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Prediction of Early Adverse Events After THA: A Comparison of Different Machine-Learning Strategies Based on 262,356 Observations From the Nordic Arthroplasty Register Association (NARA) Dataset

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Objective. Preoperative risk prediction models can support shared decision-making before total hip arthroplasties (THAs). Here, we compare different machine-learning (ML) approaches to predict the six-month risk of adverse events following primary THA to obtain accurate yet simple-to-use risk prediction models.

Methods. We extracted data on primary THAs (N = 262,356) between 2010 and 2018 from the Nordic Arthroplasty Register Association dataset. We benchmarked a variety of ML algorithms in terms of the area under the receiver operating characteristic curve (AUROC) for predicting the risk of revision caused by periprosthetic joint infection (PJI), dislocation or periprosthetic fracture (PPF), and death. All models were internally validated against a randomly selected test cohort (one-third of the data) that was not used for training the models.

Results. The incidences of revisions because of PJI, dislocation, and PPF were 0.8%, 0.4%, and 0.3%, respectively, and the incidence of death was 1.2%. Overall, Lasso regression with stable iterative variable selection (SIVS) produced models using only four to five input variables but with AUROC comparable to more complex models using all 32 variables available. The SIVS-based Lasso models based on age, sex, preoperative diagnosis, bearing couple, fixation, and surgical approach predicted the risk of revisions caused by PJI, dislocations, and PPF, as well as death, with AUROCs of 0.61, 0.67, 0.76, and 0.86, respectively.

Conclusion. Our study demonstrates that satisfactory predictive potential for adverse events following THA can be reached with parsimonious modeling strategies. The SIVS-based Lasso models may serve as simple-to-use tools for clinical risk assessment in the future.

INTRODUCTION

Although primary total hip arthroplasty (THA) is a safe and efficient intervention, early adverse events, such as revision and death, occur. Approximately 2% to 3% of primary THAs are revised within the first postoperative year, with dislocation (12%–33%), periprosthetic joint infection (PJI; 11%–23%), and periprosthetic fracture (PPF; 5%–18%) being the most frequently

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registered reasons.[1–4] Furthermore, despite the constantly reducing rates, postoperative mortality remains a recognized complication, especially among older adult patients.[5] Recently, incidence rates of approximately 0.9% to 1.2% have been reported at 1 year after the primary THA.[4,6,7]

With an aging and increasingly obese population, the incidence of primary THAs is expected to increase by up to 200% by 2030.[8–10] Simultaneously, primary THAs are increasingly being performed among more obese patients with more comorbidities who are also known to be at elevated risk of short-term complications.[1,11,12] Consequently, based on the recent trends, increases of 31% to 70% in the volumes of revision THA have been estimated in the United States, England, and Wales by 2030.[13,14] Overall, the estimated increases in both primary and revision THAs impose a substantial challenge to health care systems worldwide, and novel strategies for optimizing treatment outcomes and avoiding unnecessary complications are needed.

To alleviate the revision burden and minimize any unnecessary risks, directing the right type of treatment to the right individual and identifying high-risk patients requiring more intensive follow-up play a central role. To preoperatively evaluate the risk of revision and death following primary THA, several multivariable risk prediction models have been introduced.[15–20] Although the issue is global, these models have typically been developed and internally validated using data from a single arthroplasty register. Furthermore, the majority of the presented models rely on conventional regression modeling strategies[16] that might be outperformed by machine-learning (ML)–based approaches, especially when the event of interest is rare.[21] However, to achieve improved performance, ML methods require typically much more data than the conventional approaches,[22] and, hence, the best results are expected to be achieved when the amount of data, in terms of both the number of cases as well as variables included, is scaled up as high as possible.

In the present study, we applied a range of well-established ML algorithms with varying complexity to the Nordic Arthroplasty Register Association (NARA) dataset, a unified representation of the national hip arthroplasty registries of Sweden, Norway, Denmark, and Finland, to compare different modeling strategies for predicting the risk of the most common revision outcomes and death following primary THA. With the use of multinational data, we aimed at developing generalizable models that could be easily applied to evaluate preoperative risk estimates for an individual patient based on typical patient characteristics and planned surgical parameters in any modern health care setting.

