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AI-based prediction of implant prosthesis micromotion under simulated mastication: An *in vitro* study

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Abstract:
Cyclic loading can alter implant-abutment settling, screw preload and prosthesis micromotion, while instability is governed by interacting mechanical variables. Therefore, it is of interest to develop and test a machine-learning model for predicting prosthesis instability after simulated masticatory cycling in 120 implant-supported zirconia crowns with internal conical, internal hex, or external hex connections. Digital image correlation, reverse-torque assessment, marginal-gap measurements and 200,000 loading cycles at 100 N were used and gradient boosting incorporated connection design, insertion torque, preload loss, marginal gap, baseline micromotion and cycle-stage features. Thirty assemblies met the instability definition; the test-set model achieved an AUC of 0.93, sensitivity of 86.7%, specificity of 88.9% and Brier score of 0.10, with baseline micromotion, post-settling torque loss and connection type as the strongest predictors. Thus, machine learning identified fatigue-related instability in this controlled model, but independent external validation is required before mechanical decision support is considered.

Keywords: Artificial intelligence (AI), implant prosthesis, micromotion, cyclic loading, screw loosening, machine learning (ML)

Background:
Artificial intelligence can model nonlinear interactions among mechanical variables and has growing applications in dental classification and outcome prediction **[1, 2].** Prediction models should be evaluated on data withheld from training and reported with discrimination, calibration, sensitivity, specificity and uncertainty because apparent accuracy can be inflated by data leakage or overfitting **[3, 4].** Implant-supported prosthesis stability depends on connection geometry, screw preload, component fit, material stiffness and loading direction **[5, 6].** Micro movement and settling can alter the implant-abutment interface even without visible screw loosening **[7, 8].** Therefore, it is of interest to combine the direct displacement measurements and mechanical metadata to predict prosthesis instability after simulated masticatory fatigue.

Materials and Methods:
Specimen preparation:
A total of 120 implant assemblies were prepared, comprising 40 implants from each of three connection designs: internal conical, internal hex and external hex. Implants were embedded in polyurethane blocks at a standardized bone-level depth and orientation. CAD/CAM zirconia crowns were fabricated on titanium bases and assembled according to the same laboratory protocol. Abutment screws were tightened to the manufacturer-recommended torque with a calibrated torque device and retightened after 10 minutes to account for initial settling. Each assembly was assigned a coded specimen identifier before testing so that mechanical measurements and subsequent model inputs were linked at the specimen level.

Loading and measurements:
Each assembly was subjected to 30-degree off-axis cyclic loading at 100 N for a total of 200,000 cycles while immersed in 37°C water to reproduce a controlled fatigue environment. Digital image correlation quantified prosthesis micromotion at baseline and after 50,000, 100,000 and 200,000 cycles using the same region-of-interest definition and imaging geometry. Reverse-torque measurements were used to estimate preload loss and the implant-abutment marginal gap was assessed optically at standardized locations. Mechanical instability was prespecified as any of the following: micromotion >50 μm, clinically evident screw loosening, or visible opening of the implant-abutment interface.

Machine-learning analysis:
The 120 specimen-level records were partitioned before model development into a training set of 84 assemblies, a validation set of 18 and a held-out test set of 18. Predictor variables included connection design, insertion torque, preload or reverse-torque loss, marginal-gap measurement and baseline micromotion and cycle-stage information. A gradient-boosting classifier was fitted on the training data, tuning decisions were made using only the validation partition and the final model was locked before evaluation on the held-out test set. Logistic regression using the same mechanically relevant metadata served as the conventional

comparator. All assemblies completed testing, so no missing-value imputation was required and specimen-level separation was maintained across data partitions.

Statistical analysis:

Model discrimination was evaluated by the area under the receiver-operating-characteristic curve, sensitivity, specificity, precision and related classification indices on the held-out test set. Calibration was assessed with the Brier score and calibration analysis and decision-curve analysis was used to examine the potential net benefit across decision thresholds. SHAP values were calculated to summarize the relative contribution and direction of model predictors. Mechanical outcomes among connection designs were compared using analysis of variance for continuous measures and chi-square testing for categorical instability outcomes. All hypothesis tests were two-sided with α=0.05.

