



Using Medications for Prediction of Revision after Total Joint Arthroplasty



Maria C.S. Inacio, PhD ^a, Nicole L. Pratt, PhD ^a, Elizabeth E. Roughead, PhD ^a, Stephen E. Graves, MD, PhD ^b

^a Quality Use of Medicines and Pharmacy Research Centre, Medicine and Devices Surveillance Centre of Research Excellence, Sansom Institute, School of Pharmacy and Medical Sciences, University of South Australia, GPO Box 2471, Adelaide, SA, Australia

^b Australian Orthopaedic Association, National Total Joint Replacement Registry, Level 6, Bice Building, Royal Adelaide Hospital, The University of Adelaide, Adelaide, SA, Australia

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ABSTRACT

This study evaluated the ability of a pharmacy based co-morbidity measure (RxRisk-V) to predict odds of one and five years revision in total hip arthroplasty (THA) and total knee arthroplasty (TKA) and compared its performance to the more commonly used co-morbidity measures in orthopaedics (Charlson and Elixhauser). 11,848 patients with THAs and 18,972 with TKAs performed between 2001 and 2012 were evaluated. Using a combination of conditions, identified by both the pharmacy and diagnoses based coding algorithms, models with acceptable predictive ability of THA and TKA revision were developed. These findings suggest prescription based co-morbidity measures can positively contribute to case-mix adjustment and outcome prediction in this patient population.

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Background

The incidence of joint arthroplasty in several countries has dramatically increased in the past couple of decades [1–4]. Along with the increase in incidence, a change in patient profiles has also been observed [5,6]. Patients with multiple co-morbid conditions, a factor that would have precluded joint arthroplasty in the past, are now undergoing these procedures and the number of co-morbid conditions in patients undergoing primary elective arthroplasty has doubled over the last 20 years in many countries [5,6]. The higher prevalence of multimorbidity in patients undergoing arthroplasty may be due to a number of factors, including an ageing population with poorer health, improvements in pre-operative management and post-operative rehabilitation, advances in the treatment of the co-morbid conditions, and improvement in identifying diseases. Regardless of the mechanism, arthroplasty patients now have more co-morbid conditions [7–11] and a higher prevalence of specific conditions including diabetes, obesity, rheumatologic conditions, renal disease, cardiovascular disease and depression [12–15], all of which have been implicated in poor post-arthroplasty outcomes [12–17].

Information regarding joint arthroplasty procedures is available in existing data sources such as claims data, which include inpatient hospitalisation data, outpatient service data, and prescription data. Using these data there are several ways to ascertain patient co-

morbidity profiles [18–20]. Many observational studies have used validated diagnoses based coding algorithms (i.e. specifications of how to identify each condition), such as the Elixhauser [21,22], Charlson [23,24], or one of their variations, to obtain co-morbidities from claims data [18,20]. Both of these co-morbidity measures use historical or encounter specific administrative data to ascertain co-morbidities. The measures' scoring is based on their ability to predict mortality [21,23]. In various settings these measures have been adapted to predict length of stay, readmission, costs, and other health-related outcomes [11,22,25–27]. In joint arthroplasty research, the number of co-morbidities, as well as some of the individual conditions identified by the Charlson and Elixhauser measures have been found to be associated with revision arthroplasty [7–9,12,15–17,28–30]. The Charlson and Elixhauser measures predictive performance for revision has only been evaluated in total hip arthroplasty (THA) patients in one study [7]. An additional way to ascertain patient co-morbidity is to utilise medication prescription claims data, which can potentially offer a more comprehensive patient co-morbidity profile. Prescription history captures patients undergoing treatment for less serious co-morbidities that may not require hospitalization or other encounters but are of interest when studying joint arthroplasty outcomes. For example, receiving medication for gastro-oesophageal reflux disease (GORD) would be captured by the prescription based algorithm. GORD is not included in the Charlson or Elixhauser algorithms. Using algorithms that include conditions such as GORD may be important for predicting joint revision, as the medication most commonly used to treat GORD has been found to be associated with higher risk of pneumonia [31] and clostridium difficile infections [32], both of which are common nosocomial infections. One of the most commonly used prescription based co-morbidity measure in health services and pharmacoepidemiological research [25,33] is the RxRisk-V [34], which evolved from the Chronic

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Reprint request: Maria C.S. Inacio, MS, PhD, Quality Use of Medicines and Pharmacy Research Centre, Medicine and Devices Surveillance Centre of Research Excellence, Sansom Institute, School of Pharmacy and Medical Sciences, University of South Australia, GPO Box 2471, Adelaide 5001, South Australia, Australia.

Disease Score. Unlike the diagnoses based measures, the RxRisk-V was developed to predict costs [34,35], and was later adapted to predict mortality [36]. In orthopaedics, few studies have used pharmacy records to ascertain co-morbidities [25,33], and to our knowledge none have evaluated the performance of pharmacy-based co-morbidity measures in predicting revision arthroplasty.

In order to evaluate the utility of using prescription claims data and a prescription based coding algorithm to identify co-morbidities in a joint arthroplasty cohort we compared the prescription-based co-morbidity measure performance in revision prediction to the more commonly used diagnoses based measures. Specifically, we (1) evaluated the association between both the number of co-morbidities and specific conditions measured by the RxRisk-V, Charlson, and Elixhauser measures with one year and five years revision arthroplasty. Additionally, we (2) compared the predictive ability of the RxRisk-V, Charlson, and Elixhauser co-morbidities measures, individually and in combination, with regards to one year and five years risk of arthroplasty revision. Our study hypothesis was that the RxRisk-V would perform better as a predictor of revision outcome due to the larger number of conditions identified by this co-morbidity measure.

