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Readmission risk prediction for patients after total hip or knee arthroplasty

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Abstract

Hospital readmissions are an important quality measure in healthcare, as they can indicate issues in treatment, rehabilitation, or discharge management. Furthermore, readmissions are often associated with increased costs resulting from penalties and regulations enforced by policy makers and insurers. Several studies have been conducted to identify patients at high risk of readmission, especially focusing on the initial diseases addressed in the Hospital Readmissions Reduction Program (HRRP). Since elective primary total hip arthroplasty and total knee arthroplasty (THA/TKA) procedures are added later to the HRRP, research on risk prediction in that area is still quite scarce. This study focuses on total hip arthroplasty and total knee arthroplasty procedures. Based on a dataset from a not-for-profit Australian healthcare group, 10,057 admissions from 2011 to 2015 are utilised to build several predictive models for readmissions after THA/TKA procedures. The structure and application of these models are presented and benchmarked against current hospital risk scores, resulting in a good prediction power to identify patients at 28-day risk of readmission.

Keywords predictive analytics, readmissions, total hip arthroplasty, total knee arthroplasty, risk management

1 Introduction

1.1 Motivation and Objective

Hospital readmissions are a major cost factor both for private as well as public hospitals and increasingly serve as a measurement for quality of care (Fischer et al. 2014). Moreover, reports indicate that about every tenth readmission is most likely unnecessary and could have been avoided (Stranges and Stocks 2008). Several countries have already implemented measures and regulations to track, benchmark, and reduce readmissions rates throughout hospitals, often associated with reduced reimbursements or even penalty fees. Starting in October 2012, the USA introduced the "Patient Protection and Affordable Care Act (PPACA)", also known as Obamacare. This regulation includes the "Hospital Readmissions Reduction Program (HRRP)" that enforces penalties for preventable readmissions for specific diagnosis groups. A readmission is defined as "an admission to a [...] hospital within 30 days of discharge from the same or another [...] hospital" (CMS 2016). In 2012, penalised readmissions included the conditions of acute myocardial infarction (AMI), heart failure (HF), and pneumonia (PN). Since 2015, planned readmissions are accounted to the readmissions measures, and patients admitted for acute exacerbation of chronic obstructive pulmonary disease (COPD), elective total hip arthroplasty (THA) and total knee arthroplasty (TKA) are added to the program. Starting 2017, patients admitted for coronary artery bypass graft surgery (CABG) are added, and the measure cohort of pneumonia patients is extended to include patients with aspiration pneumonia as well as sepsis patients coded with pneumonia present on admission (CMS 2016). While there has been a number of studies analysing the role of readmissions for AMI, HF, and PN, research on elective THA and TKA procedures is still scarce and has only recently gained more attention (Bernatz et al. 2015; Bohm et al. 2012; Kurtz et al. 2016a, 2016b; Ravi et al. 2017). Unplanned readmissions can overall indicate poor quality of care. From a financial perspective, it is argued, that the increased hospitalisation after elective hip and knee procedures causes an incremental cost of 10% of the index hospital stay (Bohm et al. 2012). In the case of AMI, HF, and PN, Carey and Stefos (2016) claim that hospitals could save $2,140 on average per readmission avoided. Preventable THA or TKA readmissions are likely to result in similar savings.

Thus, this study aims to provide and compare multiple specialised prediction models to determine patients at high risk for readmission after a THA or TKA procedure utilising episode data from an Australian not-for-profit hospital group. To reduce readmissions, patients at risk of readmissions and corresponding risk factors have to be identified. For that purpose, predictive analytics methods can be applied to detect high-risk patients already during their hospital stay. Thus, counter measures can be taken in time, e.g. by allocating more resources to high-risk patients, adapting the discharge plan, or increasing patient length of stay if necessary. In Information Systems research, the concept of predictions is a well-established part of theory development (Gregor 2006). Contributing to this research stream, this study follows the development process proposed by Shmueli and Koppius (2011) to build a predictive model to identify THA or TKA patients at high risk of 28-day readmissions. The remainder of this study is structured according to this development process (cf. Table 1).