PATIENTS AND METHODS

Study population. Initially, all primary THAs registered in the NARA dataset between 1995 and 2018 were extracted for analysis. The dataset consists of pooled data from the national hip arthroplasty registries of Sweden, Norway, Denmark, and Finland and has been described in more detail previously.[23,24] Ethical approval for the register-based study was granted by the appointed authority in each participating country: the Swedish Ethical Review Authority (1184-18/2019-00812), the Finnish National Institute of Health and Welfare (Dnro THL/1743/5.05.00/2014), the Norwegian Data Inspectorate (ref 24.1.2017: 16/01622-3/CDG), and the Danish Data protection agency (1-16-02-54-17).

The initial dataset consisted of 848,787 primary hip arthroplasties. Because of several changes in clinical practice regarding the use of implant materials, femoral head size, and fixation, we restricted our analyses to primary THAs performed since 2010, representing the most current clinical practice (Figure 1).

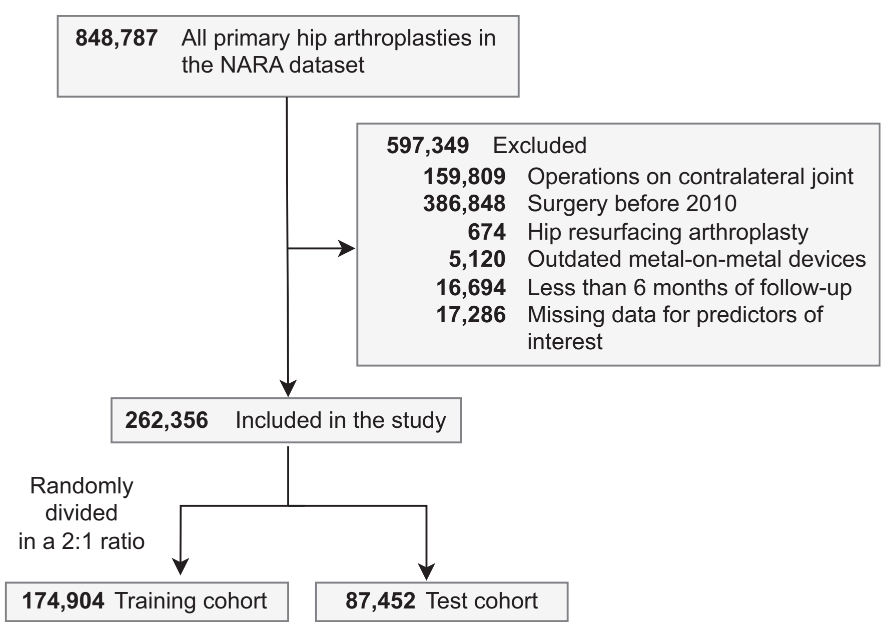

Figure 1. Selection of patients into the study. NARA, Nordic Arthroplasty Register Association.

Furthermore, we retained only primary THAs that had a minimum follow-up time of at least 6 months to exclude operations performed close to the last available date in the dataset for which the occurrence of primary outcomes could not be verified. To prevent dependent observations after bilateral arthroplasty, we included only the first operation reported for each patient. Finally, because some ML algorithms required the use of complete data, we included only patients with complete information for all candidate predictors to enable direct comparison of the predictions obtained using different methods. Because only 6% of the patients were excluded because of missing data, the excluded data points were assumed to be missing completely at random and not induce any bias in the present analyses.[25,26] Overall, this left us with a total of 262,356 primary THAs. Finally, the data were divided in a 2:1 ratio into separate training (random sample of 67% of the population, n = 174,904) and test (random sample of 33% of the population, n = 87,452) cohorts, used for developing and internally validating the models, respectively.

