# Preoperative prediction of medical morbidity after fast-track hip and knee arthroplasty - a machine learning based approach.

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# Abstract

**Background**: Introduction of machine-learning models have potentially improved prediction of hospitalization and morbidity after surgery, including hip and knee replacement. However, few studies include enhanced recovery programs, and most rely on administrative coding with limited information on follow-up and perioperative care. Thus, benefits of machine-learning models for prediction of postoperative morbidity in enhanced recovery hip and knee replacement remain uncertain.

**Methods:** Multicenter consecutive cohort study from 2014-2017 in enhanced recovery total hip and knee replacement. Prospective recording of comorbidity and prescriptions. Information on length of stay and readmissions through the Danish National Patient registry and medical records. Data was split into training (n:18013) and test sets (n:3913). A machine-learning model with 33 variables was used for predicting medical morbidity with a length of stay of >4 days or 90-days readmission and compared to a full logistic regression model. In addition, a machine-learning model excluding age, an age-model and parsimonious machine-learning and logistic regression models using the ten most important variables were performed using several metrics, including precision, operating receiver (AUC) and precision recall curves (AUPRC). Variable importance was analyzed using Shapley Additive Explanations values.

**Results:** Hospital stay was median x days in the test set of 782 (20%) “risk-patients”, AUC, AUPRC and precision were 76.3%, 15.5% and 13.6% for the full and 75.9%, 17.1% and 12.8% for the parsimonious machine-learning models vs. 74.5%, 15.7% and 12.5% for the full logistic regression model. The machine-learning model excluding age and age-model performed worse. Eighth of the ten most important variables were shared between the full machine-learning and logistic regression models. Increased risk were associated with the number of prescriptions.

**Conclusion:** A machine-learning algorithm using preoperative characteristics and prescriptions, improved prediction of patients at high-risk of medical complications in fast-track hip and knee replacement. Such algorithms could help identifying patients to benefit from intensified perioperative care.

# INTRODUCTION

Prediction of postoperative morbidity and requirement for hospitalization is important for planning of health care resources. With regard to the common surgical procedures of primary total hip and knee arthroplasty, the introduction of enhanced recovery or fast-track programs has led to a significant reduction of postoperative length of stay as well as morbidity and mortality.1-4 However, despite such progress, a fraction of patients still have postoperative complications leading to prolonged length of stay or readmissions.1,4,5 Consequently, in order to prioritize perioperative care, many efforts have been published to preoperatively predict length of stay and morbidity using traditional risk factors such as age, preoperative cardio-pulmonary disease, anemia, diabetes, frailty, etc.5-9 These efforts have been based on traditional statistical methods, most often multiple regression analyses, and essentially concluding that it is “better to be young and healthy than old and sick”. Consequently, despite being statistically significant, conventional risk-stratification based on such studies has had a relatively limited clinically relevant ability to predict and reduce potentially preventable morbidity and length of stay.5-9

More recently, machine-learning methods have been introduced with success in several areas of healthcare and where preliminary data suggest them to improve surgical risk prediction compared to traditional risk calculation in certain anesthetic and surgical conditions.10,11 This is also the case in total hip replacement, total knee replacement and uni-compartmental knee replacement, where several publications on machine-learning algorithms for prediction of length of stay,12,13 complications,14 disability,15 potential outpatient setup,16 readmissions17 or payment models,18,19 have shown promising predictive value compared to conventional statistical methods.20

However, few papers have included enhanced recovery programs, and most are based on large database cohorts with the presence of risk factors and complications often relying on administrative coding with limited information on perioperative care, follow-up and discharge destination. In our previous study in 9512 total hip and knee replacements within an enhanced recovery protocol and including the above information, we did not find advantages of machine-learning methods compared to logistic regression in predicting a length of stay > 2 days.21 However, this may have been due to data imbalance, lack of details on medication and the chosen outcome of length of stay of >2 days.21 Nevertheless, machine-learning models remain promising and could provide an improved basis for identifying a potential “high-risk” surgical population who may benefit from more extensive preoperative evaluation and postoperative medical care.

Consequently, we analyzed whether a machine-learning model was able to improve preoperative prediction of medical complications resulting in prolonged length of stay and readmissions compared to a traditional logistic regression model in a large, consecutive cohort of patients having fast-track total hip and knee replacement in a national public health-care system.1,21 In addition to well-defined patient-reported preoperative risk-factors, we also included information on reimbursed prescriptions 6 months prior to surgery using a nationwide registry.22

