Machine Learning Augmented with Radiomics Predicts Patient-Specific Risk and Time to Total Hip Arthroplasty

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INTRODUCTION:

The progression of hip osteoarthritis (OA) is non-linear, and predicting the time between developing symptomatic OA and requiring a total hip arthroplasty (THA) is currently poorly understood. As the socioeconomic burden of hip OA continues to rise, early identification of patients at highest risk of progression could enable targeted interventions and inform health policy. Radiomics, the analysis of large numbers of imaging features related to size, shape, and texture within regions, represents a promising avenue for risk stratification. We aimed to develop a machine learning model to predict time to THA using clinical, radiological, and radiomic features.

METHODS:

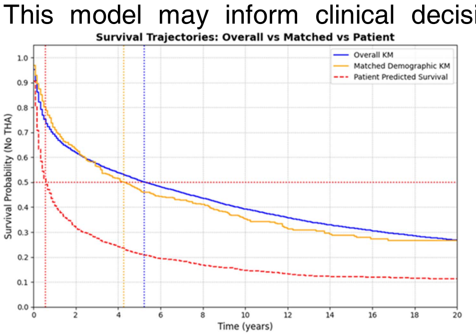
Anteroposterior pelvis radiographs of 28,840 hips (15,912 patients)—including asymptomatic contralateral hips evaluated for THA due to degenerative hip disease—were obtained from a single academic institute between 2000-2024. Hips with prior arthroplasty, inadequate imaging, or <12 months of radiographic follow-up were excluded. We trained Random Survival Forest models to predict time to THA using 314 input features encompassing demographics (n=4), radiological measurements (n=4), and radiomics (n=306). Separate models were developed using clinical, radiological, and radiomic features individually, as well as in combination. Model performance was assessed using five-fold cross-validation. Discriminative ability was measured using area under the curve (AUC) and concordance index (C-index), while calibration was evaluated using Brier score.

RESULTS:

The combined model performed best (AUC=0.81, C-index=0.73, Brier score=0.17), demonstrating strong predictive accuracy and calibration. Radiological-only (AUC=0.77) performed comparably, followed by radiomics (AUC=0.71), and clinical-only (AUC=0.55). The five most important features, in order, were minimum joint space width, hip extrusion index, Tönnis angle, sourcil brightness asymmetry, and lateral center-edge angle.

DISCUSSION AND CONCLUSION:

We developed a machine learning model that accurately predicts patient-specific risk and time to THA. Radiological data alone provided strong predictive performance, with incremental but meaningful gains from radiomics and clinical variables. This model may inform clinical decision-making, guide patient counselling, and enable earlier, personalised care.



Selected Patient Summary

Side:	Left
Age:	63
BMI:	28.98
Sex:	Male
Race:	White
mJSW:	2.01
LCEA:	17.10
Tonnis Angle:	12.30
Extrusion Index:	23.56

Figure 1. Model-generated survival output for a randomly sampled patient.
The red dashed curve shows the ML–predicted survival trajectory for the patient, representing their estimated probability of remaining THA-free over time. For reference, the blue curve shows the KM survival curve for the entire cohort, while the orange curve shows the KM curve for a demographically matched subgroup based on age, BMI, sex, and race. The model also outputs a patient summary, which includes their automated radiological measurements.

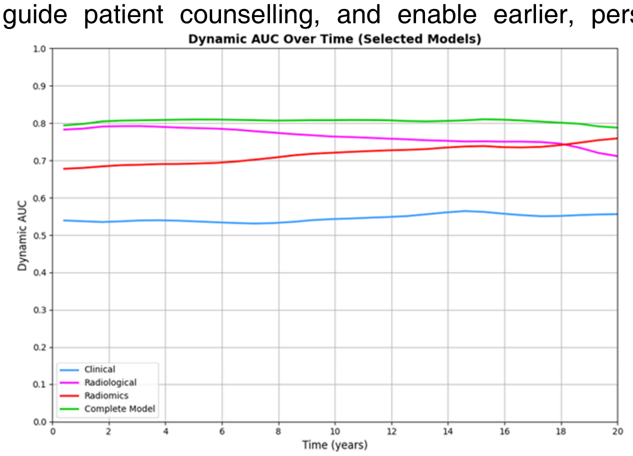


Figure 2. AUC-over-time curves for all model combinations.
Each curve reflects model predictive accuracy at yearly timepoints, measuring how well each model predicted whether a patient had or had not undergone THA by that point in their projected follow-up since baseline evaluation.