Study outcomes and candidate predictors. For each primary operation, we considered as our main outcomes of interest the first revision surgical procedure owing to the three most common reasons, PJI, dislocation or PPF, and death, during the first 6 postoperative months. During modeling, each of these outcomes was treated as a separate binary outcome for which specific risk prediction models were developed. Other reasons for revision were not considered for risk prediction modeling. In all countries, revision procedure was defined as a surgical procedure including the exchange or removal of any component(s). The candidate predictors considered for risk prediction models included previously identified risk factors for adverse events following THA. The considered patient characteristics included age,[19,27] sex,[19,28] simultaneous bilateral operation,[29] and primary diagnosis,[19,28,30] whereas surgical characteristics included fixation type,[31] the use of trochanteric osteotomy,[32] surgical approach (posterior or nonposterior, including anterior, anterolateral, and others),[19,28,30] bearing couple (recoded based on the combination of cup and caput materials),[29,33] the diameter of the femoral head,[19,28] and the presence of hydroxyapatite coating on the cup or stem.[34] The candidate predictors and other baseline information have been summarized in more detail in Table 1.

Model development and statistical analysis. Optimally, a prediction model suitable for clinical use should be both accurate and easy to use, using only data that are essential for the predictions. To identify the best modeling approach for each prediction task, we applied a range of ML algorithms to the primary THA data in the training cohort, namely logistic regression, classification tree modeling, random forest (RF), gradient-boosting machines (GBMs), penalized logistic regression with both Lasso penalty (Lasso regression) and Ridge penalty (Ridge regression), naive Bayes, and neural networks, which are among the most common and popular methods used widely for binary classification in various application areas.[35] Among the applied models, logistic regression is considered as the most conventional approach and can be used as a reference for the other ML algorithms. Here, the logistic regression models were trained using all candidate predictors without any additional variable selection. Finally, we also applied Lasso regression in combination with the stable iterative variable selection (SIVS) procedure previously suggested as an efficient method for developing simple-to-use risk prediction models with fewer variables but retaining the same discrimination performance as the more complex models.[19,36,37] The discrimination performances of the ML models were evaluated in the test cohort in terms of the area under the receiver operating characteristic curve (AUROC). For approximating model complexity, we determined the number of nonzero regression coefficients or variables and model-generated intervariable interactions with nonzero influence in top-performing algorithms. The calibration of predicted risks, that is, the agreement between the observed outcomes and predictions, was evaluated by grouping individuals by deciles of the predicted risk. Further information on the applied ML methods, their hyperparameters, and used software packages can be found in the Supplementary Material.

All statistical analyses and mathematical modeling were conducted using R statistical computing environment version 4.0.3 (R Core Team, 2016. R Foundation for Statistical Computing, Vienna, Austria. URL https://www.R-project.org/). In addition to method-specific packages reported in the Supplementary Material (Supplementary Table S1), R packages *ggplot2*,[38] and *pROC*[39] were used for the visualization of results and evaluation of AUROC values, respectively. Comparisons between the characteristics of training and test cohorts were performed using the Mann-Whitney test for continuous variables and the chi-squared test for categorical variables. The level of significance in all statistical comparisons was set at $P < 0.05$.

RESULTS

Characteristics of the study population. The patients in the study cohort were, on average, aged 68 years, were typically female (59%), and had their hips operated for primary osteoarthritis (79%), mostly using uncemented fixation (42%) (Table 1). No statistically significant differences were observed between the characteristics of the training and test cohorts. Of the 262,356 hips included, within 6 months, 2,074 (0.8%) were revised because of PJI, 1,104 (0.4%) because of dislocation, and 759 (0.3%) because of PPF (Table 2). Other reasons for revision were registered for 756 (0.3%) hips. A total of 3,144 (1.2%) deaths occurred during the first 6 postoperative months.

Table 1. Patient and procedure characteristics for the included operations in the training and test cohorts. All other variables except for country and laterality were considered during predictive modeling*

