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# Is it feasible to develop a supervised learning algorithm incorporating spinopelvic mobility to predict impingement in patients undergoing total hip arthroplasty?

A proof-of-concept study

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## Aims

Precise implant positioning, tailored to individual spinopelvic biomechanics and phenotype, is paramount for stability in total hip arthroplasty (THA). Despite a few studies on instability prediction, there is a notable gap in research utilizing artificial intelligence (AI). The objective of our pilot study was to evaluate the feasibility of developing an AI algorithm tailored to individual spinopelvic mechanics and patient phenotype for predicting impingement.

## Methods

This international, multicentre prospective cohort study across two centres encompassed 157 adults undergoing primary robotic arm-assisted THA. Impingement during specific flexion and extension stances was identified using the virtual range of motion (ROM) tool of the robotic software. The primary AI model, the Light Gradient-Boosting Machine (LGBM), used tabular data to predict impingement presence, direction (flexion or extension), and type. A secondary model integrating tabular data with plain anteroposterior pelvis radiographs was evaluated to assess for any potential enhancement in prediction accuracy.

## Results

We identified nine predictors from an analysis of baseline spinopelvic characteristics and surgical planning parameters. Using fivefold cross-validation, the LGBM achieved 70.2% impingement prediction accuracy. With impingement data, the LGBM estimated direction with 85% accuracy, while the support vector machine (SVM) determined impingement type with 72.9% accuracy. After integrating imaging data with a multilayer perceptron (tabular) and a convolutional neural network (radiograph), the LGBM's prediction was 68.1%. Both combined and LGBM-only had similar impingement direction prediction rates (around 84.5%).

## Conclusion

This study is a pioneering effort in leveraging AI for impingement prediction in THA, utilizing a comprehensive, real-world clinical dataset. Our machine-learning algorithm demonstrated promising accuracy in predicting impingement, its type, and direction. While the addition of imaging data to our deep-learning algorithm did not boost accuracy, the potential for refined annotations, such as landmark markings, offers avenues for future enhancement. Prior to clinical integration, external validation and larger-scale testing of this algorithm are essential.

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## Take home message

- This study highlights the feasibility of using an artificial intelligence algorithm to predict impingement in total hip arthroplasty based on individual spinopelvic mechanics and patient phenotype.
- The algorithm demonstrated promising accuracy, potentially guiding surgeons in preoperative planning and intraoperative decision-making.

## Introduction

Instability and dislocation represent frequent postoperative complications following primary total hip arthroplasty (THA), often necessitating early revision surgery.[1] Documented incidence rates range from 0% to 5%,[2] while recent comprehensive data analyzing over 16,000 THAs highlighted an adjusted instability risk between 0.17% and 1.74%.[3] Mounting evidence challenges the perceived safety of the traditional Lewinnek zone, and has underscored that a significant number of hip dislocations occur within the purported "safe zone" for cup positioning.[2,4] Several surgical factors play a pivotal role in hip stability, encompassing the preservation of dynamic and static hip stabilizers and restoration of joint biomechanics.[5] Accurate offset restoration also holds evident biomechanical benefits by enhancing the abductor moment arm and reducing joint reaction forces. This may be particularly beneficial for patients with a rigid spine,[6] potentially mitigating impingement and dislocation risks.[7,8] Nevertheless, the single most important objective for achieving stability is precise implant positioning, tailored to the individual's biomechanics and phenotype.[5,9] This involves not only the specific anatomical characteristics of the patient, but also functional aspects such as spinopelvic interactions.

Current research consensus indicates that, due to individual variances in spinopelvic anatomy, there is no one-size-fits-all optimal cup position.[10] Spinopelvic motion involves the complex coordination between the spine, pelvis, and hips to facilitate postural adjustments. The variation in sacral slope (ΔSS) is an essential metric for measuring such dynamic shifts in spinopelvic mobility.[5,11] A rigid spinopelvic structure results in diminished pelvic extension and reduced acetabular anteversion during the transition to a seated position. Consequently, there is an increased reliance on hip joint flexion, amplifying the chances of anterior impingement and subsequent posterior dislocation when seated.[12] With the integration of innovative surgical technologies, such as computer navigation and robotic arm assistance, the emphasis has shifted towards personalized, functional component placement in THA.[10,13] The current workflow with CT-based robotic systems features a virtual range of motion (ROM) tool, offering real-time feedback on impingement and the ramifications of component orientation changes.[14] An added benefit of robotic arm-assisted (RO) THA is its capacity for ample data collection during the preoperative planning stage and intraoperatively.