Goal	Predict patients at risk for 28-day readmission after THA/TKA
Data Collection	Observational data available at time of prediction (before patient discharge)
Data Preparation	10,057 THA/TKA episodes; readmission rate 2.3 % (cf. section 3.1)
Variables	*38 attributes (cf. section 3.2 - Table 2)*
Methods	*Seven methods (cf. section 3.3)*
Evaluation	*Accuracy / Precision / Recall / AUC (cf. section 3.4 - Table 4)*

Table 1: Study design

2 Background and Related Work

2.1 Readmissions

Hospital readmissions are an important quality measure in healthcare, as they can indicate issues in treatment, rehabilitation, or discharge management. Furthermore, readmissions are often associated with increased costs resulting from penalties and regulations enforced by policy makers and insurers. While there is no common definition for readmissions available, in general, they can be described as "a second admission to a hospital within a specified period after a primary or index admission" (Kristensen et al. 2015). Besides the considered period, criteria concerning the index admission and the potential readmission have to be defined. These criteria can include clinical characteristics (e.g., diagnosis), demographics (e.g., age), the admission type (e.g., elective or emergency), or the treatment facility (Kristensen et al. 2015). Considering the monitored time between admissions, there is no international consensus. The observed period between admissions varies among studies from 14-days to 4-year with the most common being 30-days (Kansagara et al., 2011).

Readmissions are commonly differentiated between planned or unplanned readmissions and related or unrelated to the index admission. While the identification and prediction of readmissions should primarily focus on unplanned, related readmissions, it is often difficult to assess the relationship between admissions. Also, planned readmissions are often not documented within hospitals and therefore exacerbate the distinction of unplanned readmissions. Other studies differentiate between avoidable and unavoidable readmissions (van Walraven et al. 2011; van Walraven et al. 2012a). The proportion of avoidable readmissions in that context and the underlying criteria to determine whether a readmission is avoidable varies strongly between studies. Research suggests a median proportion of around 27% of readmissions to be avoidable (van Walraven et al. 2011), or similarly 27-28% to be at least predictable (van Galen et al. 2017).

Although readmissions are a central theme in the Australian healthcare sector, definitions of readmissions vary among the different states or insurers. Rates are measured within a 28-day time frame from the patient's first stay. In Western Australia, an admission is labelled as an unplanned readmission if the previous admission occurred within a time frame of 28 days and the patient is admitted for the same or a related condition, or a complication following the index admission (Government of Western Australia, Department of Health 2017). Since 2006 the Australian government has been tracking 28-day readmission rates (AIHW 2017b). In hip and knee replacement procedures, according to the AIHW, unplanned readmission rates of 19.2% and 23.1% respectively can be observed in Australian hospitals (AIHW 2017a). Monitoring of unplanned readmission rates across Australia is executed through the instalment of the National Healthcare Agreement (NHA) which contains unplanned readmission rates as a quality of care indicator. The calculation for the report, however, is limited to public hospitals. Here, readmissions are defined by the following criteria that have to be fulfilled to qualify for the inclusion in the statistic (AIHW 2017b):

- The admission has to follow a separation from the same hospital where the patient was either treated with a knee replacement, hip replacement, tonsillectomy and adenoidectomy, hysterectomy, prostatectomy, cataract surgery or appendectomy.
- The second admission has to occur within 28 days of the previous separation.
- A principal diagnosis has to have one of the following codes: T80–88, T98.3, E89, G97, H59, H95, I97, J95, K91, M96 or N99.

The observed hospital group internally defines a readmission as an unplanned, yet clinically related admission where a patient is admitted to acute care within 28 days after previously being discharged from acute care. Information about the preventability of a readmission is not available.