Characteristics	Training cohort (n = 174,904)	Test cohort (n = 87,452)
Country, n (%)		
Denmark	39,715 (22.7)	19,653 (22.5)
Norway	30,335 (17.4)	15,229 (17.4)
Sweden	73,003 (41.7)	36,558 (41.8)
Finland	31,851 (18.2)	16,012 (18.3)
Age, mean (SD), y	68.1 (11.1)	68.1 (11.0)
Sex, n (%)		
Female	102,199 (58.4)	51,406 (58.8)
Male	72,705 (41.6)	36,046 (41.2)
Laterality, n (%)		
Right	98,995 (56.6)	49,635 (56.8)
Left	75,909 (43.4)	37,817 (43.2)
Simultaneous bilateral operation, n (%)		
No	173,455 (99.2)	86,723 (99.2)
Yes	1,449 (0.8)	729 (0.8)
Preoperative diagnosis, n (%)		
Primary osteoarthritis	138,661 (79.3)	69,331 (79.3)
Hip fracture	19,146 (10.9)	9,515 (10.9)
Nontraumatic femoral head necrosis	3,988 (2.3)	2,109 (2.4)
Rheumatoid arthritis	1,752 (1.0)	900 (1.0)
Ankylosing spondylitis	175 (0.1)	81 (0.1)
Developmental dysplasia of the hip	5,209 (3.0)	2,524 (2.9)
Slipped capital femoral epiphysis	206 (0.1)	84 (0.1)
Perthes disease	649 (0.4)	283 (0.3)
Combination of slipped capital femoral epiphysis and Perthes disease	78 (<0.1)	34 (<0.1)
Other inflammatory	495 (0.3)	227 (0.3)
Others	4,545 (2.6)	2,364 (2.7)
Fixation, n (%)		
Cemented	63,801 (36.5)	31,840 (36.4)
Hybrid	16,990 (9.7)	8,577 (9.8)
Inverse hybrid	20,423 (11.7)	10,323 (11.8)
Uncemented	73,690 (42.1)	36,712 (42.0)
Surgical approach, n (%)		
Anterior, anterolateral and others	77,873 (44.5)	38,779 (44.3)
Posterior	97,031 (55.5)	48,673 (55.7)
Bearing couple, n (%)		
CoC	9,030 (5.2)	4,372 (5.0)
CoX	26,723 (15.3)	13,570 (15.5)
CoP	3,688 (2.1)	1,943 (2.2)
MoP	25,475 (14.6)	12,666 (14.5)
MoX	108,615 (62.1)	54,247 (62.0)
Other	1,373 (0.7)	654 (0.8)
Hydroxyapatite coating (cup), n (%)		
No	146,844 (84.0)	73,633 (85.5)
Yes	28,060 (16.0)	13,819 (14.5)
Hydroxyapatite coating (stem), n (%)		
No	107,777 (61.6)	53,622 (61.3)
Yes	67,127 (38.4)	33,830 (38.7)
Caput size, n (%)		
22 mm	1,120 (0.6)	521 (0.6)
28 mm	31,712 (18.1)	16,127 (18.4)
32 mm	85,458 (48.9)	42,651 (48.8)
36 mm	54,543 (31.2)	27,160 (31.1)
>36 mm	1,991 (1.1)	968 (1.1)
Other	80 (0.1)	25 (<0.1)
Trochanteric osteotomy, n (%)		
No	174,582 (99.8)	87,269 (99.8)
Yes	322 (0.2)	183 (0.2)

(Continued)

Table 1. (*Cont'd*)

*CoC, ceramics on ceramics; CoP, ceramics on conventional (noncrosslinked) polyethylene; CoX, ceramics on polyethylene crosslink; MoP, metal on conventional (noncrosslinked) polyethylene; MoX, metal on polyethylene crosslink.

Comparison of the ML methods. Overall, GBM was the best-performing ML algorithm with AUROCs of 0.61 (95% confidence interval [CI] 0.59–0.63), 0.68 (95% CI 0.65–0.70), and 0.77 (95% CI 0.74–0.79) for revisions caused by PJI, dislocation, and PPF, respectively, as well as with an AUROC of 0.87 (95% CI 0.86–0.88) for death (Table 3). However, in terms of AUROCs, there were no substantial differences among the six top-performing models, including GBM, conventional logistic regression, Lasso regression, Ridge regression, Lasso regression with SIVS, and RF. Compared with GBM, the largest difference among these was a lower AUROC of RF (AUROC 0.85, 95% CI 0.84–0.86) for predicting death.