In pursuit of enhancing postoperative outcomes, a few studies have endeavoured to predict instability and establish a personalized safe zone for component placement.[9,15,16] However, there remains a conspicuous absence of studies leveraging artificial intelligence (AI) to predict instability or impingement.

To this end, our study evaluated the feasibility of developing an AI algorithm tailored to individual spinopelvic mechanics and patient phenotype for predicting impingement. We also explored whether integrating imaging data could further enhance its accuracy.

## Methods

### Study design and participants

We conducted an international, multicentre prospective cohort study across two centres in the UK and Luxembourg, aiming to evaluate the feasibility of an AI algorithm predicting impingement in THA based on patient phenotype and individual spinopelvic mechanics. The study adhered to the ethical standards of the 1964 Declaration of Helsinki,[17] and secured ethical approval from the Hôpitaux Robert Schuman institutional review board (Ref. CIVLU-21–09-037787). The cohort comprised adult patients undergoing primary RO THA. We excluded patients undergoing revision surgery for any reason.

### Imaging protocols and radiological analysis

The preoperative imaging protocol for all participants included a CT for surgical planning and weightbearing anteroposterior (AP) pelvis radiographs. This was complemented by standing and relaxed-seated position lateral spine radiographs. For the seated images, patients were instructed to sit naturally, ensuring that their femora remained parallel to the ground. All spinopelvic radiological measurements were performed by two independent researchers from each institution, with at least one being a consultant surgeon (TV, FG, PP, AF, FM, RP). The sacral slope (SS) was defined as the angle subtended by a horizontal line and a tangential line to the S1 superior endplate. The ΔSS from standing to relaxed-seated position was used to quantify spinopelvic mobility. The pelvic incidence (PI) was defined as the angle between a line joining the tangent to the S1 endplate and a line joining the femoral head to the S1 endplate centre.[18]

### Surgical techniques and implant details

Surgeries in each institution were performed using the MAKOplasty total hip application system, version 4.0 (Stryker, USA). All participants received the following implants: a cementless, proximally coated femoral stem (Accolade II; Stryker); a porous acetabular shell (Trident Acetabular System; Stryker); a highly cross-linked polyethylene liner (X3 10° or 0°; Stryker); and a ceramic head (Biolox δ; CeramTec, Germany).

A personalized 3D plan was generated using the preoperative CT. Spinopelvic parameters were inputted into the MAKO software (version 4.0), which includes a virtual ROM (vROM) tool for real-time impingement feedback. The surgical plan was determined with a focus on replicating the native anatomy as closely as possible. The native centre of rotation, leg length, and combined offset were aimed to be restored using the contralateral side as a guide. The acetabular component was carefully positioned to achieve adequate bony coverage, avoid anterior prominence, and prevent irritation of the psoas tendon, which could lead to postoperative groin pain. In cases of dysplastic acetabula, special attention was given to the posterior wall to assess any deficiencies. The femoral stem sizing and positioning were calculated to preserve leg length and native offset, ensuring

