Research Article

Artificial Intelligence Prediction of Prosthetic Complications in Implant-Supported Restorations: A Pilot Study

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Abstract

Background
Implant-supported restorations demonstrate high long-term survival; however, technical and biological complications such as screw loosening, ceramic chipping or fracture, loss of retention, framework fracture, and peri-implant inflammatory disease remain clinically relevant. Artificial intelligence (AI) and machine-learning methods may facilitate individualized risk estimation by integrating patient-, implant-, prosthetic-, occlusal-, radiographic-, and maintenance-related variables.

Objective
To develop and demonstrate a clinically oriented machine-learning framework for predicting prosthetic and prosthesis-associated biological complications in implant-supported restorations and to define methodological requirements for subsequent prospective validation.

Methods
A prospective prediction-model framework was designed around patient- and restoration-level variables, including age, smoking, diabetes, history of periodontitis, bruxism or parafunction, implant location, implant dimensions, implant angulation, prosthetic material, retention mode, cantilever extension, occlusal characteristics, peri-implant clinical and radiographic parameters, and maintenance adherence. Logistic regression, random forest, and gradient-boosting models were prespecified as candidate approaches. A synthetic dataset of 60 restorations was used solely to demonstrate the proposed analytical workflow and statistical presentation.

Results
The synthetic demonstration dataset contained 60 restorations, of which 18 (30.0%) were assigned a composite complication outcome within a simulated 12-month follow-up period. The simulated complication categories included screw loosening (n=8), ceramic chipping (n=5), loss of retention (n=4), peri-implant inflammation (n=3), screw fracture (n=2), and framework fracture (n=1); categories were permitted to overlap. In the demonstration analysis, simulated ROC-AUC values were 0.78 for logistic regression, 0.87 for random forest, and 0.84 for gradient boosting. These values are synthetic demonstration outputs and do not represent clinical model performance.

Conclusion
A machine-learning framework integrating patient, implant, prosthetic, occlusal, peri-implant, and maintenance variables may provide a structured approach for future prediction of complications associated with implant-supported restorations. However, the numerical findings presented here are simulation-based and cannot be interpreted as evidence of clinical predictive performance. A prospective, adequately powered, multicentre study with prespecified outcome definitions, rigorous internal validation, external validation, calibration assessment, and evaluation of clinical utility is required before clinical implementation.

Keywords Artificial intelligence; machine learning; dental implants; implant-supported restorations; prosthetic complications; screw loosening; ceramic chipping; loss of retention; peri-implant disease; risk prediction; prosthodontics.

1. Introduction

Implant-supported crowns and fixed dental prostheses are established treatment options for partially and completely edentulous patients. Long-term studies demonstrate high implant and prosthesis survival; however, survival does not imply complication-free function. Technical events such as veneer fracture or chipping, screw loosening, loss of retention, loss of access-hole restoration, and framework fracture, together with biological complications involving peri-implant tissues, remain relevant causes of maintenance and repair.[1]

The clinical challenge is therefore not limited to determining whether a complication has occurred. An important objective of contemporary implant maintenance is to identify restorations with characteristics associated with increased future complication risk and to determine whether intensified monitoring may be appropriate.[2] Risk is multifactorial and may involve interactions among patient factors, previous periodontal disease, smoking,

systemic conditions, bruxism or parafunction, implant location and dimensions, prosthetic design, retention mode, material, cantilever extension, occlusal characteristics, peri-implant tissue status, and maintenance adherence.[3]

The European Federation of Periodontology S3-level clinical practice guideline emphasizes structured risk assessment, prosthetically driven implant therapy, maintainable prosthetic contours, professional monitoring, and supportive peri-implant care.[4]

Artificial intelligence provides a methodological opportunity to integrate multiple predictors and model potentially nonlinear relationships. Recent reviews have documented increasing applications of AI and machine learning in implant dentistry, including implant prognosis, implant classification, radiographic assessment, treatment planning, and identification of peri-implant pathology.[5] Nevertheless, current prediction-model literature remains limited by methodological heterogeneity, selection bias, inconsistent outcome definitions, internal-only validation, and inadequate external validation.[6]