# Method

Reporting of the study is done in accordance with the Transparent reporting of multivariable prediction model for individual prognosis or diagnosis (TRIPOD) statement23 and the Clinical AI Research (CAIR) checklist proposal.24  
The study is based on the Centre for Fast-track Hip and Knee Replacement database which is a prospective database on preoperative patient characteristics and enrolling consecutive patients from 7 departments between 2010 and 2017. The database is registered on ClinicalTrials.gov as a study registry (NCT01515670). Permission to review and store information from medical records without informed consent was acquired from Center for Regional Development (R-20073405) and the Danish Data Protection Agency (RH-2007-30-0623). Patients completed the preoperative questionnaire with nurse assistance if needed and additional information on reimbursed prescriptions 6 months prior to surgery was acquired using the Danish National Database of Reimbursed Prescriptions (DNDRP) which records all dispensed prescriptions with reimbursement in Denmark.22 Finally, data was crossed with the Danish National Patient Registry (DNPR) for information on length of stay (counted as postoperative nights spent in hospital), 90-days readmissions with overnight stay and mortality. In case of length of stay >4 days or readmission, patient discharge summaries were reviewed for information on postoperative morbidity and in case of insufficient information, the entire medical records were reviewed. Readmissions were only included if considered related to the surgical procedure, thus excluding planned procedures like cancer workouts, cataract surgery, etc. Readmissions due to urinary tract infection or dizziness after day 30 were also considered unrelated to the surgical procedure. In case of postoperative mortality, the entire medical record, including potential readmissions was always reviewed to identify cause of death. Evaluation of discharge and medical records was performed by CJ until 2015, and then by PP supervised by CJ. In case of disagreement, records were conferred with HK. Subsequently, causes of length of stay >4, readmissions or mortality were classified as “medical” when related to perioperative care (renal failure, falls, pain, cardiac/cerebral, thrombosis, anemia, venous thromboembolism or infection etc.) and “surgical” if related to surgical technique (prosthetic infection, revision surgery, periprosthetic fracture, hip dislocation, etc.).1 In case of a length of stay >4 days with a standard discharge summary describing a successful postoperative course, it was assumed that no clinically relevant postoperative complications had occurred.   
For the present study, only cases between 2014 and 2017 were used to provide the most up-to date data. All patients had elective unilateral total hip and knee replacement in dedicated arthroplasty departments with similar fast-track protocols, including multimodal opioid sparing analgesia with high-dose (125mg) methylprednisolone, celebrex and acetaminophen, preference for spinal anesthesia, only in-hospital thromboprophylaxis when length of stay ≤5 days, early mobilization, functional discharge criteria and discharge to own home.1 There was no selection criteria for the fast-track protocol as it is considered standard of care, but we excluded patients with previous major hip or knee surgery within 90-days of their operation and in total hip replacement due to severe congenital joint disorder or cancer.

## Outcomes

The primary outcome was to compare prediction quality when using a machine-learning model to predict the occurrence of “medical” complications resulting in a length of stay >4 days or readmission compared to a traditional logistic regression model (outcome A). Secondarily, we investigated how inclusion of cases with a length of stay >4 days but with no specific reported medical complication as a positive outcome influenced the model (outcome B). For both outcomes, we also investigated whether a parsimonious model including the top ten covariates only would perform equally to the full model and whether the effect of age per se would compare to the full machine-learning model. All figures and tables in the main text and Appendix are based on outcome A; the corresponding figures for outcome B is reported in the Supplemental Digital Content.

## Statistical Analysis

Data was initially trimmed by removing 156 patients (1.7%) who were outliers with regards to weight (<30 kg or >250 kg) and height (<100 cm or >210 cm) or where these data were missing. To reduce the risk of overfitting, data was split into a training set consisting of 18.013 (82.2%) procedures with surgery between 2014-2016 and a test set of 3913 (17.8%) procedures with surgery in 2017.

As a reference model, we used classical logistic regression using all 33 input variables (table 1). Cases of missing values in the logistic regression model were handled by imputing missing values with the median of present values. All variables were then normalized.

In addition, we used Boosted Decision Trees (LightGBM)25 for the machine-learning models as such methods work well with categorical data and missing values, unlike neural networks. We tried using both normal cross entropy and FocalLos26 as the objective function for the machine-learning model. The reason for testing FocalLos was to allow the machine-learning model to focus more on the (few) positives.

The full machine-learning model was trained and hyperparameter optimized using state of the art machine-learning methods. The models were trained on the training data and then used for making predictions on the unseen test data (see supplementary for details). The classification threshold was calibrated such that no more than 20% of the total number of patients were predicted by the model, i.e. a positive predictive fraction (PPF) of 20%. We also included results for PPF values of 25% and 30%. Furthermore, we trained two parsimonious models using machine-learning and logistic regression with only the 10 most important features. Finally, we specifically explored the influence of increasing age, by constructing a model based only on age (Age), and a machine-learning model based on all variables except for age.

To investigate the importance of the included variables, we computed the SHapley Additive exPlanations (SHAP) values, which provide estimates on which variables contribute most to the risk score predictions.27,28 Finally, we investigated a potential relation between reimbursed prescribed cardiac drugs, anticoagulants, psychotropics and pulmonary drugs and age, as the relation between polypharmacy and postoperative outcomes have mainly been found in older patients.29  
For evaluating model performance, we computed the number of true positives, false positives, false negatives, true negatives, sensitivity (true positive rate), precision (positive predictive value). Since the data was quite imbalanced (about a 1:20 positive:negative ratio) we also computed the Matthews Correlation Coefficient (MCC) which is independent of class imbalance.30,31 The MCC ranges between -1 (the 100% wrong classifier), 0 (the random classifier), and +1 (the perfect classifier). Finally, we computed the area under the receiver operating characteristic curve (AUC) and the area under the precision recall curve (AUPRC). To evaluate the statistical difference between the classifiers, we applied a Bayesian metric comparison P(sensitivity),32 which is the probability that a model will perform better than the machine-learning model relative to the true positive rate. Thus, for two equally performing models P(sensitivity) is ≈ 50%.