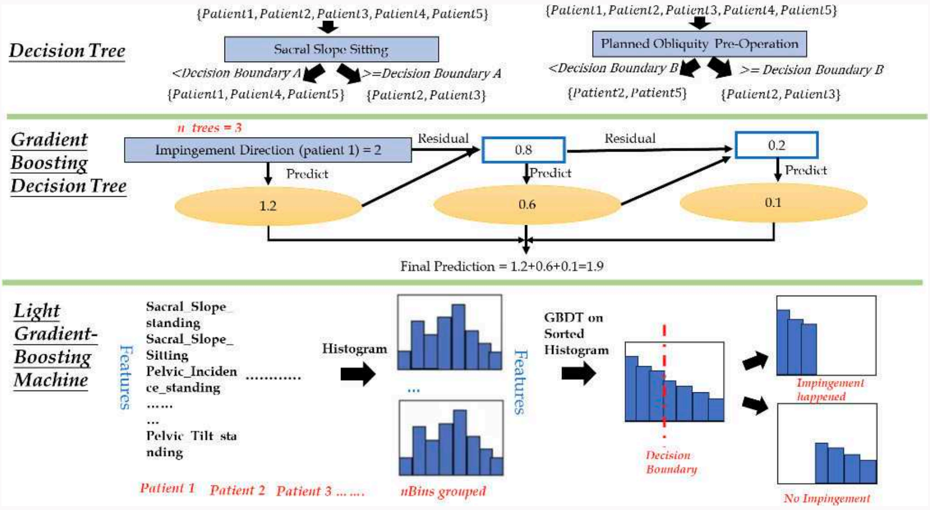


**Fig. 1**

Schematic representation of our artificial intelligence model, illustrating the decision tree, which commences from a distinct feature such as 'Sacral Slope Sitting' or 'Planned Obliquity'. This bifurcates further into leaves based on specific criteria. For example, the left leaf encompasses patients with a 'Sacral Slope Sitting' measurement beneath Decision Boundary A, whereas its right counterpart includes those exceeding this. In a hierarchical decision tree, these leaves can split further, based on more features, until the model converges or reaches its maximum depth. Such convergence aligns with predefined metrics integral to information gain. GBDT, Gradient-Boosted Decision Tree.

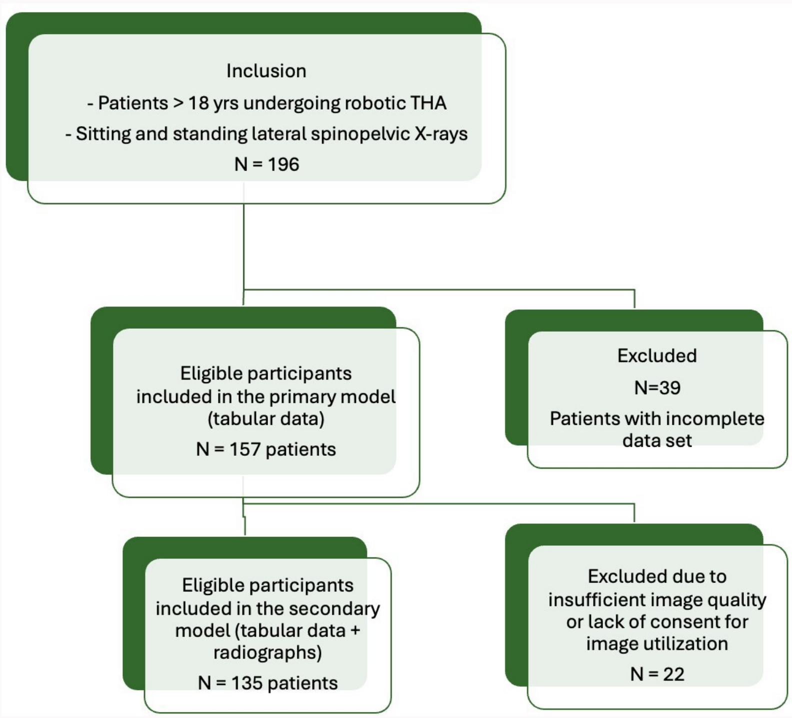


**Fig. 2**

Figure depicting the flow of patients throughout the study and models. THA, total hip arthroplasty.

that the stem did not underfill the canal or compromise the calcar. Spinopelvic motion was also taken into account; for example, in patients with a stiff pelvis fixed in anterior tilt, increasing the offset and/or the inclination and anteversion of the cup was considered. Conversely, in 'stuck sitting' patients, our approach included the removal of posterior osteophytes, a decrease in cup anteversion, an increase in femoral offset, or a decrease in femoral anteversion. At the planning stage, hips were assessed for impingement in standardized stances: 15° extension, external rotation, and abduction in standing; and 110° flexion, 40° internal rotation, and 10° adduction in sitting. Any detected impingement was further categorized by its direction (anterior/posterior) and type (bone-bone, implant-implant, or implant-bone). Additionally, planned stem version, acetabular component orientation, and baseline characteristics were recorded. Our dataset included various scenarios of impingement identified intraoperatively, which were essential for training the AI model to recognize and

