals do not come without difficulties. Several forecasted barriers to the new implementation include the immense amount of required planning, the monetary cost of conversion, a temporary shortage of coders qualified to

assign the new ICD-10 codes, and the initial loss of productivity and efficiency associated with the re-training of coders, physicians, and staff.

Because ICD-10 has been in widespread use for several years in many areas outside of the United States, many studies have already been conducted analyzing the relative successes and failures of the new system. With regards to the early benefits that have been investigated, a recent study out of Denmark evaluated the accuracy of ICD-10 diagnosis codes for each of the nineteen comorbidities that make up the Charlson comorbidity index (CCI).[59] The Charlson comorbidity index is a predictive scoring system of ten-year mortality that is made up of nineteen comorbidities, each assigned a designated number of points.[60] It is often considered to be similar to, but more precise than, the American Society of Anesthesiologists (ASA) score. The study authors used 950 patients from the Danish National Registry of Patients to evaluate the sensitivity and positive predictive values of ICD-10 codes for all nineteen Charlson comorbidities. The least accurate ICD-10 codes were 82.0% accurate, while the best were 100%. The average for all conditions was 98% sensitivity, with eighteen of the nineteen conditions greater than 90%. This study was conducted four years after the implementation of ICD-10 in Denmark, indicating that there is great potential for high quality data capture with ICD-10, once the system has been established and functioning for several years.

Further studies evaluating the accuracy of ICD-10 codes around the world haven't been quite as clear-cut. As an example, a different study out of Denmark investigated the accuracy of the ICD-10 code for syncope in inpatient and emergency department visits. In this study, they found that this code was only sensitive to 62.7%.[61] While this is not nearly as strong as the ICD-10 codes for Charlson comorbidities addressed above by a

different Danish study in which most comorbidities were greater than 90% sensitive, this still represents a sensitivity that is far better than the ICD-9 code sensitivities discovered in the present study for non-morbid obesity, morbid obesity, and anemia. Similarly, a study by Henderson et al. out of Australia evaluated the quality of data collection by ICD-10 codes for a number of comorbidities. This analysis produced a range of sensitivities, varying from 62% (peripheral vascular disease) to 94% (metastatic neoplasms).[62] Again, while these vary in quality, they all far exceed the ICD-9 code sensitivities found in the present study.

Finally, various emerging studies indicate that for some data elements, ICD-10 coding still falls victim to significant inaccuracies. In a recent study from Australia, investigators looked at the ability of ICD-10 codes to accurately document such variables as sepsis, cholecystitis, viscous perforation, peritonitis, and pneumonia. For these elements, ICD-10 sensitivities were as low as 7.1%, 4.3%, 10.6%, 2.0%, and 13.8%, respectively in one hospital system, and 16.5%, 2.4%, 13.0%, 0.4%, and 11.8%, respectively in a separate hospital system.[63] These are alarmingly low sensitivities and perhaps indicate specific variables for which ICD-10 coding is not well suited. While it was not indicated in the study how long the hospital systems had been using ICD-10 coding, the study period spanned six years, suggesting these low sensitivities were likely not a result of the "learning curve" that would be associated with the early stages of the transition from ICD-9 to ICD-10.

With regards to this so-called "learning curve," a prior study looked to see if this truly exists and whether ICD-10 coding quality changes over time.[64] This was a study performed in Switzerland and was conducted by randomly selecting 3,500 patients from

three different hospitals at two year intervals (1999, 2001, 2003). In these patients, the study authors evaluated the accuracy of ICD-10 coding for seventeen Charlson index comorbidities and twenty-nine Elixhauser index comorbidities. As a whole, ICD-10 coding sensitivity for the Charlson comorbidities steadily increased from 36.5% to 42.5% to 42.8%. In the Elixhauser group, coding sensitivity increased from 34.2% to 38.6% to 41.6%. On an individual scale, ICD-10 coding sensitivity increased for thirty of thirty-six total comorbidities and decreased for ten of thirty-six comorbidities. While overall, we make the case that these sensitivities would be considered rather poor, particularly for research use as part of a national database, it is encouraging that ICD-10 coding sensitivities showed the capacity in this study to improve in quality over time.

Though it is still unclear exactly how ICD-10 will work out compared to ICD-9, it is already showing promising signs of establishing itself as an upgrade to the previous system. A main goal of ICD-10 was to increase the accuracy of coding, coming in the form of thousands of new codes able to capture diagnoses and procedures at a more granular level than ever before. While it in fact does appear in the early stages that ICD-10 is accomplishing its goal of increased coding accuracy, it is yet unclear whether this accuracy will be high enough to make the data suitable for research purposes. In the coming years as ICD-10 is implemented in the United States, it will be of paramount importance to evaluate the coding accuracies of the new system, much in the same way as the present study. Studies such as these will aid in determining whether national databases constructed from new ICD-10 discharge codes are appropriate for research usage.