Among the top-performing models, Lasso regression with SIVS was able to produce models with the least complexity but with similar accuracy as the more complex models (Figure 2A). In total, the SIVS-based model for PJI included only four (13%) variables and models for dislocation, PPF, and death, only five (16%) variables each of the available 32 with nonzero influence on risk predictions. Among all input data, Lasso with SIVS identified age, sex, preoperative diagnosis, bearing couple, fixation, and surgical approach as the minimum set of variables sufficient for accurate risk predictions (Figure 2B). In contrast, all the competing methods used nearly all 11 available variable types and associated information to reach similar AUROCs. In all comparisons, logistic regression, conventional Lasso regression, and Ridge regression had virtually the same performance and variables. Because of the good performance with the minimum number of input variables, SIVS-based Lasso models were considered for further evaluation as practical risk prediction models.

Simple-to-use risk prediction models obtained using Lasso regression with SIVS. The variables and regression coefficients obtained for each outcome using Lasso regression with SIVS are summarized with example risk calculations in Table 4. Additional details on using the regression

Table 2. The rates of short-term revision outcomes and death following primary total hip arthroplasty in the study population

Outcome	All patients (N = 262,356)	Training cohort (n = 174,904)	Test cohort (n = 87,452)
Revision procedure, n (%)	4,767 (1.8)	3,133 (1.8)	1,634 (1.9)
Periprosthetic joint infection	2,074 (0.8)	1,373 (0.8)	701 (0.8)
Dislocation	1,104 (0.4)	696 (0.4)	408 (0.5)
Periprosthetic fracture	759 (0.3)	504 (0.3)	255 (0.3)
Aseptic loosening	298 (0.1)	202 (0.1)	96 (0.1)
Other	458 (0.2)	304 (0.2)	154 (0.2)
Reason missing	74 (<0.1)	54 (<0.1)	20 (<0.1)
Death, n (%)	3,144 (1.2)	2,091 (1.2)	1,053 (1.2)

Table 3. Discrimination performance of the applied machine-learning methods in terms of the AUROC in the independent test cohort*

Method	Periprosthetic joint infection AUROC (95% CI)	Dislocation AUROC (95% CI)	Periprosthetic fracture AUROC (95% CI)	Death AUROC (95% CI)
Gradient-boosting machines	0.61 (0.59–0.63)	0.68 (0.65–0.70)	0.77 (0.74–0.79)	0.87 (0.86–0.88)
Lasso regression	0.61 (0.59–0.63)	0.67 (0.64–0.69)	0.76 (0.73–0.79)	0.87 (0.85–0.88)
Lasso regression with SIVS	0.61 (0.59–0.63)	0.67 (0.64–0.69)	0.76 (0.73–0.78)	0.86 (0.85–0.87)
Logistic regression	0.61 (0.59–0.63)	0.67 (0.64–0.69)	0.76 (0.73–0.78)	0.87 (0.85–0.88)
Ridge regression	0.61 (0.59–0.63)	0.67 (0.64–0.69)	0.75 (0.73–0.78)	0.87 (0.85–0.88)
Random forest	0.61 (0.59–0.63)	0.68 (0.65–0.70)	0.77 (0.74–0.79)	0.85 (0.84–0.86)
Neural network	0.61 (0.59–0.63)	0.66 (0.64–0.69)	0.75 (0.72–0.78)	0.86 (0.85–0.87)
Naive Bayes	0.59 (0.57–0.61)	0.66 (0.64–0.69)	0.72 (0.70–0.75)	0.85 (0.83–0.86)
Classification tree	0.60 (0.58–0.62)	0.55 (0.53–0.57)	0.74 (0.71–0.76)	0.85 (0.84–0.86)

*AUROC, area under receiver operating characteristic curve; CI, confidence interval; SIVS, stable iterative variable selection.