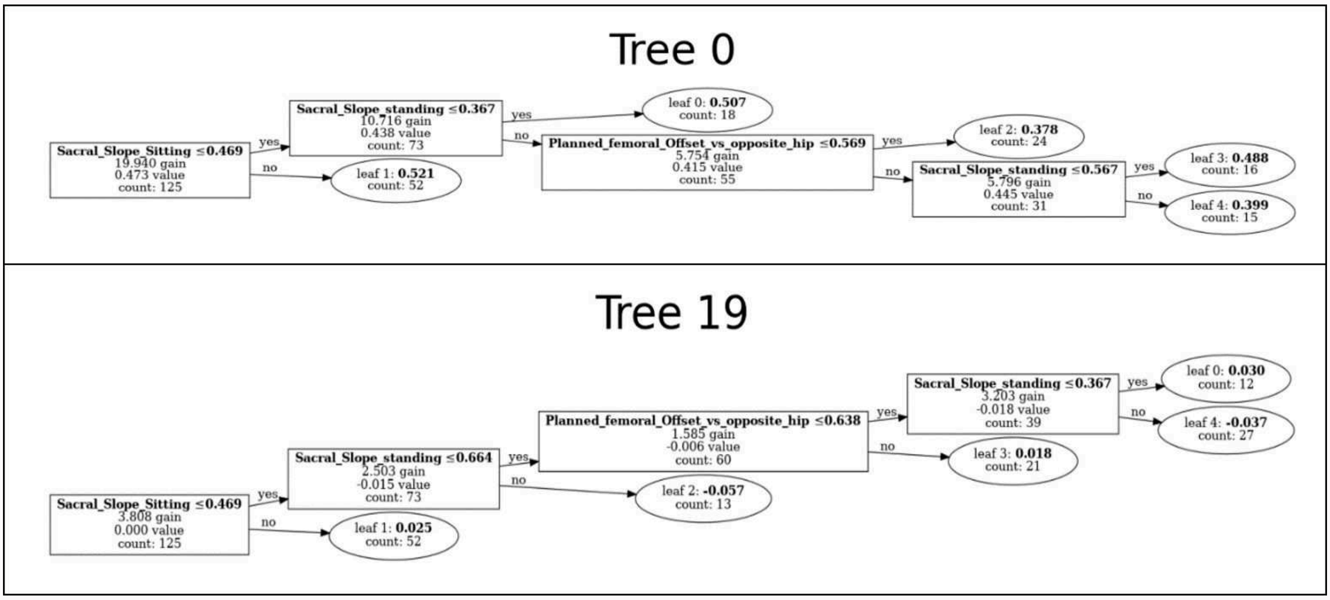


**Fig. 3**

Examples of sub-decision trees in Light Gradient-Boosting Machine.

**Table I.** Baseline and spinopelvic characteristics of the studied cohort.

| Variable | Patient undergoing robotic arm-assisted THA (n = 157) |
|---|---|
| Mean age, yrs (range) | 65 (32 to 88) |
| **Sex, n (%)** | |
| Female | 79 (50.6) |
| Male | 77 (49.4) |
| **Laterality, n (%)** | |
| Right | 81 (51.9) |
| Left | 75 (48.1) |
| Mean sacral slope standing, ° (SD) | 37.8 (8.8) |
| Mean sacral slope sitting, ° (SD) | 15.2 (12) |
| Mean pelvic incidence, ° (SD) | 53.1 (12.4) |
| Mean pelvic tilt in standing position, ° (SD) | 15.5 (8.4) |

THA, total hip arthroplasty.

**Table II.** Surgical planning parameters and impingement characteristics.

| Variable | Patient undergoing robotic arm-assisted THA (n = 157) |
|---|---|
| Median planned offset versus opposite hip, mm (IQR) | -1 (-3 to 3) |
| Median planned offset versus preoperative hip, mm (IQR) | -2 (-5.75 to 1) |
| Mean planned acetabular component obliquity, ° (SD) | 40.4 (1.3) |
| Mean planned acetabular component version, ° (SD) | 20.4 (1.5) |
| Median planned femoral stem version, ° (IQR) | 14 (10 to 15) |
| Impingement, n (%) | 100 (64.1) |
| **Impingement direction, n (%)** | |
| Anterior (in flexion) | 77 (77) |
| Posterior (in extension) | 23 (23) |
| **Type of impingement, n (%)** | |
| Bone-on-bone | 52 (52) |
| Implant-on-implant | 7 (7) |
| Implant-on-bone | 41 (41) |

THA, total hip arthroplasty.

predict impingement effectively under real-world conditions. Intraoperative adjustments to the surgical plan, such as modifications to the offset and component positioning, were frequently necessary based on real-time feedback and intraoperative trialling.

### Model description

In this study, we focused on two AI models designed to predict impingement during hip arthroplasty surgery, taking into account the individual phenotype, component positioning, and spinopelvic mechanics. Our primary model, Light Gradient-Boosting Machine (LGBM),[19] employed AI using tabular data to predict: 1) the presence of impingement; 2) whether impingement will occur in flexion or extension; and 3) the type of impingement (bone-on-bone, implant-on-implant, implant-on-bone).