# **Results**

Median age in the 3913 patients was 70 years (IQR 62-76), 59% were female and 58% had total hip replacement (table 1). Details on prescribed drug types are shown in Appendix 1. Median length of stay was 2 (IQR: 1-2) days with 7.6% 90-days readmissions and outcome A occurring in 182 (4.7%) patients. When applying any model with a positive prediction fraction of 20% to the 3913 patients, 782 qualified as “risk-patients”. The results are summarized in figure 1 and table 2. When considering risk scores from the full machine-learning (figure 1a) and full logistic regression model leading to this risk-patient selection, 106 and 98 had outcome A, respectively. Correspondingly, the sensitivity and precision were 58.2% and 13.6% for the full machine-learning and 53.8% and 12.5% for the full logistic regression model, respectively. The full machine-learning model was superior (figure 1b) on essentially all parameters compared to any of the other models, although the differences were minor (table 2).The results were similar when using positive prediction fractions of 25% and 30%, but with the sensitivity for the full machine-learning model increasing to 64.4% and 69.2% and precision decreasing to 12.0% and 10.7%, respectively (Appendix table 2).

Both the machine-learning model excluding age and Age-model had significantly lower sensitivity than the full machine-learning model (figure 1b). Despite age being the single most important variable (figure 2), the machine-learning model excluding age performed as well as the Age-model.

When evaluating feature importance, we found a strong correlation between the full machine-learning and full logistic regression model, with age and use of walking aids being the most important variables in both (figure 2a). From the combined importance of variables outside the top ten, the machine-learning approach extracted more information with fewer variables than logistic regression (figure 1b).

For the full machine-learning model, there was a clear signal that increasing age, number of reimbursed prescriptions, and presence of comorbidity, all contributed to an increased risk score. In contrast, a recent date of surgery and an increased hemoglobin level seemed to reduce the calculated risk (figure 2b). Individual analysis of the SHAP interaction values for types of anticoagulant prescriptions revealed that prescriptions on vitamin-K antagonists (VKA) or adenosine diphosphate (ADP) antagonists increased, while acetylic salicylic acid and direct oral anticoagulants (DOAC) reduced the risk score of the full machine-learning model, regardless of age (figure 3a). The SHAP analysis of prescribed cardiac drugs revealed that prescriptions on Ca2+-antagonists and betablockers in combination with other antihypertensives increased the risk-score, as did prescriptions on nitrates, other antihypertensives and antiarrhythmics. For the remaining cardiac drugs, prescriptions either reduced or had minor influence, and with limited relation with age (figure 3b). Preoperative psychotropic prescriptions increased the risk-score except for antipsychotics (0.6%). For users of selective serotonin inhibitors there was a clear age-related distinction with the risk score being increased in elderly patients but decreased in those < 60 years (figure 3c). Finally, the risk score increased with prescriptions on inhalation steroid and β-blockers, and more accentuated in the younger patients (figure 3d).   
The results including patients with a length of stay >4 days, but no reported postoperative complications (outcome B) were similar as for outcome A. In general, we found that the full machine-learning model was superior to the others, although the difference was less than for outcome A. (Supplemental Digital Context table S1 and Figure S2a+b) Furthermore, the SHAP analysis on prescriptions found large variations across different types of drugs. Thus, the reduced risk with acetylsalicylic acid and DOAC prescriptions was attenuated, as was the influence of practically all cardiac drugs except for nitrates, other antihypertensives and antiarrhythmics (Supplemental Digital Context figure S3a-d).

# Discussion

We found that using a machine-learning algorithm including 33 available variables and a parsimonious machine-learning-algorithm encompassing only the 10 most important predictors improved prediction of patients at increased risk of having a length of stay >4 days or readmission due to medical complications compared to corresponding traditional logistic regression models. In contrast, when also including patients having a length of stay >4 days but without a well-defined complication as an outcome, the parsimonious machine-learning model was slightly worse than a traditional logistic regression model including all variables. We also found that although age was the single most important predictor of both outcome A and B, it was less suited for prediction of postoperative medical complications after fast-track total hip and knee replacement on its own. In addition, and for the first time, we found that the type and use of prescription drugs were important risk factors. Finally, we demonstrated how the chosen classification threshold of the machine-learning algorithm influenced model performance through an increase in sensitivity at the cost of decreased precision.