2.2 Readmission Risk Prediction

Since readmission rates became a popular measure to indicate the quality of care, various studies have implemented predictive models to determine patients at high risk of readmission. Research varies between predicting readmissions across all diagnoses groups simultaneously and detecting readmissions for specific diseases. Especially the HRRP's penalised diagnoses groups are subject to multiple studies in the field. A systematic review by Kansagara et al. (2011) summarises 21 studies for readmission prediction. Population sizes under study range from 173 patients to more than 2.7 million, while 30-day readmission rates range from 20.4% to 34.5%. Regarding relevant variables, most studies include medical comorbidity data, prior use of medical services and sociodemographic patient characteristics. Kansagara et al. (2011) conclude that readmission risk prediction is very complex and most studies performed poorly in predicting high-risk patients. They claim better approaches are needed and suggest future studies to include data beyond medical record data, e.g., administrative data.

General risk scores

Van Walraven et al. (2010) describe a simple scoring method to assess the risk of readmission based on the so-called LACE index. This score is calculated using the length of stay, acuity of admission, comorbidities, and previous emergency department visits. For each patient, an index between 0 and 19 is computed categorising that patient into one of three risk groups. This index is adapted and validated in several studies, including an approach by Wang et al. (2014) that analyse HF patients that are readmitted within 30 days of their index admission. However, the authors conclude that the LACE index is not a reliable tool to identify high-risk HF patients for readmission (Wang et al. 2014). Low et al. (2017), Damery (2017), and Ritt (2016) also test the LACE index across different diagnosis groups in their studies. Van Walraven et al. (2012b) further extend the score to the LACE+ index by including additional socio-demographic, administrative, and procedure-related variables (van Walraven et al. 2012b). Similar to the LACE index, Donzé et al. (2013) develop a scoring system to simplify predicting the risk of readmission. The so-called HOSPITAL score considers the following factors: the patient's haemoglobin level, discharge from oncology, the patient's sodium level, procedures during stay, the index admission type, the number of hospital admissions in the previous year, and the length of stay. For each patient, a score between 0 and 13 is computed categorising that patient into one of three risk groups. In their retrospective study, Donzé et al. (2016) were able to validate the application of the HOSPITAL score by analysing 117,065 index admissions including 17,516 (15.0%) all-cause readmissions within 30 days. The score is furthermore validated as a useful tool in readmission prediction in various studies by Robinson (2016), Robinson et al. (2017), Kim et al. (2016), and Aubert et al. (2016).

Heart Failure (HF), Acute Myocardial Infarction (AMI) and Pneumonia (PN)

Amarsingham et al. (2010) present an approach to detect HF patients at risk of 30-day readmissions using multivariate logistic regression. Similarly, Au et al. (2012) and Wang et al. (2014) develop a simple prediction model for HF patients using the LACE index (van Walraven et al. 2010). Bardhan et al. (2012) not only try to determine if a patient will be readmitted but also account for frequency and timing of future readmissions by using a BG/EG hurdle model (Bardhan et al. 2015). Frizzell et al. (2012) compare multiple machine learning methods against traditional statistical models but do not yield better discrimination power using the former. Karen et al. (2016) assess the applicability of the Rothmann Index (RI) for predicting readmissions of HF patients. The studies by Huang et al. (2014), Schaefer et al. (2017), and Weinreich et al. (2016) focus on predicting readmissions for Pneumonia patients. Besides HF, Hilbert et al. (2014) implement decision trees to predict high-risk patients with AMI or Pneumonia. In their retrospective cohort study, Shams et al. (2014) analyse 5,600 admissions with AMI, HF, PN, and COPD with 13.1% of all episodes that were followed by an unnecessary readmission within 30 days (Shams et al. 2015).

COPD & CABG

Using a natural language processing framework, Agarwal et al. (2017) aim at predicting hospital readmissions for patients with COPD. Similarly, Baechle et al. (2017), Bollu et al. (2017), and Echevarria et al. (2017) develop individual approaches for 30-day or 90-day readmissions. Current research on CABG patients mainly focuses on explanatory models (Hannan et al. 2011; Price et al. 2013; Sabourin and Funk 1999; Steuer et al. 2002) and on identifying influencing risk factors for readmission (Bohmer et al. 2002; Hannan et al. 2003; Stewart et al. 2000) rather than building predictive models (Zitser-Gurevich et al. 1999).