Gradient-Boosted Decision Trees (GBDT) and LGBM generate multiple trees sequentially across iterative learning

**Table III.** Variables used in the artificial intelligence model.

| Predictors | Outcomes |
|---|---|
| Sacral slope standing | Impingement |
| Sacral slope sitting | Impingement direction |
| Pelvic incidence | Type of impingement |
| Pelvic tilt in standing position | |
| Planned offset versus opposite hip | |
| Planned offset versus preoperative hip | |
| Planned acetabular component obliquity | |
| Planned acetabular component version | |
| Planned femoral stem version | |

**Table IV.** Comparative accuracy of different models on predicting impingement, direction, and type.

| Input | Output | LGBM | LR | SVM |
|---|---|---|---|---|
| Predictors | Impingement | 0.702177 | 0.630020161 | 0.652620968 |
| Predictors impingement | Direction | 0.85037 | 0.853870968 | 0.818225806 |
| Predictors + impingement + direction | Type | 0.677778 | 0.702540323 | 0.728689516 |

LGBM, Light Gradient-Boosting Machine; LR, linear regression; SVM, support vector machine.

**Table V.** Comparison of results of Light Gradient-Boosting Machine with or without age, sex, and laterality.

| Variable | Impingement | Direction | Type |
|---|---|---|---|
| With baseline demographics | 0.667265 | 0.858205 | 0.619402 |
| Without baseline demographics | 0.702177 | 0.85037 | 0.677778 |

steps. Figure 1 illustrates the workflow of the GBDT, with three distinct prediction phases for impingement types, each executed by a different decision tree in a consecutive manner. Succeeding trees are trained to predict the residual between the preceding tree's prediction and the true values, until either the residuals nullify or the pre-set maximum tree count is met (in this case, 3). The LGBM represents a refined variant of GBDT, designed with the intention of fine-tuning both learning algorithms and engineering parameters for enhanced precision. It also employs gradient-based one-side sampling to adjust sample weights during training, focusing on underfitted data while maintaining the original distribution.

In our second model, we integrated tabular data with plain AP pelvis radiographs to assess for any potential enhancement in prediction accuracy. To incorporate imaging data, we combined the table multilayer perceptron (MLP) with a deep convolutional neural network (CNN) using the Widedeep framework.[20] This approach efficiently processes features from both data types. The radiological analysis combined a CNN classifier and a MLP classifier. Out of 135 samples, each fold used 108 samples for training and the remaining 27 for validation. Each sample consisted of a table feeding its predictive components into the MLP classifier to derive tabular features, and a radiograph feeding into the CNN classifier to derive image features. These features from both classifiers were merged and trained against the true category labels of impingement information using cross-entropy loss. The CNN segment was designed not to concentrate on specific measurements, but rather to identify complex patterns in the images that might be overlooked by medical professionals, thereby complementing the precise measurements detailed in the tabular data.

## Results

Of the 196 adult patients screened for RO THA, 157 were included in the primary analysis due to complete datasets (Figure 2). The participants' ages spanned from 32 to 88 years, with an almost even sex representation: 49.4% males (n = 77) and 50.6% females (n = 79). Analyzing anatomical parameters, mean standing SS was 37.8° (SD 8.8°) and 15.2° (SD 12°) when seated. Mean PI was 53.1° (SD 12.4°) and mean standing spinopelvic tilt (SPT) was 15.5° (SD 8.4°). The mean planned acetabular version and inclination were 20.4° (SD 1.5°) and 40.4° (SD 1.3°), respectively, while the median femoral stem version was 14° (IQR 10 to 15). Prior to employing AI for impingement prediction, each case underwent manual impingement modelling using the robotic software to establish baseline data. The vROM tool revealed that over 60% of participants showed signs of impingement, with anterior impingement in about three-quarters of participants. Bone-on-bone impingement was the most common, seen in nearly 50% of cases, followed by implant-on-bone at around 40%. These manually curated data were then used to train and