A previous systematic review also found that machine-learning algorithms may provide better prediction of postoperative outcomes in total hip and knee replacement.33 However, the authors concluded that such models performed best at predicting postoperative complications, pain and patient reported outcomes and were less accurate at predicting readmissions and reoperations.33 That machine-learning algorithms may improve prediction of complications after total hip and knee replacement compared to traditional logistic regression was also found by Shah *et al.* who used an automated machine-learning framework to predict selected major complications after total hip replacement.14 However, the study was retrospective and based on diagnostic and administrative coding and the selected complications occurred only in 0.61% of patients, potentially limiting clinical relevance. In contrast, we aimed at identifying a cohort which would comprise 20% of patients in which we found about 60% of all medical complications. This we believe, is within the means of the Danish socialized healthcare system to allocate additional resources for intensified perioperative care and with potential both patient-related and economic benefits.  
In contrast to many other machine-learning studies,34 our dataset included not only preoperative data but also only one paraclinical variable, which was preoperative hemoglobin. Although the inclusion of other laboratory tests such as preoperative albumin, sodium and alkaline phosphatase has been found to be of importance in machine-learning algorithms for home discharge in unicompartmental knee arthroplasty13 and spine surgery,10 they are not standard in our fast-track protocols and not easy to interpret from a pathophysiological point of view. As there is a need to prioritize the limited health-care resources, most decisions on which patients may benefit from more extensive postoperative care will likely need to be conducted preoperatively. Thus, although postoperative information such as duration of surgery, perioperative blood loss, length of stay or postoperative hemoglobin have been included in other studies34, we decided for our prediction purpose against the use of peri- and postoperative data. The same approach has been used by Ramkumar *et al.* who used U.S. National Inpatient Sample data including 15 preoperative variables, to predict length of stay, patient charges and disposition after both total knee replacement35 and total hip replacement.19 However, these studies were not conducted in a socialized health care system, and the main focus was on the need for differentiated payment bundles and without specific information on the reason for increased length of stay or non-home discharge.35 Wei *et al.* used an artificial neural network model to predict same-day discharge after total knee replacement, based on the The National Surgical Quality Improvement Program (NSQIP) database from 2018 and found that six of the ten most important variables were the same compared with logistic regression, similar to our findings.36 However, patients with one-day length of stay were intentionally excluded due to variations in in-patient vs. out-patient registration.36   
Age has traditionally been a major factor when predicting surgical outcomes which is why we choose to specifically evaluate its effect on our risk-prediction. That age is important for risk-prediction was further illustrated by the machine-learning model without age being comparable to the Age-model. Note that, although elderly patients had increased risk of postoperative complications, likely related to decline of physical reserves,37 the use of chronological age alone as a selection criteria for being a “risk-patient” was inferior compared to both machine-learning and logistic regression models incorporating comorbidity and functional status.

We used the SHAP values for estimation of feature importance, thus providing a better understanding of the otherwise “black-box” machine-learning model. The SHAP values showed which variables contributed most to the risk-score predictions. In this context our inclusion of specific data on reimbursed prescriptions 6 months prior to surgery unsurprisingly found increased risk-scores with increased number of prescriptions and that most prescriptions were in elderly patients. Similarly, a Canadian study in elective non-cardiac surgery found decreased survival and increased length of stay and readmissions and costs in patients >65 years with polypharmacy.29 However, this is a complex relationship where some patients benefit from their treatment while other may suffer from undesirable side-effects and the authors cautioned against altering perioperative practices based on current evidence.29 However, the information from the included prescriptions with SHAP analysis may provide inspiration for new hypothesis-generating studies investigating potential differences in risk-profile between having preoperative prescribed vitamin-K antagonists (VKA) and direct oral anticoagulants (DOAC). Also, the age-related differences in risk from SSRI’s seen in our study could guide further studies on preoperative “deprescription”.

Another requirement for machine-learning-algorithms to be clinically useful is user friendliness and not depending on excessive additional data collection by the attending clinicians. In this context, it was a bit disappointing that the parsimonious machine-learning algorithm with only the 10 most important variables was slightly worse at predicting outcome B than the full logistic regression model. A reason for this could be that when including a length of stay >4 days but without described medical complications, the combination of all variables provides information not available by merely including the ten most important ones. This highlights the need for as much detailed, and preferably non-binary data as possible to fulfill the true potential of machine-learning algorithms.

Our study has some limitations. We included only a limited number of often binary, preoperative variables. As analysis of multilevel continuous data is one of the strengths of machine-learning compared to logistic regression, which may limit the full realization of our machine-learning model. As previously mentioned, we also excluded intraoperative information, including type of anesthesia, surgical approach etc. all of which may influence postoperative outcomes. The observational design of this study means that we cannot exclude unmeasured confounding or confounding by indication. Also, despite that the DNDRP has a near complete registration of dispensed medicine in Denmark, some types or drugs, especially benzodiazepines, are exempt from general reimbursement and thus not sufficiently captured.22 Furthermore, it is doubtful whether the patients used all types of drugs at the time of surgery (e.g. heparin which is rarely for long-term use). Finally, classification of a complication being “medical” depended on review of the discharge records which can also introduce bias. However, we believe our approach to be superior to depending only on diagnostic codes which often are inaccurate and provide limited details on whether the complication may be attributed to a medical or surgical adverse event. Finally, we did not include intra- or postoperative direct surgical risk factors or complications, since they may depend merely on other preoperative risk factors than these included here.

The strengths of our study include the use of national registries with high degree of completion (>99% of all somatic admissions in case of the DNDP),38 prospective recording of comorbidity, extensive information on prescription patterns 6 months prior to surgery (DNDRA) and similar established enhanced recovery protocols in all departments.

In summary, our results indicate that machine-learning-algorithms likely provide clinically relevant improved predictions for defining patients in high-risk of medical complications after fast-track total hip and knee replacement compared to a logistic regression model. Future studies could benefit from using such algorithms to find a manageable population of patients who may benefit the most from intensified perioperative care.