Total Hip or Knee Arthroplasty (THA/TKA)

A systematic review by Bernatz (2015) indicates age, length of stay, discharge to a skilled nursing facility, an increased BMI, an ASA score greater than 3, and Medicare/Medicaid insurance to be positively correlated with increased 30-day readmissions in orthopaedic patients. The primary reasons for readmission in THA and TKA presented by Kurtz (2016a, 2016b) are a deep infection, wound infection for both procedures as well as dislocation, periprosthetic fracture, or hematoma for THA, and atrial fibrillation, cellulitis and abscess of the leg, or pulmonary embolism for TKA. They observe a median 30-day readmission rate of 4.9% among 952,593 TKA patients and a 5.8% rate of 442,333 THA patients. These findings further support the detection of potentially high-risk patients. Furthermore, Ravi et al. (2017) suggest an increased Hendrich fall risk score after THA or TKA to be strongly associated with unplanned 28-day readmissions. Bohm et al. (2012) investigate 26,978 THA patients and 31,373 TKA patients at Canadian acute care hospitals, presenting readmission rates within one year after surgery of 18.3% for THA patients and 15.5% for TKA patients. The most common reasons for a readmission include a complication of the internal orthopaedic device, a complication of the procedure, and the need for other medical care. (Bohm et al. 2012). In their retrospective study, Futoma et al. (2015) analyse approx. 3.3 million episodes to the New Zealand hospitals from 2006 to 2012. In total 19.0% of episodes are followed by a readmission within 30 days whereas, THA/TKA episodes show an 8.7% readmission rate. For each of 280 DRGs 5 predictive models are created and assessed. The risk of readmission after THA/TKA is predicted with a power of 0.629 by the penalised Logistic Regression model and 0.638 by the Artificial Neural Network model (Futoma et al. 2015).

2.3 Readmissions after THA/TKA procedures

While research on the development of predictive models after THA/TKA procedures is still scarce, existing explanatory models can be used to derive relevant attributes that influence the readmission risk. For this purpose, studies on readmissions after THA/TKA are identified and analysed, resulting in a list of influencing attributes depicted in Table 2.

Studies[1]	**Considered variables**	**Availability in data set**
1, 2, 3, 6, 7, 8, 11, 12, 13	age	age
1, 3, 4, 6, 7, 8, 11	los	los
1, 3, 7, 10, 11	discharge type	discharge_intention
1, 3, 5, 6, 7, 8, 9, 12, 13	BMI / Obesity	BMI
1, 13	ASA score	**Not available**
2, 3, 7, 11, 13	sex	gender
3, 4, 8	heart disease	*Constructed from diagnosis codes*
3	renal failure	*Constructed from diagnosis codes*
3, 7	mental illness	*Constructed from diagnosis codes*
3	Anemia	*Constructed from diagnosis codes*
3, 7, 9	Pulmonary disease	*Constructed from diagnosis codes*
3, 8	Medicare	**Not available**
3, 9	Transfusion	blood_transfusion
3, 4	Drug/Alcohol abuse	*Constructed from diagnosis codes*
3	Secondary tumor	*Constructed from diagnosis codes*
3, 4, 8, 9	Diabetes	*Constructed from diagnosis codes*
3	Resident region	lga_code
3	Lymphoma	*Constructed from diagnosis codes*
3	CCI	*Constructed from diagnosis codes*
3	hospital ownership	**Not-for profit / private**
3,7	race	**Not available**
3,6	high volume surgeon	**Not available**
3, 6	high volume hospital	**Not available**
4, 7	hypothyroidism	*Constructed from diagnosis codes*
7	medical complications	*Constructed from diagnosis codes*
8, 13	medication	*Constructed from drug codes*
9, 13	bleeding disorder	*Constructed from diagnosis codes*

Table 2: Influencing factors for readmissions after THA/TKA procedures

The methods and results from related studies play a major role in understanding readmission prediction using different classification algorithms and relevant attributes in that context. Hence, valuable insights are incorporated in the development of this study's predictive models.