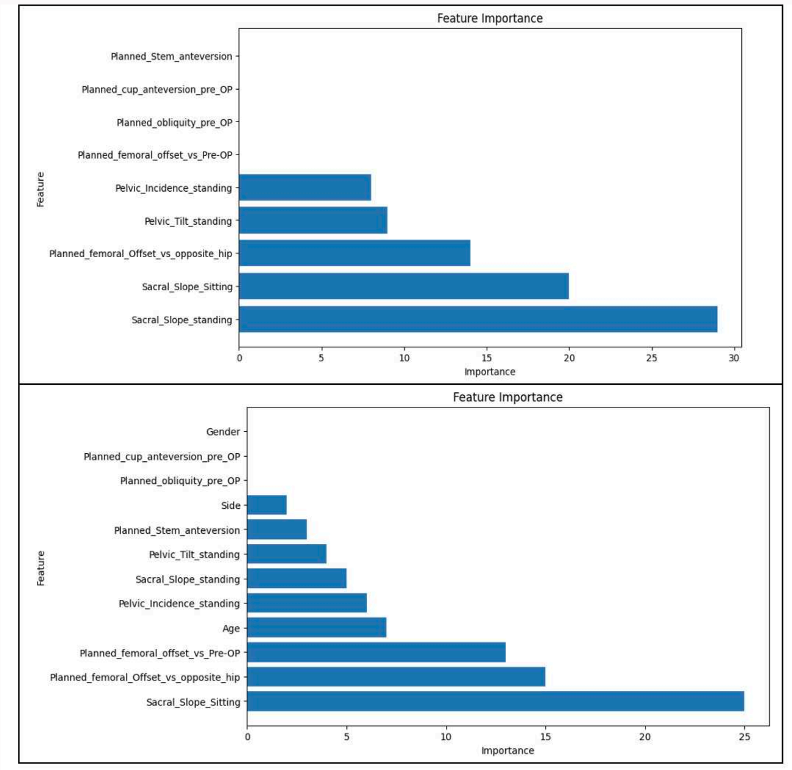


**Fig. 4**

Feature importance when training the Light Gradient-Boosting Machine with (below) and without (above) baseline characteristics.

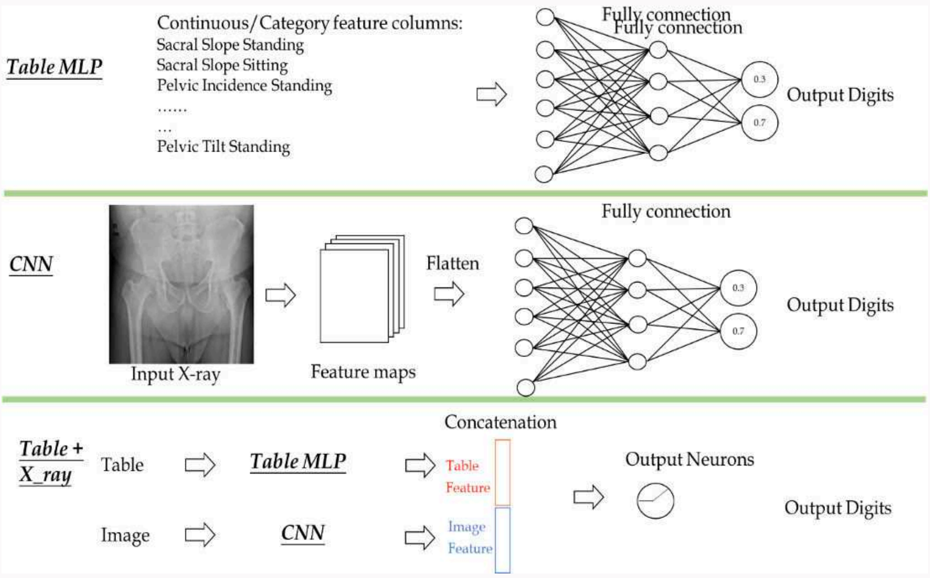


**Fig. 5**

Illustrations of the tabular model, the convolutional neural network (CNN) model, and the model combining CNN and table multilayer perceptron (MLP).

validate the AI models, enabling them to predict impingement based on the observed patterns and surgical planning parameters.

### Exploring the feasibility of an AI algorithm to predict impingement

To examine the feasibility of a predictive algorithm, we analyzed the baseline spinopelvic characteristics (Table I) and the surgical planning and impingement parameters (Table II). From those, we identified nine essential predictors for our model (Table III). To ensure a rigorous training and validation process given our dataset size, we used fivefold cross-validation. Acknowledging the potential variability, we incorporated ten random seeds to guide the train-validate data split and to determine model parameters. In the primary model, 125 samples from each fold were used for training and 32

**Table VI.** Prediction accuracies obtained from combining imaging and tabular data versus imaging alone.

| Input | Output | Table MLP + CNN (image + tabular) | LGBM (tabular) | Table MLP (tabular) | CNN (image) | SVM (tabular) |
|---|---|---|---|---|---|---|
| Predictors | Impingement | 0.675328 | 0.681225 | 0.645613 | 0.64188 | 0.6375783475783476 |
| Predictors + impingement | Direction | 0.843903 | 0.845499 | 0.840741 | 0.388889 | 0.8134757834757835 |
| Predictors + impingement + direction | Type | 0.664217 | 0.645014 | 0.643621 | 0.3218 | 0.6583475783475784 |