Prediction-model reporting has evolved substantially with the development of TRIPOD+AI, which provides updated guidance for prediction models developed using regression or machine-learning methods. PROBAST+AI additionally provides an updated framework for evaluating risk of bias and applicability in prediction models using regression or AI methods.[7]

Therefore, the present work describes a simulation-based pilot framework for predicting prosthetic and prosthesis-associated biological complications in implant-supported restorations. The purpose is methodological rather than clinical: to demonstrate how routinely available clinical and prosthetic variables could be incorporated into an interpretable prediction pipeline and to identify requirements for a future prospective validation study.[8]

2. Aim and Objectives

2.1 Primary Aim

To develop and demonstrate a clinically interpretable machine-learning framework for predicting prosthetic and prosthesis-associated biological complications in implant-supported restorations.

2.2 Objectives

1. To identify clinically accessible candidate predictors that may contribute to complication prediction.
2. To compare logistic regression, random forest, and gradient-boosting approaches within a predefined analytical framework.
3. To examine the potential contribution of patient, implant, prosthetic, occlusal, peri-implant, and maintenance-related variables.
4. To demonstrate an approach for converting predicted probabilities into clinically interpretable risk categories.
5. To define methodological and sample-size requirements for a subsequent prospective multicentre validation study.

3. Materials and Methods

3.1 Study Design

This manuscript presents a simulation-based methodological pilot framework for a future prospective prediction-model study.

The numerical dataset used in the present manuscript is synthetic and was created solely to demonstrate the structure of the proposed analysis, tables, and figures. It does not represent observations from patients and must not be interpreted as clinical evidence.

The framework is intended to be implemented subsequently using prospectively collected, de-identified clinical data.

The future prospective study should follow TRIPOD+AI recommendations for prediction models developed using regression or machine-learning methods. Risk of bias and applicability should be considered using PROBAST+AI.

3.2 Proposed Study Population

The definitive prospective study would recruit patients receiving implant-supported single crowns and short-span fixed dental prostheses.

The primary unit of analysis would be the restoration. Each eligible restoration should have completed definitive loading and should have a minimum of 12 months of documented follow-up.

Inclusion Criteria

- Adult patients receiving implant-supported single crowns or short-span fixed dental prostheses.
- Definitive prosthetic loading completed.
- Availability of baseline prosthetic and implant records.
- At least 12 months of planned clinical follow-up.
- Availability of adequate maintenance and complication records.[9]

Exclusion Criteria

- Inadequate baseline documentation.
- Restorations with incomplete prosthetic records.
- Cases lacking sufficient follow-up to establish the primary outcome.
- Major prosthetic modifications performed before baseline assessment that prevent reliable characterization of the original restoration.[10]

3.3 Sample Size Considerations

The present synthetic dataset contains 60 restorations and is not intended to establish an adequate sample size for clinical model development.[11]

For the definitive study, sample-size planning should consider the expected complication incidence, number and complexity of candidate predictor parameters, anticipated model performance, shrinkage requirements, missing-data assumptions, and desired precision of calibration and risk estimates.[12]

Because the proposed candidate predictor set is substantially larger than can be reliably supported by only 18 simulated events, the present 60-restoration dataset should not be used to justify definitive model development.[13]

3.4 Outcome Definition

Primary Outcome

The primary outcome is the occurrence of at least one clinically documented complication during the prespecified follow-up period.

Complications will be categorized as:

1. Screw loosening.
2. Screw fracture.
3. Ceramic chipping or fracture.
4. Loss of retention or decementation.
5. Framework fracture.
6. Loss or failure of access-hole restoration.
7. Peri-implant inflammatory disease requiring clinical management.

Because these events may have different mechanisms, the definitive study should retain both a prespecified composite primary outcome and individual complication categories for secondary analyses.[14]

Secondary Outcome

Time from definitive prosthetic loading to the first documented complication will be evaluated as a time-to-event outcome in the definitive prospective cohort.