Methods

Study Design, Setting, and Cohort

A retrospective study was conducted on a cohort of patients that were subsidized by the Australian Government Department of Veterans' Affairs (DVA) and who underwent THA and TKA procedures between 2001 and 2012. De-identified administrative inpatient encounter information and prescription medicine, inpatient and outpatient, data for this captured population was obtained.

The cohort included adult patients (≥ 18 years old) who underwent primary unilateral THA and TKA procedures. Using International Classification of Disease, 10th Revision, Australian Modification (ICD-10-AM) codes, THA (4931800) and TKA procedures (4951800, 4952100, 4952102, 4952400) were identified. Only patients with primary diagnoses associated with elective primary arthroplasty procedures were included.

Co-morbidity Measures and Data Sources

The RX Risk-V [34], the prescription based co-morbidity measure coding algorithm, usually determines the presence of 45 conditions [35]. It was developed by the United States' Department of Veterans' Affairs in an attempt to predict costs associated with certain patient care. In this study, a modified RxRisk-V was used with 42 conditions- ostomy, neurogenic bladder, and urinary incontinuity were excluded. The sum of the conditions calculated the RxRisk-V score.

The Charlson co-morbidity measure coding algorithm used inpatient hospitalizations for a determined period of time to calculate a weighted score based on the presence of 17 conditions [24,27]. An unweighted Charlson score was used in this study because the published weights for this score are based on mortality prediction and we evaluated the outcome of revision joint arthroplasty.

The Elixhauser co-morbidity measure coding algorithm also used inpatient hospitalizations during a specific period to calculate co-morbidities. The most commonly used form of the algorithm was used to identify the presence of 30 conditions [21,37]

The RxRisk-V and Charlson have six common conditions, the Elixhauser and RxRisk have 10 common conditions, and the Charlson and Elixhauser have 12.

Using the DVA administrative databases, all inpatient hospitalizations and prescription medicine history were obtained. The database contains details of all prescription medications, medical, allied health services and hospitalizations provided to veterans for which DVA pays a subsidy. In the dataset, medications are coded according

to the World Health Organization Anatomic, Therapeutic and Chemical Classification (ATC), and the Pharmaceutical Benefits Schedule (PBS) item codes. Hospitalizations are coded according to the ICD-10-AM. DVA also maintains a client file, which contains information on gender, date of birth, date of death, and family status for a treatment population that in September 2011 was 242,000 people. In this study, the 12 month period preceding the discharge date of the arthroplasty procedure was used to ascertain the co-morbidities according to the two diagnoses based co-morbidity measures and the 12 month period preceding the admission date of the arthroplasty was used for the medication based measure. The hospitalization for the arthroplasty procedure was included in the calculation of the diagnostic co-morbidity measures (ICD-10-AM adapted Charlson and Elixhauser).

Outcomes

One year and five years post-operative revision procedures were the main endpoints of this study. In THAs, the ICD-10-AM procedure codes used to identify revisions were: 4932100, 4932400, 4932700, 4933000, 4933300, 4933900, 4934200, 4934500, and 4934600. In TKAs, the codes used were: 4951200, 4951500, 4952700, 4953000, 495301, 4953300, 4955400, and 9056200.

Covariates

Age (continuous), gender (male vs. female), primary diagnosis for surgery, operative year (2001–2012, ordinal variable, reference = 2001), and whether the cases were performed in a public or private hospital were evaluated in all models as potential confounders. Primary diagnosis for the hips were categorized into the most common primary diagnosis: primary coxarthrosis (M160), other primary coxarthrosis (M161) (reference), coxarthrosis unspecified (M169), other primary gonarthrosis (M171), unspecified osteonecrosis pelvis thigh (M8795), other (all other ICD-10-AM codes). Primary diagnosis for the knees were categorized into the most common primary diagnosis: rheumatoid arthritis non specific lower leg (M0696), other primary coarthrosis (M161), primary gonarthrosis bilateral (M170), other primary gonarthrosis (M171) (reference), gonarthrosis unspecified (M179), and other (all other ICD-10-AM codes).

Statistical Analysis

All analyses were stratified by procedure type (THA and TKA). Frequencies, proportions, medians and interquartile ranges (IQR) were used to describe the study cohorts, distribution of co-morbidities by each algorithm and surgical outcomes. Cumulative incidence of revision, accounting for the competing risk of deaths, was assessed. Logistic regression models were used to evaluate the association between both the (1) number of co-morbidities (both continuous and in categories) and (2) specific conditions and revision surgery. Effect modification by age and gender was evaluated. When modelling the (1) number of co-morbidities, bivariate models were first created and then covariate confounding was evaluated by adding additional variables to the model. Final models were adjusted by age, gender, and primary diagnosis unless otherwise specified. The number of co-morbidities (scores) for measures were modelled as continuous (data not shown) and categorical variables. RxRisk-V (possible value range 0–42) was categorized into the following value levels: 0, 1–2, 3–4, 5–6 and ≥ 7 . The Elixhauser (range 0–30) and Charlson (range 0–17) possible value range number of conditions were categorized into 0 vs. 1–2 vs. ≥ 3 . There were two final models developed for each comorbidity measure (six total) and one model with a combination of conditions from all measures for each outcome. Therefore, we developed seven models for each outcome for a total of 14 final models for the THAs and 14 final models for the TKAs analyses. Model performance was evaluated based on its

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