CNN, convolutional neural network; LGBM, Light Gradient-Boosting Machine; MLP, multilayer perceptron; SVM, support vector machine.

for validation. The results presented are averages from ten random seeds; each seed was further averaged across the five folds. Based on previous studies,[21] we opted for the LGBM algorithm over deep-learning methods,[19] given its robust performance with tabular data. We opted for a set of 20 trees for impingement prediction (Figure 3). The results from the LGBM model for impingement occurrence, direction, and type can be seen in Table IV. We also present a comparison with other algorithms' accuracy metrics. The logistic regression (LR) model processes weighted input features and uses a sigmoid function for predictions. In contrast, the support vector machine (SVM) organizes input sample features in a high-dimensional space, subsequently classifying these samples.[22]

**Model accuracy**

Using a dataset with nine spinopelvic characteristics and surgical planning parameters, the LGBM yielded 70.2% accuracy. When provided with impingement data, both LGBM and LR estimated impingement direction with approximately 85% accuracy. When provided with the impingement direction, SVM reached an accuracy of 72.9% for type prediction (Table IV). Since impingement prediction was crucial, we selected the LGBM as our primary model. Subsequently, we explored the impact of integrating baseline demographics to our model. We noted that adding these characteristics (age, sex, laterality) neither improved prediction accuracy nor added value. Instead, they seemed to introduce potential misclassification risks. Variable importance assessment in LGBM, shown in Figure 4, indicated that age, laterality, and sex were non-dominant during training. Given these findings and a slight drop in accuracy (Table V), we omitted age, sex, and laterality from the final model.

**Tabular data and radiograph-based impingement prediction**

To evaluate the impact of integrating imaging data on prediction accuracy, we tested both a MLP and a CNN. For each tabular data entry, a corresponding radiograph was used. This combined dataset underwent fivefold cross-validation, with ten unique random seed settings. Of the 135 samples, each fold employed 108 samples for training and the remaining 27 for validation (Figure 5). Table VI presents the comparative performance of all models. The main observations were first that the LGBM on tabular data achieved the highest impingement prediction accuracy of 68.1%, with the combined image and tabular approach following closely at 67.5%, surpassing other tabular methods and the CNN (imaging only). Second, both the image-tabular combination and the LGBM performed similarly on impingement direction prediction, with accuracies of 84.39% and 84.54%, respectively. Lastly, the combined method achieved the highest impingement type prediction accuracy at 66.4%.

The image-based CNN demonstrated low precision, likely due to the limited dataset of 135 images and minimal radiograph annotations.

## Discussion

In our pilot study, we demonstrated the viability of a deep-learning algorithm for predicting impingement based on individual spinopelvic mechanics and patient phenotype. The pilot algorithm exhibited good accuracy in predicting impingement and type (bone-on-bone, implant-on-implant, implant-on-bone) and excellent accuracy in determining its direction. The algorithm's input consisted of preoperative data, accessible from any 2D or 3D surgical planning software. This encompassed projected changes in offset, planned femoral stem version, cup orientation, and spinopelvic metrics. For arthroplasty surgeons without access to CT-based navigation or robotic systems offering vROM,[23,24] a refined AI algorithm predicting impingement based on individual patient phenotypes could be instrumental. This prediction tool could guide preoperative planning and prepare surgeons for potential intraoperative challenges.

While various studies have delved into the risks of hip dislocation following THA, to the best of our knowledge our research is the first attempt to harness AI for impingement prediction in THA.[25] Parallel to our work but distinct in not utilizing AI, Pryce et al[26] pioneered a geometrical model through computer-aided design (CAD). Widmer,[27] in another related endeavour, employed a 3D CAD model, analyzing hip movements to identify an impingement-free zone that was tailored to the individual prosthesis. Elkins et al[28] used a validated metal-on-metal THA finite element model to delineate optimal acetabular orientations that would both minimize wear and enhance component stability. Despite these commendable attempts to visualize impingement, previous studies have neither fully integrated the spinopelvic parameters into their predictive models, nor expanded on the potential of AI.