Administrative considerations

A final implication of the findings in the current study is the effect such inaccuracies in ICD-9 coding have on the administrative and billing aspects of healthcare in the United States. This has not been previously discussed in this paper, as this study was conducted to evaluate ICD-9 codes as they pertain to research purposes, rather than billing purposes. However, a brief discussion of this separate but similarly important aspect of ICD-9 coding is appropriate.

With the rollout of ICD-10 as a replacement for ICD-9 codes, one of the principal purposes of this implementation was to increase the accuracy of payment data, decrease the number of unpaid claims, and decrease payment fraud within the healthcare system.[65-67] Beginning with the advent of diagnosis related groups (DRGs) in the 1980s, hospitals now bill based on the complexity of a given patient's hospital stay. As would be expected, comorbidities such as obesity and anemia contribute to a patient's hospital visit complexity and associated hospital charges. One can imagine, if a hospital is only identifying 19% of non-morbidly obese patients, 48% of morbidly obese patients, and 19% of anemic patients, there is a tremendous amount of 'waste' in the system for which the hospital is not charging for inpatient stays. This generally translates into higher profit margins for insurance companies and decreased payment to healthcare providers.[65,66] Not only that, but with such inaccurate coding, it presents a significant challenge to those examining methods by which to control healthcare costs.[65] How can cost control measures truly be implemented without an accurate knowledge of where costs originate in the first place? Poor ICD-9 coding obscures national trends in healthcare requirements and delivery. A final consideration regarding the ICD-9 code findings of the current study

is the void that remains for fraud within the system. With such inaccurate coding of comorbidities, there is no clear idea of the true cost of a given hospital visit, thus increasing the potential for fraudulent billing practices.[67] Each of these elements concerning the administrative and billing components of the United States healthcare system further strengthen the case that the current inaccuracies of ICD-9 discharge codes are cause for great concern.

Limitations

This investigation has its limitations. The study was performed at one hospital system, so the findings may not apply to all hospitals in a given database. However, because the Yale-New Haven hospital system contributes data to many national databases, we believe it to be a clinically relevant sample. Moreover, as an example, our hospital population had an obesity rate of 36.0% compared to reported CDC rates of 35.7%.

Another limitation specific to the obesity arm relates to the argument that assigning the ICD-9 code 278.00 ("Obesity, unspecified") to patients with a BMI over 40 is not necessarily incorrect, as occurred in 32 (1.5%) patients. That being said, previous studies that used administrative databases to examine both obesity and morbid obesity as separate variables have consistently used the "Obesity, unspecified" code to identify patients with BMIs of 30-39.9, reserving the "Morbid obesity" code for those with a BMI over 40.[27,43] Because of this historical pattern, we attempted to be consistent with prior studies in our evaluation of these ICD-9 discharge codes. Similarly, we acknowledge that the ICD-9 codes V85.3 and V85.4 also exist as a secondary method to document a

patient's specific BMI, though these are rarely used in the existing literature.[12,51] Nevertheless, including V85.3 for non-morbid obesity and V85.4 for morbid obesity in the overall analysis only marginally increased the ICD-9 code sensitivities, to 0.21 and 0.54, respectively.

Similarly, a limitation specific to the anemia arm relates to the ICD-9 codes that were used for comparison. The authors attempted to compare preoperative hematocrit values with the same ICD-9 discharge codes that would be used to generate the comorbidity variable of "anemia," based on what has been outlined previously by the NIS. We realized that it is certainly possible that other administratively coded databases use alternative combinations of ICD-9 discharge codes in order to determine a diagnosis of anemia. The NIS was chosen because of its current prolific use in medical and orthopaedic surgery research.

Conclusion

In light of the orthopaedic surgery community's increasing reliance on large national databases, it is important to consider the data source. As demonstrated by this study of obesity and anemia, ICD-9 coding is prone to significant inaccuracies that we argue are too great to be acceptable for research-quality data. These disparities have the potential to sway patient management, alter treatment decisions, and propagate potentially inaccurate conclusions in the literature.

Though not the primary focus of the current study, these findings also have significant implications for billing and administrative entities within the United States

healthcare system. As we look to the coming years and the impending implementation of the ICD-10 coding system, there is emerging evidence that the quality of ICD-10 coding will be an improvement over the current ICD-9 system. However, it remains to be seen whether the data will be of sufficient quality for research purposes. Until then, though database research is a powerful tool, we must be careful to fully understand the quality of the data elements we use in order to reach meaningful conclusions. In this way, we will better capitalize on the power of database research to improve our knowledge and practice of orthopaedic surgery.

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