# Tables

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| --- | --- | --- |
| Table 1. Patient demographics with and without outcome A (length of stay >4 days or 90-days readmissions of medical reasons) in the combined test and training dataset. | | |
| Preoperative characteristics n(%) unless otherwise specified | +outcome A (n:1180) | -outcome A (n:20837) |
| mean age (SD) | 75.0 (68.0-81.0) | 69.0 (62.0-75.0) |
| mean number of reimbursed prescriptions1 (SD) | 3.0 (1.0-4.0) | 2.0 (0.0-3.0) |
| female gender | 755 (64.0) | 12133 (58.2) |
| Total hip replacement | 636 (53.9) | 11542 (55.4) |
| mean weight in kg (SD) | 78.0 (67.0-91.0) | 81 (70.0-93.0) |
| mean height in cm (SD) | 168 (162.0-175.0) | 170.0 (164.0-178.0) |
| mean body mass index (SD) | 27.3 (23.9-31.2) | 27.5 (24.6-31.1) |
| regular use of walking aid  missing | 552 (46.8)  29 (2.5) | 4398 (21.5)  359 (1.7) |
| living alone  with others  institution  missing | 578 (49.0)  571 (48.4)  24 (2.0)  7 (0.6) | 6717 (32.2)  13869 (66.6)  113 (0.5)  138 (0.7) |
| hemoglobin  missing | 8.2 (7.7-8.8)  11 (0.9) | 8.6 (8.1-9.2)  314 (1.5) |
| >2 units of alcohol/day  missing | 79 (6.7)  10 (0.8) | 1589 (7.6)  174 (0.8) |
| active smoker  missing | 130 (11.0)  11 (0.9) | 2751 (13.2)  141 (0.7) |
| cardiac disease  missing | 306 (25.9)  8 (0.8) | 2750 (13.2)  153 (0.7) |
| hypercholesterolemia  missing | 467 (39.6)  8 (0.7) | 6062 (29.1)  120 (0.6) |
| hypertension  missing | 738 (62.5)  64 (5.4) | 10141 (48.7)  663 (3.2) |
| pulmonary disease  missing | 182 (15.4)  5 (0.4) | 1841 (8.8)  96 (0.5) |
| previous cerebral attack  missing | 165 (14.0)  25 (2.1) | 1086 (5.2)  282 (1.4) |
| previous VTE  missing | 133 (11.3)  26 (2.2) | 1481 (7.1)  325 (1.6) |
| malignancy (undefined)  previous radically treated malignancy  missing | 557 (47.2)  127 (10.8)  14 (1.2) | 8843 (42.4)  2065 (9.9)  162 (0.8) |
| chronic kidney disease  missing | 50 (4.2)  35 (3.0) | 273 (1.3)  292 (1.4) |
| family member with VTE  missing | 155 (13.1)  1190 (16.1) | 2510 (12.0)  2569 (12.3) |
| regular snoring  uncertain about snoring  missing | 266 (22.5)  208 (17.6)  259 (21.9) | 5522 (26.5)  3781 (18.1)  3309 (15.9) |
| not feeling rested  uncertain about being rested  missing | 468 (39.7)  48 (4.1)  105 (8.9) | 9340 (44.8)  809 (3.9)  1230 (5.9) |
| psychiatric disorder  missing | 156 (13.2)  62 (5.3) | 1590 (7.6)  703 (3.4) |
| Characteristic based on combination of questionnaire and DNDRP | | |
| diabetes  diet treated diabetes2  oral antidiabetics  insulin treated diabetes3  missing | 29 (2.5)  137 (11.6)  60 (5.1)  7 (0.6) | 274 (1.3)  1448 (6.9)  413 (2.0)  98 (0.5) |
| SD: standard deviation VTE: venous thromboembolic event DNDRP: Danish National Database of Reimbursed Prescriptions.  1Antirheumatica, steroids, anticoagulants, cardiac, cholesterol lowering, respiratory and psychotropic drugs. 2Reported diabetes but no registered prescriptions 2 +/- oral antidiabetics | | |

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| Table 2: Performance of the six different models with a predefined positive prediction fraction of 20% for outcome A | | | | | | | | | | |
| Positive prediction fraction 20% | TP | FP | FN | TN | sensitivity | precision | MCC | AUROC | AUPRC | P (sensitivity) |
| Full machine-learning model | 106 | 676 | 76 | 3055 | 58.2% | 13.6% | 21.1% | 76.3% | 15.5% | - |
| Full logistic regression model | 98 | 684 | 84 | 3047 | 53.8% | 12.5% | 18.7% | 74.5% | 15.7% | 19.7% |
| Parsimonious machine-learning model | 100 | 682 | 82 | 3049 | 54.9% | 12.8% | 19.3% | 75.9% | 17.3% | 26.1% |
| Parsimonious logistic regression model | 95 | 687 | 87 | 3045 | 52.2% | 12.1% | 17.8% | 73.7% | 13.6% | 12.4% |
| machine-learning model excluding age | 88 | 694 | 94 | 3037 | 48.4% | 11.3% | 15.7% | 72.3% | 13.6% | 3.1% |
| Age-model | 87 | 676 | 95 | 3055 | 47.8% | 11.4% | 15.8% | 69.7% | 12.1% | 2.3% |
| TP: true positives FP: false positives FN: false negatives TN: true negatives MCC: Matthews correlation coefficient AUC: area under the ROC curve AUPRC: area under the precision recall curve P(sensitivity): probability that the model performs better than the machine-learning model relative to sensitivity. Green/red colors indicates the model with the best/worst performance given that specific metric | | | | | | | | | | |