All outcome definitions should be prespecified before model development and adjudicated using standardized clinical criteria.[15]

3.5 Candidate Predictors

Domain	Candidate variables	Rationale
Patient	Age, sex, smoking, diabetes, previous periodontitis, bruxism/parafunction	May modify biological and mechanical risk
Implant	Site, diameter, length, number, angulation, implant system	May influence load distribution and prosthetic biomechanics

Prosthesis	Single crown/FPD, material, retention mode, cantilever, framework design	Design and material may influence distinct complication patterns
Occlusion	Antagonist type, parafunction, occlusal contacts, occlusal scheme	Excessive or unfavourable loading may contribute to mechanical events
Peri-implant status	Probing depth, bleeding on probing, suppuration, plaque status, radiographic bone level	Relevant to biological complications
Maintenance	Recall interval, professional maintenance, oral-hygiene adherence	Supportive care influences long-term peri-implant health
Restoration history	Previous prosthetic repair, previous screw loosening, previous chipping	May identify restorations with established maintenance vulnerability

3.6 Data Collection and Preprocessing

For the future prospective study, data collection should use a standardized case-report form and predefined coding dictionary.

Data preprocessing will include:

- range and consistency checks;
- duplicate detection;
- assessment of missingness patterns;
- prespecified handling of missing data;
- categorical encoding;
- scaling where required;
- identification of implausible values;
- documentation of all preprocessing procedures.[15,16]

All preprocessing procedures must be performed within the model-development pipeline to avoid information leakage.

For categorical and binary variables, coding schemes should be defined before model fitting. Continuous predictors should preferably be retained in continuous form rather than arbitrarily categorized.

Class imbalance should be addressed using methods restricted to training data, such as class weighting or appropriately implemented resampling.[13,17]

3.7 Machine-Learning Models

Three candidate approaches are proposed.

3.7.1 Logistic Regression

Multivariable logistic regression will serve as an interpretable baseline model and will estimate the probability of experiencing at least one complication during follow-up.

Penalized regression may be considered in the definitive dataset to reduce overfitting where appropriate.

3.7.2 Random Forest

Random forest will be used as a nonlinear ensemble method capable of modelling interactions and nonlinear associations without requiring every functional form to be prespecified.[18]

3.7.3 Gradient Boosting

Gradient boosting will be evaluated as a second nonlinear ensemble approach.

Hyperparameter optimization should be conducted exclusively within the training data using nested resampling or nested cross-validation.[19]

3.8 Model Development and Validation

The definitive study should distinguish clearly between:

1. Model-development data.
2. Internal-validation data.
3. External-validation data.

Internal validation should quantify optimism in model performance. Bootstrap validation or repeated cross-validation may be used depending on the final sample size and modelling strategy.

External validation should subsequently be performed using an independent dataset obtained from a different centre, time period, or clinical population.[20]

Random splitting of a small dataset into training and test subsets should be avoided when this substantially reduces the information available for model development.

3.9 Model Performance

Model performance should be evaluated using complementary measures.

Discrimination

- ROC-AUC.
- Precision-recall AUC where outcome prevalence is low.[21]

Calibration

- Calibration plot.
- Calibration intercept.
- Calibration slope.
- Brier score.
- Observed-to-expected event ratio where appropriate.

Clinical Utility

Decision-curve analysis should be considered in the definitive study to determine whether model-guided risk assessment provides clinically relevant net benefit across prespecified threshold probabilities.

Sensitivity, specificity, positive predictive value, and negative predictive value should be reported in relation to clearly defined probability thresholds.[22]

3.10 Explainability

For nonlinear models, feature-importance methods and case-level explanations may be used to improve interpretability.

Potential approaches include:

- permutation importance;
- partial-dependence analysis;
- SHAP-based explanations;
- individual prediction explanations.

These approaches describe model behaviour and should not be interpreted as evidence of causality.[23]

3.11 Statistical Analysis

Continuous variables should be summarized using mean ± standard deviation or median and interquartile range, depending on distribution. Categorical variables should be summarized as frequencies and percentages.