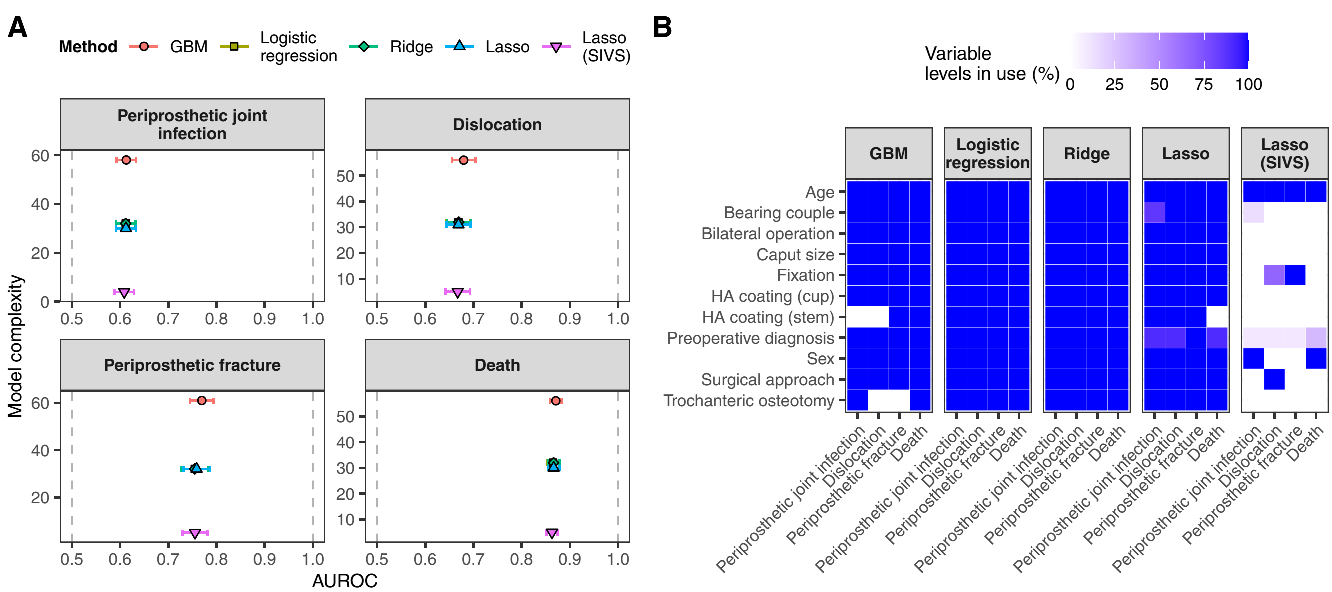

Figure 2. Evaluation of the variables used by the top-performing models. (A) The complexity of the models in terms of the number of regression coefficients or variables and intervariable interactions (specifically in GBMs) with nonzero influence on model predictions versus discrimination performance in terms of AUROC in the test cohort. Horizontal lines indicate 95% confidence intervals. Ridge regression, conventional Lasso regression, and logistic regression had nearly identical performance. (B) Summary of the variables with nonzero influence identified by different modeling approaches. The color indicates the fraction of variable levels with nonzero influence in the final models. AUROC, area under the receiver operating characteristic curve; GBM, gradient-boosting machine; HA, hydroxyapatite; SIVS, stable iterative variable selection.

Table 4. Regression coefficients[a] in the Lasso models built using stable iterative variable selection procedure*

Variable	Regression coefficient (β) for model			
	PJI	Dislocation	PPF	Death
Age (per 10 years)	0.132	0.164	0.353	0.802
Sex				
Female	–	–	–	–
Male	0.496	–	–	0.502
Preoperative diagnosis				
Primary osteoarthritis	–	–	–	–
Hip fracture	0.389	0.980	0.583	2.265
Nontraumatic femoral head necrosis	–	–	–	1.281
Rheumatoid arthritis	–	–	–	–
Others	–	–	–	2.777
Fixation				
Uncemented	–	0.801	2.606	–
Cemented	–	–	–	–
Hybrid	–	0.775	0.890	–
Inverse hybrid	–	–	2.039	–
Bearing				
MoX	–	–	–	–
MoP	–	–	–	–
CoX	–	–	–	–
CoC	−0.542	–	–	–
CoP	–	–	–	–
Other	–	–	–	–
Surgical approach				
Anterior, anterolateral, and others	–	–	–	–
Posterior	–	0.355	–	–
Example calculations[b]				
Raw patient score (sum of patient value × β coefficient)	1.379	2.565	3.231	8.280
Intercept	−6.013	−7.501	−10.214	−11.345
Transformed score = $\frac{1}{1+\exp(-(\mathit{Intercept}+\mathit{Raw\ score}))}$	0.010 or 1.0%	0.007 or 0.7%	0.001 or 0.1%	0.045 or 4.5%

*CoC, ceramics on ceramics; CoP, ceramics on conventional (noncrosslinked) polyethylene; CoX, ceramics on polyethylene crosslink; MoP, metal on conventional (noncrosslinked) polyethylene; MoX, metal on polyethylene crosslink; PJI, periprosthetic joint infection; PPF, periprosthetic fracture.