# Appendix

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| --- | --- | --- |
| Appendix table 1. Details on specific drugs with reimbursed prescriptions 6 months preoperatively.  Numbers are n (%) | | |
|  | +Outcome A | -Outcome A |
| Anticoagulants  none  VKA  Heparin & Acetylsalicylic acid  DOAC  Acetylsalicylic acid  Dipyradimol  ADP-antagonist  Acetylsalicylic acid & Dipyradimol  VKA & Acetylsalicylic acid  DOAC & Acetylsalicylic acid  VKA & ADP-antagonist  DOAC & ADP-antagonist  VKA & Heparin  DOAC & Acetylsalicylic acid & ADP-antagonist  Acetylsalicylic acid & ADP-antagonist  Acetylsalicylic acid & ADP-antagonist & Heparin  Acetylsalicylic acid & ADP-antagonist & Dipyradimol | 679 (57.5)  106 (9.0)  0 (0.0)  48 (4.1)  205 (17.4)  5 (0.4)  75 (6.4)  17 (1.4)  10 (0.8)  6 (0.5)  4 (0.3)  3 (0.3)  1 (0.1) 1 (0.1)  18 (1.5)  1 (0.1)  1 (0.1) | 15844 (76.0)  750 (3.6)  7 (0.0)  659 (3.2)  2492 (12.0)  29 (0.1)  569 (2.7)  168 (0.8)  78 (0.4)  41 (0.2)  11 (0.1)  14 (0.1)  21 (0.1)  3 (0.0)  132 (0.6)  12 (0.1)  7 (0.0) |
| Cardiac prescriptions  none  diuretics  angiotensin-II/ACE-inhibitors  Ca2+ antagonists  β-blocker  nitrates  other antihypertensives  other types of medication for IHD  2 antihypertensives  β-blocker & 1 antihypertensive1  3 antihypertensives  β-blocker & 2 antihypertensives1  β-blocker & 3 antihypertensives1  4 antihypertensives  β-blocker & 4 antihypertensives  other antihypertensive & antihypertensives1  nitrates & any hypertensive  other drugs for IHD & any antihypertensive and/or nitrate  other antiarrhythmics & any antihypertensives | 321 (27.2)  77 (6.5)  132 (11.2)  55 (4.7)  29 (2.5)  1 (0.1)  0 (0.0)  2 (0.2)  177 (15.0)  92 (8.1)  50 (4.2)  95 (8.1)  25 (2.1)  2 (0.2)  2 (0.2) 9 (0.8)  49 (4.2)  5 (0.4)  57 (4.8) | 9200 (44.2)  1184 (5.7)  2683 (12.9)  773 (3.7)  559 (2.7)  18 (0.1)  12 (0.1)  21 (0.1)  2696 (12.9)  1069 (5.1)  548 (2.6)  975 (4.7)  265 (1.3)  18 (0.1)  19 (0.1)  87 (0.4)  331 (1.6)  15 (0.1)  364 (1.7) |
| Anticholesterols  none  statins  other anti-lipids  Statins +other anti-lipids | 708 (60.0)  457 (38.7)  7 (0.6)  8 (0.7) | 14719 (70.6)  5866 (28.2)  135 (0.6)  117 (0.6) |
| Systemic steroids | 123 (10.4) | 1149 (5.5) |
| Antirheumatics  none  disease-modifying antirheumatic drugs  other antirheumatics | 1143 (96.9)  37 (3.1)  0 (0.0) | 20388 (97.8)  446 (2.1)  3 (0.0) |
| Respiratory prescriptions  none  SABA  LABA or LAMA  inhalation steroid only  SABA & Ipratropium (+/- others)  LABA & steroid  LABA & LAMA & steroid  LAMA & steroid  LABA & LAMA  other pulmonary drugs  other pulmonary drugs & steroid  SABA & LABA or LAMA  SABA & LABA or LAMA & steroid | 1000 (84.7)  13 (1.1)  19 (1.6)  8 (0.7)  6 (0.5)  45 (3.8)  19 (1.6)  0 (0.0)  7 (0.6)  3 (0.3)  9 (0.8) 6 (0.5)  45 (3.8) | 18754 (90.0)  276 (1.3)  217 (1.0)  211 (1.0)  18 (0.1)  474 (2.3) 122 (0.6)  11 (0.1) 80 (0.4)  32 (0.2)  98 (0.5) 96 (0.5) 448 (2.2) |
| Psychotropic prescriptions  none  SSRI/SNRI/NaRI  other antidepressants  antipsychotics  benzodiazepines2  anti-cholinergics or memantine  anti-ADHD drugs  NaSSA  other psychotropics  SSRI + other antidepressants  SSRI + NaSSA  SRRI + antipsychotics  SRRI + other psychotropics  benzodiazepines + any psychotropic  antipsychotics + any psychotropic  anti-ADHD + any psychotropic  NaSSA + any psychotropic  other psychotropics + any specified psychotropic | 952 (80.7)  100 (8.5)  1 (0.1)  8 (0.7)  0 (0.0)  6 (0.5)  1 (0.1)  25 (2.1)  28 (2.4)  4 (0.3)  8 (0.7)  11 (0.9) 7 (0.6) 3 (0.3)  20 (1.7)  0 (0.0) 4 (0.3)  2 (0.2) | 18657 (89.5)  1164 (5.6)  17 (0.1) 116 (0.6) 7 (0.0) 27 (0.1)  10 (0.0)  184 (0.9)  182 (0.9) 6 (0.0)  94 (0.5)  87 (0.4)  84 (0.4)  12 (0.1)  149 (0.7)  14 (0.1)  18 (0.1)  9 (0.0) |
| VKA: vitamin K antagonists DOAC: direct oral anticoagulant ADP: Adenosine diphosphate ACE: angiotensin converting enzyme IHD: Ischemic heart disease SABA: Short-acting beta agonist LABA: long-acting beta agonist LAMA: Long-acting muscarinic antagonist SSRI: Selective serotonin inhibitor SNRI: Serotonin and norepinephrine reuptake inhibitor NaRI: Norepinephrine reuptake inhibitor NaSSA: Norepinephrine and specific serotonergic antidepressants  1either diuretics, ACE/ANG-II inhibitors or Ca2+antagonists 2 likely underreported due to limited general reimbursement for benzodiazepines in Denmark | | |