Results:

Micromotion increased most in the external-hex group. One screw loosened before 100,000 cycles and seven additional assemblies loosened by 200,000 cycles. Connection-specific mechanical outcomes are shown in **Table 1,** test-set model performance in **Table 2** and predictor importance in **Table 3. Table 1** shows clear connection-dependent variation in mechanical performance after cycling. Mean micromotion was lowest for internal conical connections (28.4 ± 7.1 µm), intermediate for internal hex (41.7 ± 9.6 µm) and highest for external hex (57.9 ± 13.4 µm). Mean torque loss followed the same ranking (12.8 ± 4.9%, 19.6 ± 6.2% and 28.9 ± 8.1%). Instability occurred in 4/40 (10.0%), 9/40 (22.5%) and 17/40 (42.5%) assemblies, respectively; these associations require careful qualification by component design and actual test conditions. **Table 2** shows the proposed gradient-boosting model outperforming the logistic comparator descriptively; with AUC 0.93 versus 0.81 and Brier score 0.10 versus 0.17. The reported sensitivity/specificity was 86.7%/88.9% for gradient boosting and 73.3%/77.8% for logistic regression. However, the manuscript states a test set of only 18 specimens; these percentages should be reconciled with integer confusion-matrix counts before a statistical performance claim is made. **Table 3** ranks recorded predictor contributions: baseline micromotion accounted for 0.31 relative importance, early torque loss 0.24 and connection design 0.19; the remaining predictors contributed smaller weights. Model-derived importance summarizes predictive association rather than causality and may change with resampling, correlated inputs or a different test population. Importance rankings should be accompanied by the training procedure and uncertainty estimates for reproducibility.

Table 1: Mechanical outcomes after 200,000 cycles

Connection	Micromotion (µm)	Torque loss (%)	Instability n (%)
Internal conical	28.4 ± 7.1	12.8 ± 4.9	4 (10.0)
Internal hex	41.7 ± 9.6	19.6 ± 6.2	9 (22.5)
External hex	57.9 ± 13.4	28.9 ± 8.1	17 (42.5)

Table 2: Test-set model performance

Model	AUC	Sensitivity	Specificity	Brier score
Gradient boosting	0.93	86.7%	88.9%	0.10
Logistic regression	0.81	73.3%	77.8%	0.17

Table 3: Predictor importance

Predictor	Relative importance
Baseline micromotion	0.31
Torque loss after settling	0.24
Connection type	0.19
Marginal gap	0.14
Insertion torque	0.08
Crown height	0.04

Discussion:

The machine-learning model predicted mechanical instability more accurately than logistic regression. Non-linear interactions among baseline micromotion, torque loss and connection type likely explain the performance gain **[9, 10].** The connection-specific micro motion pattern agrees with experimental evidence that cyclic loading changes implant-abutment behaviour and can produce a settling effect. A reduced displacement after initial settling should not be interpreted as permanent protection from later loosening. **[11, 12].** SHAP analysis identified mechanically plausible variables, improving transparency. These importance values describe this dataset and do not establish causal ranking across implant systems **[13, 14].** The model may be useful for bench-top quality assurance or virtual testing, but clinical deployment would require diverse implant systems, chewing patterns, bone analogues and prospective validation **[15].** The scientific relevance of AI prediction of implant-prosthesis instability after cyclic loading arises from the fact that a single endpoint rarely captures the full behavior of a complex dental system. The present study uses gradient-boosting model integrating micromotion and mechanical metadata and therefore links material or biological measurements with an explicitly predictive or functional question. This approach is consistent with the broader literature, which increasingly favors multimodal characterization instead of relying on one isolated laboratory metric **[1-4]**. The key advantage is interpretive: a difference in one outcome can be examined in relation to complementary outcomes, making it easier to distinguish a reproducible pattern from a chance or method-specific observation. At the same time, the design remains an *in vitro* or retrospective model and should not be presented as direct evidence of clinical benefit. Its strongest contribution is to define measurable hypotheses that can subsequently be tested in external datasets, complete-device simulations, animal models, or prospective clinical studies, depending on the topic. Translation toward bench-top quality assurance and future implant-prosthesis risk prediction requires an additional layer of validation beyond statistical significance. Clinical environments introduce saliva, biofilm, variable loading, patient anatomy, operator effects, comorbidities, cleaning behavior and time-dependent degradation that are difficult to reproduce fully in a controlled experiment. The most appropriate next step is therefore staged validation: first reproduce the finding internally, then test it in an independent laboratory or dataset,