[a]The beta coefficients indicate the impact of one-unit change in a predictor variable, given in parentheses, on the response variable when the other predictors are held constant. A positive coefficient indicates risk-increasing effect and negative risk-decreasing effect. Fields without a numerical value indicate that the specific variable is not needed for predicting the risk of the designated outcome (ie, regression coefficient equals zero) and, therefore, for categorical variables, functions as a reference group.

[b]Example calculations of the average estimates of risk are given for 75-year-old female patients with hip fracture diagnosis and no simultaneous bilateral operation who are having a cemented total hip arthroplasty surgery performed using the posterior approach (no trochanteric osteotomy) and with implant components having a metal on polyethylene bearing surface, 36-mm femoral head size, and no hydroxyapatite coating on the cup. More details on the calculations and additional examples (Supplementary Tables S2-S5) can be found in the Supplementary Material.

coefficients for risk prediction and further examples (Supplementary Tables S2-S5) can be found in the Supplementary Material. For PJI, the model identified advanced age, male sex, and a preoperative diagnosis of hip fracture as risk factors, whereas ceramic-on-ceramic bearings decreased the risk compared with other bearing types. For dislocation, advanced age, a preoperative diagnosis of hip fracture, uncemented and hybrid fixations, and posterior approach were identified as risk factors. For PPF, the identified risk factors were advanced age; a preoperative diagnosis of hip fracture; and the use of uncemented, hybrid, or inverse hybrid fixations. For death, advanced age; male sex; and a preoperative diagnosis of hip fracture, nontraumatic femoral head necrosis, or other unspecified diagnosis were identified as key risk factors. All risk predictions made using the simple-to-use SIVS-based models were in good agreement with the observed outcome rates and showed no signs of substantial overfitting or underfitting (Supplementary Figure S1).

DISCUSSION

In the present study, we compared a range of ML algorithms to identify the best modeling approach for predicting the risk of the most common short-term revision outcomes (ie, PJI, dislocation, and PPF) as well as death within 6 months from the primary THA, based on the NARA dataset. We observed that there was little difference in the obtained AUROCs between the applied methods and that the complexity and number of required variables in risk prediction models can be greatly reduced with minimal loss in prediction accuracy. Finally, by using Lasso regression with SIVS, the modeling strategy requiring the fewest input variables, we developed simple-to-use preoperative risk prediction models that may assist in preoperative estimations of the expected levels of risks and clinical decision-making in the future.

A key finding in our study was that, despite the large amounts of operations in THA register data, accurate predictions can be obtained even with simpler modeling strategies. Similar benefits of Lasso regression in the reduction of input variables have also been reported before,[40] but here the Lasso regression accompanied with the SIVS procedure produced substantially simpler models without any reductions in prediction accuracy compared with the conventional Lasso. This implies that with careful variable selection, the most essential relationships with each outcome of interest can be captured with simple linear relationships and that models for revisions and death following THA based on registry data do not necessarily benefit from more sophisticated approaches involving modeling of deep intervariable interactions and complex nonlinear relationships. This observation is identical to our previous studies using the same approach in other prediction tasks.[36,37] The use of simpler modeling strategies is also more practical because the models can be applied using simple risk equations without dedicated computer software. Finally, the effect of each risk factor and the obtained results are also easier to interpret, helping to communicate the expectations of the operation with the patient.

Overall, the model for death within the first 6 postoperative months reached the highest discrimination performance and was comparable to the excellent performance observed in our previous risk prediction study using the Finnish Arthroplasty Register (FAR).[19] The Lasso regression with SIVS identified advanced age, male sex, preoperative hip fracture, nontraumatic femoral head necrosis, or other unspecified preoperative diagnosis as the most important variables increasing the risk of death. Similar findings concerning intuitive or well-established risk factors, such as advanced age,[27,41] male sex,[27,42] and hip fracture,[43] have thorough previous documentation.