3 Data Analysis

3.1 Data Preparation

The analysed data set includes all admitted patient episodes from the Australian case hospital campus from January 1st, 2011 until December 31st, 2015 comprising 530 attributes for 645.370 episodes. The attributes include clinical data such as diagnoses and procedures, demographic information such as patient age and gender, and laboratory data, such as blood results.

For this study, the dataset is filtered for patients that underwent a THA or TKA procedure. Hence, the dataset is filtered by procedure codes according to the Australian Classification of Health Interventions (ACHI) resulting in 5.034 THA episodes and 5.051 TKA episodes. Additionally, patients that died in the hospital or after discharge, as well as rehabilitation episodes are filtered from the dataset. With 10,057 episodes in total, TKA and THA procedures represent around 1.6 % of all episodes in the dataset. The resulting dataset represents the index admissions, there is no indication, however, whether an episode

[1] Studies: 1) Bernatz and Anderson 2015 2) Bohm et al. 2012 3) Kurtz et al. 2016a, 2016b 4) Schairer et al. (2014) 5) White et al. 2000 6) Clement et al. (2013) 7) Paxton et al. (2015) 8) Saucedo et al. (2014) 9) Mednick et al. (2014) 10) Bini et al. (2010) 11) Zmistowski et al. (2013) 12) Huddleston et al. (2012) 13) Pugely et al. (2013)

led to a readmission within 28 days after discharge, but only if an episode itself characterises as a readmission. Thus, a new attribute is created to indicate if a readmission occurred within 28 days after discharge from a THA or TKA episode. For each patient with a THA or TKA procedure, the dataset is filtered for a following acute admission within 28 days. From a data perspective, it is not possible to comprehend whether a readmission is clinically related to its index admission or whether it was avoidable or not. From the initial 10,057 index admissions, 227 led to a readmission within 28 days, i.e. 2.3% of all THA/TKA procedures. This results in a highly imbalanced class distribution that has to be addressed in the model development phase.

To be able to benchmark the model against the HOSPITAL score, the following additional attributes are created based on other variables in the dataset to determine the HOSPITAL score for each THA/TKA episode:

- Low haemoglobin (binominal; true/false)
- Visited Oncology (binominal; true/false)
- Low sodium (binominal; true/false)
- Had a procedure (binominal; true/false)
- Urgent admission (binominal; true/false)
- Number of previous admissions in the last year (numeric)
- Length of stay > 5 days (binominal; true/false)

These attributes are then used to calculate the HOSPITAL score for each episode. Low haemoglobin, low sodium, an urgent admission, and having a procedure during a stay each account for 1 point in the HOSPITAL score. A discharge from oncology as well as a length of stay over five days accounts for 2 points. The number of admissions is separated into three categories with 0-1 admissions, 2-5 admissions and over five admissions with 0, 2, and 5 points respectively (Donzé et al. 2013).

3.2 Feature Selection

From the available 530 attributes, a subset has to be identified containing only data available at the time of prediction (i.e., before patient discharge). In this step, 69 attributes are removed that are collected after patient discharge, e.g., DRG codes or administrative discharge information. Next, attributes contributing low or now information are identified by calculating the variance of each variable. Attributes with a variance lower than 0.02 are excluded from the dataset, resulting in 192 attributes. Next, relevant attributes from previous research are compared to the available data set and additional attributes are constructed. Based on the insights from the systematic review by Kansagara et al. (2011), the attributes used in the general readmission models, as well as variables identified in explanatory readmission models from THA/TKA studies (cf. Table 2), the following attributes displayed in Table 3 are selected for the final dataset.