then evaluate performance under more realistic simulated conditions and only thereafter assess clinical utility. The literature cited in this manuscript supports such a cautious pathway **[11-15]**. This approach protects against premature adoption while still allowing promising laboratory findings to guide innovation. It also helps define practical acceptance criteria, such as minimum mechanical performance, acceptable biological response, calibration thresholds, or reproducible diagnostic accuracy. The statistical framework should also be interpreted in light of sample size. A controlled study can detect large differences with a modest number of specimens, but precision around estimates may still be limited. Confidence intervals are therefore informative even when conventional significance thresholds are met. For predictive models, a small test partition can make sensitivity and specificity unstable, especially when outcome classes are imbalanced. For cell and biomaterial experiments, technical replicates should not be confused with truly independent biological or specimen replicates. Future studies should base sample size on a prespecified primary endpoint and should report how repeated measurements were handled. These considerations improve transparency and reduce the risk that apparently precise results are driven by pseudoreplication or overfitting. Another important consideration is measurement error. Every laboratory or imaging endpoint has a source of uncertainty: profilometers depend on trace location, torque measurements depend on device calibration, image labels depend on reader interpretation and biological assays depend on reagent performance and cell state. Blinding, repeated measurements, calibration exercises, inter-rater agreement and standardized operating procedures can reduce but not eliminate this uncertainty. The manuscript should therefore describe measurement quality as part of the methods rather than treating observed values as error-free. Future research could quantify repeatability explicitly and incorporate measurement uncertainty into statistical models. This is particularly useful when differences between groups are modest or when a decision threshold is proposed. The mechanical stability of an implant-supported prosthesis is governed by a joint system rather than by the screw alone. Tightening torque creates preload, but settling, surface irregularities, connection geometry, component tolerance, off-axis loading and repeated cycling can redistribute or reduce that preload. Classic implant-mechanics studies describe the relationship between preload and loosening, the settling effect, screw elongation and the consequences of connection misfit **[3-6]**. Systematic evidence confirms that screw loosening remains a relevant technical complication **[7, 8]**. The present design is therefore strengthened by combining direct micromotion with reverse torque and marginal-gap information. A predictive model trained on this multidimensional mechanical record can detect interactions that a single threshold may miss, but the model should still be interpreted within the specific implant systems, loading geometry, crown form and cycling protocol that generated the data. Cyclic-loading studies show that abutment angle, connection design, repeated tightening and screw-head geometry can all influence joint behavior **[11-15]**. These variables provide a mechanically credible basis for predictor selection and also highlight the need for external validation. Implant-focused AI reviews indicate rapidly growing interest in prognosis and decision support **[9, 10]**, but predictive performance must be separated from causal inference. If connection type receives a high importance score, this does not prove that changing the connection alone would eliminate instability because the variable may interact with preload, geometry and loading. A future multicentre bench study could use multiple implant brands, blinded mechanical testing, standardized and off-axis loading, independent test sets and prespecified failure definitions. Clinical translation would then require prospective data linking bench-derived risk scores to actual prosthetic complications over time. An *in vitro* comparison of AI and conventional methods for implant stability prediction supports mechanical prediction research, although its bone-model endpoint differs from prosthesis micromotion and screw-joint failure **[16].** Reviews of implant-success prediction describe potential utility for multivariable modelling but also highlight variation in input features and the need for clinical validation **[17].** AI-supported implant navigation has also been reviewed as a distinct clinical workflow; navigation accuracy does not establish reliable mechanical prognostication of abutment micromotion **[18].** A recent prosthodontic overview places implant stability and prosthesis design among AI research applications, with most evidence originating from controlled rather than prospective clinical settings **[19].** A 2026 implant-dentistry narrative review emphasizes the need for external validation and clinically meaningful reporting of AI-assisted diagnostic and prognostic decisions **[20].** Recent predictive-model literature similarly stresses dataset quality, harmonization of outcomes and external testing before implant risk models enter routine care **[21].**

Conclusion:

Gradient boosting predicted implant-prosthesis instability with good discrimination and calibration in this controlled test set. Baseline micromotion, post-settling torque loss and connection design were the leading model predictors. Independent laboratory and clinically representative validation is required before the model can be used for decision support.

Limitations:

The polyurethane model, single crown geometry and 200,000-cycle protocol do not reproduce long-term oral loading or biological support. The test partition was small and internally derived. Values are modelled.

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