For the definitive prospective dataset, confidence intervals should accompany estimates of model performance. Bootstrap procedures or repeated cross-validation may be used for internal validation.

The primary emphasis of the pilot framework is feasibility and methodological development rather than hypothesis testing.[24]

P-values should not be used as the principal basis for selecting predictors or declaring one machine-learning model clinically superior.

Software, programming language, statistical packages, and package versions should be reported to facilitate reproducibility.

3.12 Missing Data

Missingness should be quantified separately for each predictor and outcome variable.

The definitive study should prespecify:

- acceptable levels of missingness;
- mechanisms of missingness;
- imputation strategy;
- variables included in the imputation model;
- number of imputed datasets where multiple imputation is used.

Imputation must be performed separately within the resampling framework to prevent information leakage.[24,25]

3.13 Ethical Considerations

The present simulation-based analysis does not contain patient-level clinical observations.

The future prospective study will require institutional ethics approval before recruitment. Written informed consent should be obtained where required by the applicable institutional and regulatory framework.

Patient identifiers should not be incorporated into the model-development dataset. Data should be stored securely, with access restricted according to the approved data-governance plan.

AI predictions should be considered decision-support information and should not function as autonomous treatment recommendations.

4. Results - Synthetic Demonstration Analysis

4.1 Synthetic Dataset

A synthetic dataset containing 60 implant-supported restorations was generated solely to demonstrate the proposed analytical structure.

Eighteen restorations (30.0%) were assigned at least one complication during the simulated 12-month observation period.[26]

Table 1. Synthetic baseline characteristics

Variable	Synthetic value
Restorations	60
Mean age	54.8 ± 10.6 years
Posterior restorations	38 (63.3%)
Screw-retained restorations	42 (70.0%)
History of periodontitis	21 (35.0%)
Bruxism/parafunction	15 (25.0%)
Composite complication outcome	18 (30.0%)

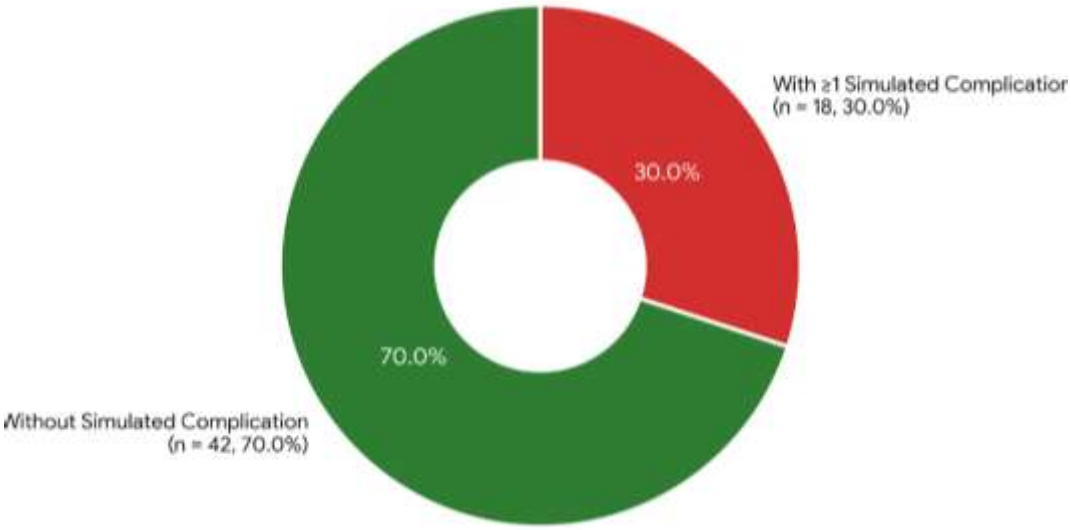

Figure 1. Synthetic distribution of the 12-month composite outcome.