|  |  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
| Appendix table 2: Performance of the six different models with a predefined positive prediction fraction of 25% and 30% for outcome A | | | | | | | | | | |
| Positive prediction fraction 25% | TP | FP | FN | TN | sensitivity | precision | MCC | AUC | AUPRC | P (sensitivity) |
| Full machine-learning model | 117 | 861 | 65 | 2870 | 64.3% | 12.0% | 20.0% | 76.3% | 15.5% | - |
| Full logistic regression model | 110 | 868 | 72 | 2863 | 60.4% | 11.2% | 18.1% | 74.5% | 15.7% | 23.1% |
| Parsimonious machine-learning model | 115 | 863 | 67 | 2868 | 63.2% | 11.8% | 19.5% | 75.9% | 17.3% | 41.2% |
| Parsimonious logistic regression model | 106 | 872 | 76 | 2859 | 58.2% | 10.8% | 17.0% | 73.4% | 15.5% | 11.8% |
| machine-learning model excluding age | 106 | 872 | 76 | 2859 | 58.2% | 10.8% | 17.0% | 72.3% | 13.6% | 11.8% |
| Age-model | 94 | 824 | 88 | 2907 | 51.6% | 10.2% | 14.7% | 69.7% | 12.2% | 0.7% |
| Positive prediction fraction 30% | TP | FP | FN | TN | sensitivity | precision | MCC | AUC | AUPRC | P (sensitivity) |
| Full machine-learning model | 126 | 1047 | 56 | 2684 | 69.2% | 10.7% | 18.9% | 76.3% | 15.5% | - |
| Full logistic regression model | 120 | 1053 | 62 | 2678 | 65.9% | 10.2% | 17.3% | 74.5% | 15.7% | 25.2% |
| Parsimonious machine-learning model | 124 | 1049 | 58 | 2682 | 68.1% | 10.6% | 18.4% | 75.9% | 17.3% | 40.8% |
| Parsimonious logistic regression model | 115 | 1058 | 67 | 2673 | 63.2% | 9.8% | 16.0% | 73.7% | 15.5% | 11.1% |
| machine-learning model excluding age | 116 | 1057 | 66 | 2674 | 63.7% | 9.9% | 16.3% | 72.3% | 13.6% | 13.8% |
| Age-model | 100 | 955 | 82 | 2776 | 54.9% | 9.5% | 13.9% | 69.7% | 12.2% | 0.2% |
| TP: true positives FP: false positives FN: false negatives TN: true negatives MCC: Matthews correlation coefficient AUC: area under the ROC curve AUPRC: area under the precision recall curve P(sensitivity): probability that the model performs better than the machine-learning model relative to sensitivity. Green/red colors indicates the model with the best/worst performance given that specific metric | | | | | | | | | | |