Our algorithm exhibited good accuracy in impingement and type prediction, and excellent accuracy in determining the direction. We used fivefold cross-validation, a recognized method to ensure model reliability and prevent overfitting.[29–32] Although no universal accuracy benchmark for AI models exists, domains like healthcare unquestionably require higher precision. Balagurunathan et al[33] outlined an AI system's evolution in medicine, from inception to market introduction. This journey starts with an idea and moves onto a discovery phase where the algorithm is established based on an initial cohort study. The subsequent mid-phase encompasses system refinement and broader population testing (clinical trials). The culmination is the late phase, where the AI product is deemed suitable for widespread deployment. Within this framework, our work resonates with the early, proof-of-concept phase.

Our model demonstrated good accuracy in predicting impingement and its direction, offering valuable insights for arthroplasty surgeons during the preoperative stage. Such information can direct necessary adjustments concerning component positioning and prepare the surgeon for potential intraoperative challenges. Nevertheless, our model's performance in predicting the impingement type showed room for improvement. Several reasons could account for this: a need for a more comprehensive and representative dataset, or a potential revision of the input variables specific to impingement type prediction. For instance, Chandler et al,[34] in a cadaveric study, indicated that factors such as the head/neck ratio and neck length influence impingement-free ROM. Therefore, integrating these parameters might enhance our model's accuracy.

When we incorporated imaging into our predictive deep-learning algorithm using a plain weightbearing AP pelvis radiograph, we observed no enhancement in accuracy. We intentionally limited our imaging input to a single preoperative AP pelvis radiograph to ensure broader applicability. This constraint, however, comes at the expense of conducting more comprehensive evaluations, such as volumetric assessments of anatomical structures or precise distance measurements. Additionally, a complete understanding of how the morphology and volume of anatomical structures, particularly the greater trochanter, influence impingement remains elusive. While CT reconstruction views and axial slices could offer a pathway to these precise measurements, the implications of adopting CT scans should be considered and weighed against their broader applicability.[35] Future studies could leverage detailed annotations, such as landmark markings or distance measurements, to enhance predictive accuracy. Furthermore, it is important to acknowledge that owing to some patients opting out of having their images used, our sample size for the AI model utilizing both tabular and imaging data was slightly reduced. This could potentially have introduced attrition bias and made our sample less generalizable.

Our study possesses several potential limitations. Although our comprehensive, prospectively collected data strengthen our conclusions, a larger sample could further refine the external validity and performance of our algorithm. Another consideration is that missing data are inevitable in real-world, everyday clinical practice. For this study, we chose to use only patients with a complete dataset. Yet, the efficiency of our algorithm could be enhanced by incorporating imputation models to accommodate and adjust for missing data.[36] Moreover, the algorithm's accuracy could vary internationally and between different ethnic groups due to phenotypic differences,[37] underscoring the need for broader validation. We relied on standing and relaxed-seated position spinal radiographs to evaluate spinopelvic motion; recent research suggests that this method might overestimate spinal stiffness.[38,39] It has also been reported that approximately 20% of osteoarthritic hips exhibit features of spinopelvic hypermobility owing to limited hip motion and a compensatory posterior pelvic tilt in the relaxed-seated position.[40–42] Therefore, integrating flexed-seated radiographs into the algorithm might enable a more accurate impingement prediction. Additionally, predicting impingement using our virtual ROM tool may not fully replicate impingement as experienced by patients, as not all aspects of impingement can be modelled with CT scans. This discrepancy highlights a potential area for future research and algorithm refinement. Moreover, we confined our imaging input to a single preoperative AP pelvis radiograph to promote broader applicability, especially for surgeons not utilizing enhanced CT preoperative planning. Future efforts could consider CT reconstruction views and axial slices for more detailed anatomical insights and measurements. Another limitation is our exclusive use of a specific femoral stem and acetabular component, necessitating validation with other prosthetic designs. It should also be acknowledged that the specific parameters chosen for hip motion in this study, aimed at assessing more extreme functional positions,[43] may not be universally applicable. Variations in impingement and accuracy results could occur if more conservative parameters are selected, potentially influencing the generalizability of our findings.

In summary, we used a high-quality, comprehensive, prospectively collected dataset emulating real-world clinical scenarios to develop a machine-learning algorithm aiming to predict impingement, its direction, and type in THA.[44] Our research represents the first study to examine the use of AI in impingement prediction and external validation of this algorithm and testing at a larger scale is imperative.

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## Data sharing

The datasets generated and analyzed in the current study are not publicly available due to data protection regulations. Access to data is limited to the researchers who have obtained permission for data processing. Further inquiries can be made to the corresponding author.

## Ethical review statement

The study adhered to the ethical standards of the 1964 Declaration of Helsinki and secured ethical approval from the Hôpitaux Robert Schuman institutional review board (Ref: CIVLU-21–09-037787).