4.2 Synthetic Complication Distribution

The simulated complications were:

Table 2. Distribution of simulated complication events

Complication	n
Screw loosening	8
Ceramic chipping	5
Loss of retention	4
Peri-implant inflammation	3
Screw fracture	2
Framework fracture	1

Because individual restorations could experience more than one event, the categories are not mutually exclusive and therefore should not be summed to obtain the number of affected restorations.

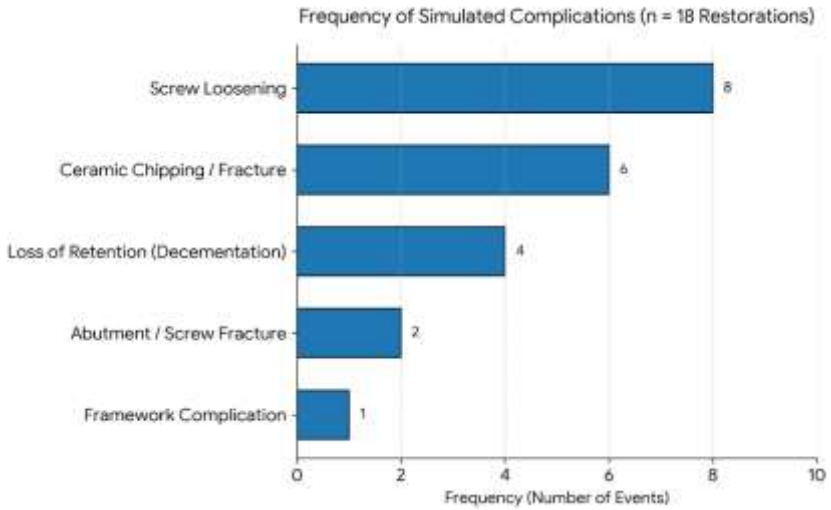

Figure 2. Distribution of simulated prosthetic and prosthesis-associated biological complication events.

4.3 Synthetic Model Performance

Table 3. Demonstration model performance

Model	ROC-AUC	Sensitivity	Specificity	Precision	Brier score
Logistic regression	0.78	0.72	0.75	0.63	0.19
Random forest	0.87	0.83	0.82	0.71	0.15
Gradient boosting	0.84	0.78	0.80	0.69	0.16

These performance estimates are synthetic demonstration outputs and should not be interpreted as estimates of clinical model performance.