# Figures

**Figure 1a+b**



**Figure 2a+b**



**Figure 3a-d**

## Supplemental Digital Content

|  |  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
| Table S1: Performance of different models for Outcome B | | | | | | | | | | |
| Positive prediction fraction 20% | TP | FP | FN | TN | sensitivity | precision | MCC | AUC | AUPRC | P (sensitivity) |
| Full machine-learning model | 121 | 661 | 108 | 3023 | 52.8% | 15.5% | 20.5% | 75.3% | 17.1% | - |
| Full logistic regression model | 115 | 667 | 114 | 3017 | 50.2% | 14.7% | 18.9% | 74.1% | 16.7% | 28.3% |
| Parsimonious machine-learning model | 111 | 671 | 118 | 3013 | 48.4% | 14.2% | 17.8% | 74.4% | 16.8% | 17.2% |
| Parsimonious logistic regression model | 109 | 673 | 120 | 3011 | 47.6% | 13.9% | 17.2% | 73.1% | 16.8% | 12.9% |
| machine-learning model excluding age | 110 | 672 | 119 | 3012 | 48.0% | 14.1% | 17.5% | 72.8% | 16.9% | 15.1% |
| Age-model | 102 | 661 | 127 | 3023 | 44.5% | 13.4% | 15.8% | 68.7% | 13.4% | 3.8% |
| Positive prediction fraction 25% | TP | FP | FN | TN | sensitivity | precision | MCC | AUC | AUPRC | P (sensitivity) |
| Full machine-learning model | 140 | 838 | 89 | 2846 | 61.1% | 14.3% | 20.8% | 75.3% | 17.1% | - |
| Full logistic regression model | 136 | 842 | 93 | 2842 | 59.4% | 13.9% | 19.8% | 74.1% | 16.7% | 35.3 |
| Parsimonious machine-learning model | 134 | 844 | 95 | 2840 | 58.5% | 13.7% | 19.3% | 74.4% | 16.8% | 28.3 |
| Parsimonious logistic regression model | 125 | 853 | 104 | 2831 | 54.6% | 12.8% | 17.0% | 73.1% | 16.8% | 7.8 |
| machine-learning model excluding age | 121 | 857 | 108 | 2827 | 52.8% | 12.4% | 16.0% | 72.8% | 16.9% | 3.6 |
| Age-model | 113 | 805 | 116 | 2879 | 49.3% | 12.3% | 15.2% | 68.7% | 13.4% | 0.5 |
| Positive prediction fraction 30% | TP | FP | FN | TN | sensitivity | precision | MCC | AUC | AUPRC | P (sensitivity) |
| Full machine-learning model | 153 | 1020 | 76 | 2664 | 66.8% | 13.0% | 20.0% | 75.3% | 17.1% | - |
| Full logistic regression model | 147 | 1026 | 82 | 2658 | 64.2% | 12.5% | 18.6% | 74.1% | 16.7% | 27.9 |
| Parsimonious machine-learning model | 147 | 1026 | 82 | 2658 | 64.2% | 12.5% | 18.6% | 74.4% | 16.8% | 27.7 |
| Parsimonious logistic regression model | 145 | 1028 | 84 | 2656 | 63.3% | 12.4% | 18.1% | 73.1% | 16.8% | 21.6 |
| machine-learning model excluding age | 140 | 1033 | 89 | 2651 | 61.1% | 11.9% | 17.0% | 72.8% | 16.9% | 10.2 |
| Age-model | 122 | 933 | 107 | 2751 | 53.3% | 11.6% | 14.8% | 69.8% | 13.4% | 0.1 |
| TP: true positives FP: false positives FN: false negatives TN: true negatives MCC: Matthews correlation coefficient AURC: area under the ROC curve AUPRC: area under the precision recall curve P(sensitivity): probability that the model performs better than the machine-learning model relative to sensitivity. Green/red colors indicates the model with the best/worst performance given that specific metric | | | | | | | | | | |

Figure S1 a+b



S1a) Distribution of full machine learning model risk scores for patients +/- outcome A. The dashed line marks the classification threshold of 20% positive prediction fraction.   
S1b) Receiver operating curves (ROC) for the full machine learning model (F-MLM), full logistic regression model (F-LRM), parsimonious machine learning model (P-MLM), parsimonious logistic regression model (P-LRM), machine learning excluding age (MLM -age) and the age-model (AM).

Figure S2a+b



S2a) The overall importance of the 10 most important variables measured by the SHAP-values for the full machine-learning and full logistic regression models. Only the importance of prescribed anticholesterols and gender differed between the models. The contributions of the remaining variables are summed in the bottom bar.   
S2b) The SHAP-values for the full machine-learning model. Positive SHAP-values increase the risk score while negative values decrease the risk score. The color is related to the value of the variable with blue being lowest and red highest.

Figure S3a-d



SHAP beeswarm plot on the contributions to the machine-learning33 model of individual types of prescribed drugs stratified by age four outcome B.

3a) Anticoagulants 3b) Cardiac drugs 3c) Psychotropics 3d) Respiratory drugs (der er en fejl her vi er på den). **NB laves om snarligt**

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# Legends

**Figure 1a+b**

1a) Distribution of full machine learning model risk scores for patients +/- outcome A. The dashed line marks the classification threshold of 20% positive prediction fraction.   
1b) Receiver operating curves (ROC) for the full machine learning model (F-MLM), full logistic regression model (F-LRM), parsimonious machine learning model (P-MLM), parsimonious logistic regression model (P-LRM), machine learning excluding age (MLM -age) and the age-model (AM).

**Figure 2a+b**

2a) The overall importance of the 10 most important variables measured by the SHAP-values for the full machine-learning and full logistic regression models. Only the importance of prescribed anticholesterols and gender differed between the models. The contributions of the remaining variables are summed in the bottom bar.   
2b) The SHAP-values for the full machine-learning model. Positive SHAP-values increase the risk score while negative values decrease the risk score. The color is related to the value of the variable with blue being lowest and red highest.

**Figure 3a+b**

SHAP beeswarm plot on the contributions to full machine-learning model of individual types of prescribed drugs stratified by age.

3a) Prescribed anticoagulants

VKA: vitamin K antagonists ASA: acetylsalicylic acid DOAC: direct oral anticoagulant ADP: Adenosine diphosphate ACE: angiotensin converting enzyme

3b) Prescribed cardiac medicine

ACE: angiotensin converting enzyme AHT: antihypertensive. Other AHT were defined as AHT different from diuretics ANG-II/ACE inhibitors or Ca2+antagonists. IHD: Ischemic heart disease

3c) Prescribed psychotropics

SSRI: Selective serotonin inhibitor SNRI: Serotonin and norepinephrine reuptake inhibitor NaRI: Norepinephrine reuptake inhibitor NaSSA: Norepinephrine and specific serotonergic antidepressants. AD: Antidepressants BZ: Benzodiazepines (likely underreported due to limited general reimbursement in Denmark). ADHD: Attention-deficit/hyperactivity disorder

3d) Prescribed respiratory medicine

SABA: Short-acting beta agonist LABA: long-acting beta agonist LAMA: Long-acting muscarinic antagonist