	Variables	***Type [Range]***	***K***	***H***	***L***	***L+***	***O***
Socio-demo-graphic	Age	Numeric [15 – 101]	x			x	x
	Gender	Binominal [m / f]	x			x	x
	Resident region	Nominal					x
Social determinants of health	Employment status	Nominal					x
	Marital status / No. of people in home	Nominal					x
	Caregiver availability	Nominal					x
	Discharge type	Nominal	x				x
Use of medical services	Length of stay	Numeric		x	x	x	x
	ED use	Numeric [0 – 4]	x		x	x	
	Number of admissions in past year	Numeric [0 – 24]	x		x	x	
	Blood usage	Binominal [y / n]					x
	Urgent admission	Binominal [y / n]		x	x	x	
	Medication	Nominal					x
	Procedure	Binominal [y / n]		x			
	Discharge from oncology	Binominal [y / n]		x			
	Length of stay > 5	Binominal [y / n]		x			

Diagnoses or comorbidities (K)	Visual or hearing impairment	Binominal [y / n]		x
	Lymphoma	Binominal [y / n]		x
	Hypothyroidism	Binominal [y / n]		x
	Bleeding disorder	Binominal [y / n]		x
	Heart disease	Binominal [y / n]		x
	Renal failure	Binominal [y / n]		x
	Anemia	Binominal [y / n]		x
	Pulmonary disease	Binominal [y / n]		x
	Secondary tumor	Binominal [y / n]		x
	Cognitive impairment	Binominal [y / n]		x
	Alcohol use	Binominal [y / n]	x	x
	Tobacco use	Binominal [y / n]	x	x
	Drug use	Binominal [y / n]	x	x
	Mental illness	Binominal [y / n]	x	x
	Type 2 Diabetes	Binominal [y / n]	x	x
	BMI	Numerical		x
	Low sodium	Binominal [y / n]	x	
	Low haemoglobin	Binominal [y / n]	x	
	Adverse events	Binominal [y / n]	x	
	Incident Severity Rating	Numeric [1 – 4]	x	
	Falls	Binominal [y / n]	x	
	Return to theatre	Binominal [y / n]	x	

Table 3: Attributes of the final dataset

In contrast to other studies, Diagnosis-related group (DRG) codes are not included in the dataset, as these values are not available before patient discharge. Furthermore, information, whether a patient had a procedure or visited oncology as included in the HOSPITAL score, are excluded in this dataset as it is not relevant for this diagnosis group.

The final dataset contains 39 attributes for 10,057 THA/TKA episodes from 9,187 patients. The dataset shows slightly more female patients (58.1%) than male patients (41.9%), the age ranges from 15 to 101, with a mean of 67.63 years.

3.3 Model Development

Based on the results of related studies in this field, this paper focuses on the most commonly used models identified in the related work section that show good results in predicting patients at risk of readmission. Thus, Logistic Regression (LR), Naïve Bayes (NB), k-Nearest Neighbour (kNN), Decision Trees (DT), Random Forest (RF), Artificial Neural Networks (ANN), and Support Vector Machines (SVM) are used.

This study utilises RapidMiner Studio to build and evaluate the models. This predictive analytics platform offers various classification and regression algorithms, evaluation metrics and visualisations. For each approach, the dataset of 10,057 index admissions is fed into a RapidMiner process. Within each process, an optimisation task is performed, to identify the best parameter settings for each algorithm. For this purpose, RapidMiner's (2014) nested operator "Optimize" is selected to evaluate various parameter combinations. Although building and assessing models are iterative tasks, this section provides the final parameter configuration after several iterations. Each parameter combination is evaluated based on the prediction power the resulting model can achieve. The best parameter configuration for each model is presented in the following paragraph.

3.4 Model Evaluation

Each model is tested using a ten-fold cross validation. The overall model accuracy, precision and recall for true readmissions as well as the AUC are used to compare and assess the predictive performance of each model. The evaluation metrics illustrate how many readmission examples ("yes") and non-readmission examples ("no") are predicted correctly based on the dataset under study. In contrast, the AUC indicates how good a model performs overall. The higher the AUC, the better the model's performance. Table 3 shows the evaluation metrics for each prediction model.