In contrast to our previous study,[19] the model for revisions owing to PPF reached substantially better performance (NARA AUROC 0.76 vs FAR AUROC 0.65). Although the revision rates were quite similar between the two studies (0.3% vs 0.5%), the current dataset contained approximately 10 times more operations, including more cases with cemented stems, potentially explaining the improvement, because the ML algorithms had substantially more material for training the models. Again, the Lasso regression with SIVS also identified risk factors associated with revisions caused by PPF before, including advanced age; preoperative diagnosis of hip fracture; and the use of uncemented, hybrid, and inverse hybrid fixations.[31,44–46]

The model predicting the risk of dislocation reached similar moderate performance as in our previous study (NARA AUROC 0.67 vs FAR AUROC 0.65)[19] and consisted of several known risk factors, such as advanced age, preoperative hip fracture diagnosis, and posterior approach.[28,30] Furthermore, Thoen et al recently reported elevated dislocation risk after the use of uncemented fixation compared with cemented and inverse hybrid fixations,[47] thus supporting the selection of uncemented and hybrid fixations as risk factors. This finding, however, could also be explained by time-dependent confounding related to the increased use of uncemented fixation in the more recent time period.

The models for revisions because of PJI reached slightly lower performance compared with our previous study using the FAR data[19] (NARA AUROC 0.61 vs FAR AUROC 0.68) as well as the risk calculator developed based on the Swedish Arthroplasty Register (AUROC 0.68).[20] However, the model consisted of previously identified risk factors, such as male sex and preoperative hip fracture.[33] The ceramic-on-ceramic bearing has also previously been associated with a reduced infection revision risk,[29,33,48] although the finding might be affected by residual confounding because this bearing type tends to be used in younger and healthier patients with fewer comorbidities.

Even though all models reached moderate to excellent discrimination performance and the model predictions were in good agreement with the observed outcome rates, our study still has several limitations. First, the completeness of revision arthroplasties in the NARA member countries is in the range of 85% to 94%,[49] indicating that not all revisions are reported to the national registries, causing potential bias for our results. Second, the NARA dataset contains only the variables that all countries can deliver, and not all key risk factors for each outcome have been included during modeling. For example, greater body mass index and the American Society of Anesthesiologists physical status classification have previously been listed as important risk factors for revisions because of infection,[16,20,29,50] and thus their inclusion might have led to even simpler models and improved performance. Similarly, the model for death might be further simplified by replacing some of the variables with the American Society of Anesthesiologists physical status classification, a significant risk factor for mortality following THA.[27,51,52] Overall, the benefit of ML methods might become more apparent after the inclusion of more complex data and novel additional risk factors. Finally, regardless of large amounts of operations in training and test cohorts from four countries, it would be beneficial to externally validate the performance of the developed models in additional patient cohorts that could reveal the potential need for the recalibration of model coefficients and to identify potentially redundant variables.[20,52]

In conclusion, the present study demonstrates that when predicting revision and death within 6 months of primary THA based on arthroplasty register data, simpler models can achieve performance equal to that of complex modeling strategies but with reduced model complexity and improved usability. The simple-to-use and intuitive models developed using Lasso regression with SIVS for PJI, dislocation, PPF, and death all reached moderate to excellent performance. Once externally validated, the developed models have potential to facilitate clinical decision-making by identifying high-risk patients and optimal surgical parameters that, in the best-case scenario, could lead to further reduced rates of adverse events in the future.

AUTHOR CONTRIBUTIONS

All authors contributed to at least one of the following manuscript preparation roles: conceptualization AND/OR methodology, software, investigation, formal analysis, data curation, visualization, and validation AND drafting or reviewing/editing the final draft. As corresponding author, Dr Venäläinen confirms that all authors have provided the final approval of the version to be published and takes responsibility for the affirmations regarding article submission (eg, not under consideration by another journal), the integrity of the data presented, and the statements regarding compliance with institutional review board/Helsinki Declaration requirements.

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