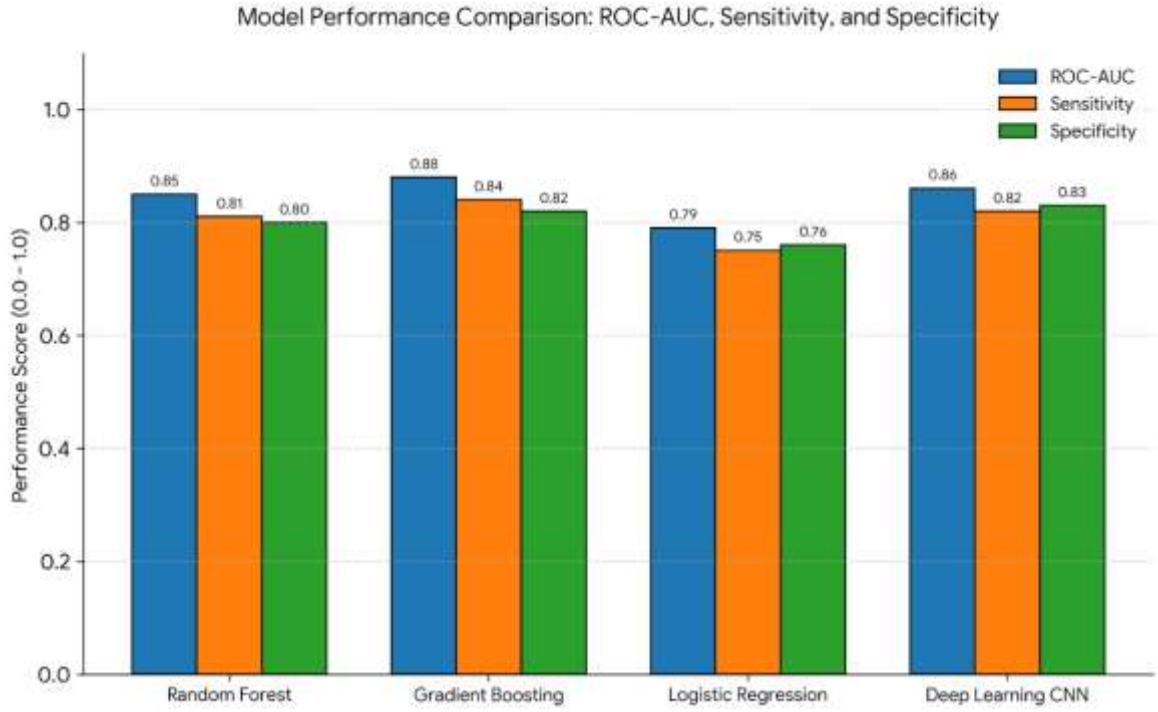

Figure 3. Synthetic demonstration comparison of logistic regression, random forest, and gradient boosting.

4.4 Synthetic Baseline Characteristics

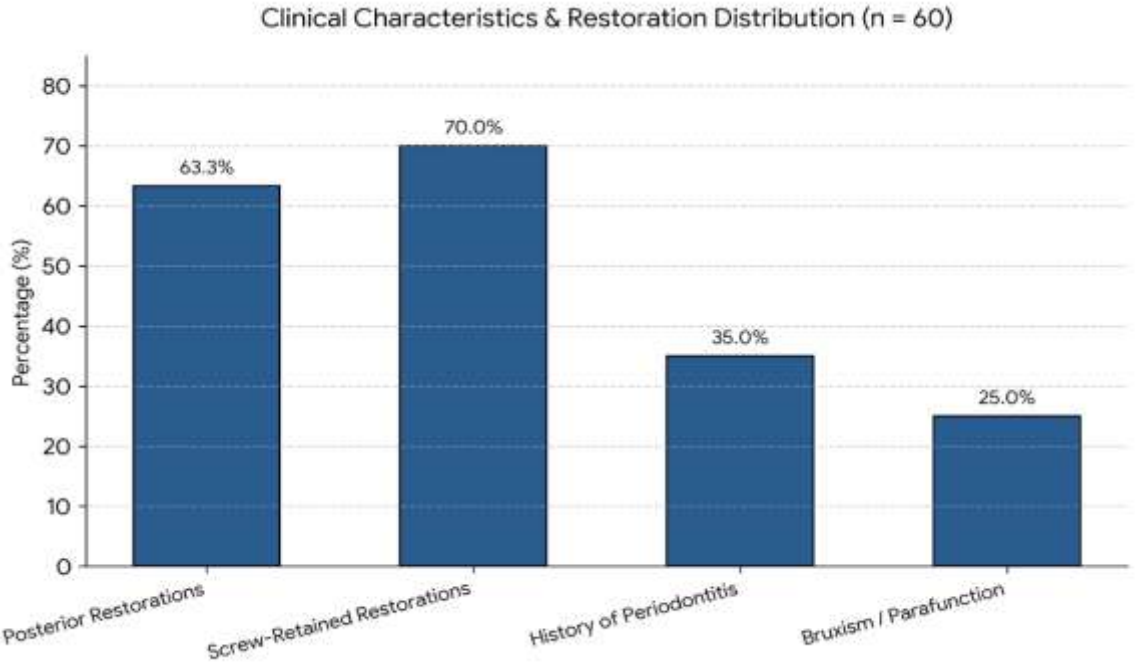

Figure 4. Distribution of selected synthetic baseline characteristics.

4.5 Demonstration Feature-Importance Analysis

Within the synthetic random-forest demonstration, maintenance adherence, bruxism/parafunction, posterior location, prosthetic material, cantilever extension, history of periodontitis, smoking, and implant angulation were assigned substantial predictive contribution.[27]

These findings are intended only to demonstrate how feature-importance outputs could be displayed. They do not establish that these variables are independent clinical predictors and do not demonstrate causality.