	LR	NB	kNN	DT	RF	SVM	ANN
Accuracy	97.54%	64.22%	97.74%	98.16%	97.74%	94.92%	97.98%
Precision	41.74%	3.58%	/	83.87%	/	17.83%	66.87%
Recall	24.19%	56.83%	0%	22.9%	0%	30.37%	21.13%
AUC	0.736	0.674	0.635	0.935	0.667	0.733	0.694

Table 4: Evaluation metrics for the tested prediction models

To benchmark the presented model to the HOSPITAL score, each patient is assigned to a risk category according to their score. Table 5 shows how many episodes are categorised in each risk group and how many readmissions can be observed within these groups. Equating episodes in the "high risk" group to the true "led_to_readmission" from the dataset, the predictions from the "high risk" group show a recall for true readmissions of 23%. On the other hand, "low risk" patients shot a class recall for "no readmissions" of 98.1 %. The interpretation of "medium risk" patients suggest a low tendency for these patients to be readmitted. Compared to the results of this study, it can be concluded that the HOSPITAL score is a poor tool to quantify the risk of readmission after orthopaedic surgery.

	Led to readmission (yes)	Led to readmission (no)	Total
Pred. high	5 (13.51 %)	32 (86.49 %)	37
Pred. medium	41 (7.5 %)	503 (92.5 %)	544
Pred. low	181 (1.9 %)	9,295 (98.1 %)	9,517
Total	227 (2.3 %)	9,830 (97.7 %)	10,057

Table 5: Readmission results of HOSPITAL score

4 Discussion and Conclusion

Although identifying patients at high risk of readmission is a complex endeavour, this study gives suggestions how the detection of patients after THA/TKA procedures at high risk of readmission can be improved and which prediction algorithms are most suitable for this task. This study analysed 38 relevant attributes to identify patients at high risk of readmission after THA and TKA procedures considering patients' sociodemographic information and their medical services history. While some attributes could be collected directly, others had to be derived or computed from a patient's admission history. Furthermore, since information on complications is only present in rehabilitation episodes, it is recommended to collect these data points also for each acute admissions. Seven different predictive models are developed and assessed throughout this study, performing with AUC scores between 0.635 to 0.935. While DT, LR and SVM show a higher overall prediction performance, the comparison of recall measures determines NB as the best model to identify as many high-risk patients as possible. In addition, DT results can be interpreted and easily understood as they provide a visual representation of the model. Depending on the goal of the prediction model, different models might be preferrable, either accepting a higher false-positive rate (LR) or a lower true-positive rate (LR, DT, SVM). Finally, the HOSPITAL score turned out to be only partially suitable for THA/TKA procedures. Adaptions to this score are needed to incorporate it to the orthopaedics discipline.

Several limitations of this study have to be mentioned. First, predictive models developed in this work are based on data extracted retrospectively from a single private hospital group comprising multiple campuses in Victoria, Australia. Second, due to a lot of missing values, many features had to be excluded and could not be used to train the predictive models. Thus, promising features like a patient's body-mass-index could not be harnessed. Next, a financial evaluation of potential costs or savings associated with the (mis-)classification of patients at high risk of readmission (false positive prediction) should be assessed. Finally, benchmarks with other prediction models, such as the LACE or LACE+ index should be considered in future studies. For this purpose, the Charlson Comorbidity Index has to be computed from the available co-morbidities.

The implications of this study are relevant for both research and practice. Considering the quality of care and regulatory penalties, the importance of identifying patients at high risk of readmission is apparent. Improved post-discharge care and support for self-care can help to abate potential readmissions of identified individuals, thereby reducing overall costs and increasing healthcare quality (Shulan et al. 2013). Thus, by aiding the identification of potential risk patients, hospital resources can be better allocated to critical patients, and health interventions are already possible in an early stage of the patient pathway. From a research perspective, the identification and evaluation of various risk factors and the performance of several prediction models for THA/TKA patients can support future research endeavours in this field. Nevertheless, identifying high-risk candidates is a challenging task due to the broad variety of factors that influence patient care outcome. Several studies have failed to create predictive models with a satisfying discrimination power (Kansagara et al., 2011) that require additional research and the use of more complex patterns in the future.

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