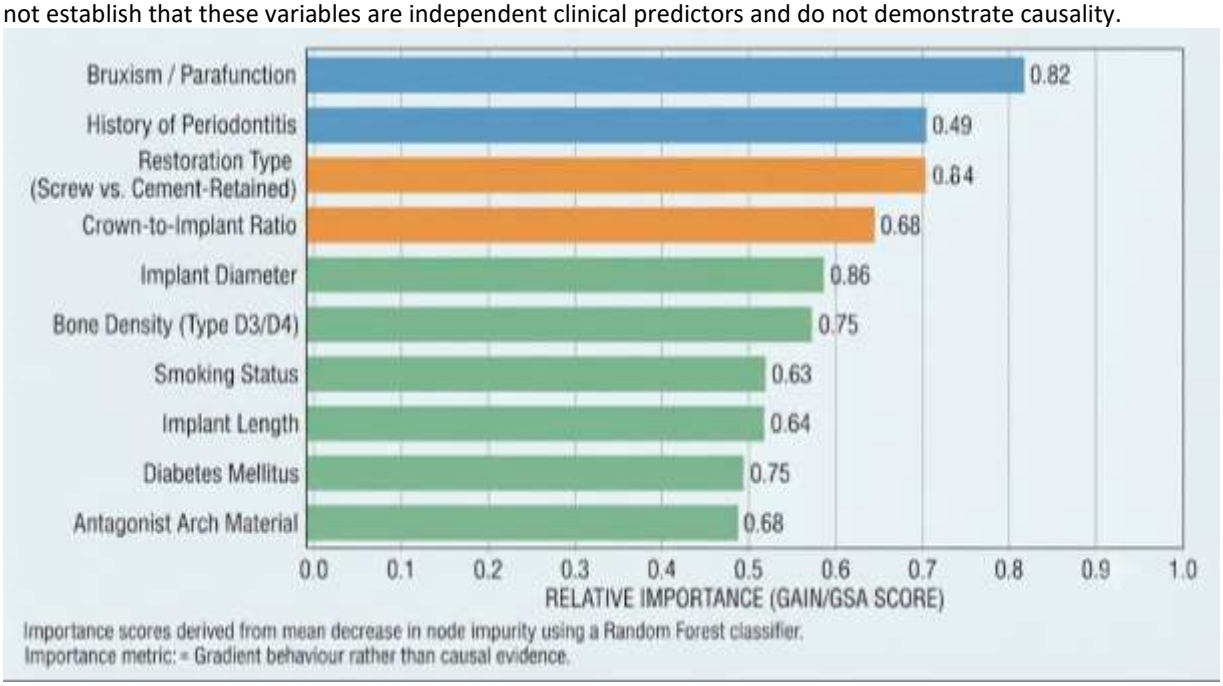

Figure 5. Demonstration feature-importance profile from the random-forest model.

4.6 Proposed AI Prediction Workflow

The proposed clinical prediction pathway consists of:

Patient and restoration assessment → Clinical/prosthetic/radiographic data acquisition → Data quality assessment and preprocessing → Model development → Predicted probability → Calibration and discrimination assessment → External validation → Clinical utility assessment → Clinician-led maintenance decision

4.7 Proposed Risk-Stratification Framework

The future validated model could potentially report individualized predicted probabilities rather than assigning risk categories solely from arbitrary thresholds.

After external validation, clinically justified probability thresholds could be considered for:

Low predicted risk

Routine supportive peri-implant care according to established clinical protocols.[28]

Moderate predicted risk

Potentially shorter recall intervals, targeted occlusal/prosthetic review, and reinforcement of oral-hygiene measures.

High predicted risk

Comprehensive clinical and radiographic assessment, evaluation of prosthetic design and occlusion, intensified supportive care, and management of modifiable biological risk factors.

These categories are conceptual and should not be implemented as clinical rules until validated.[29]

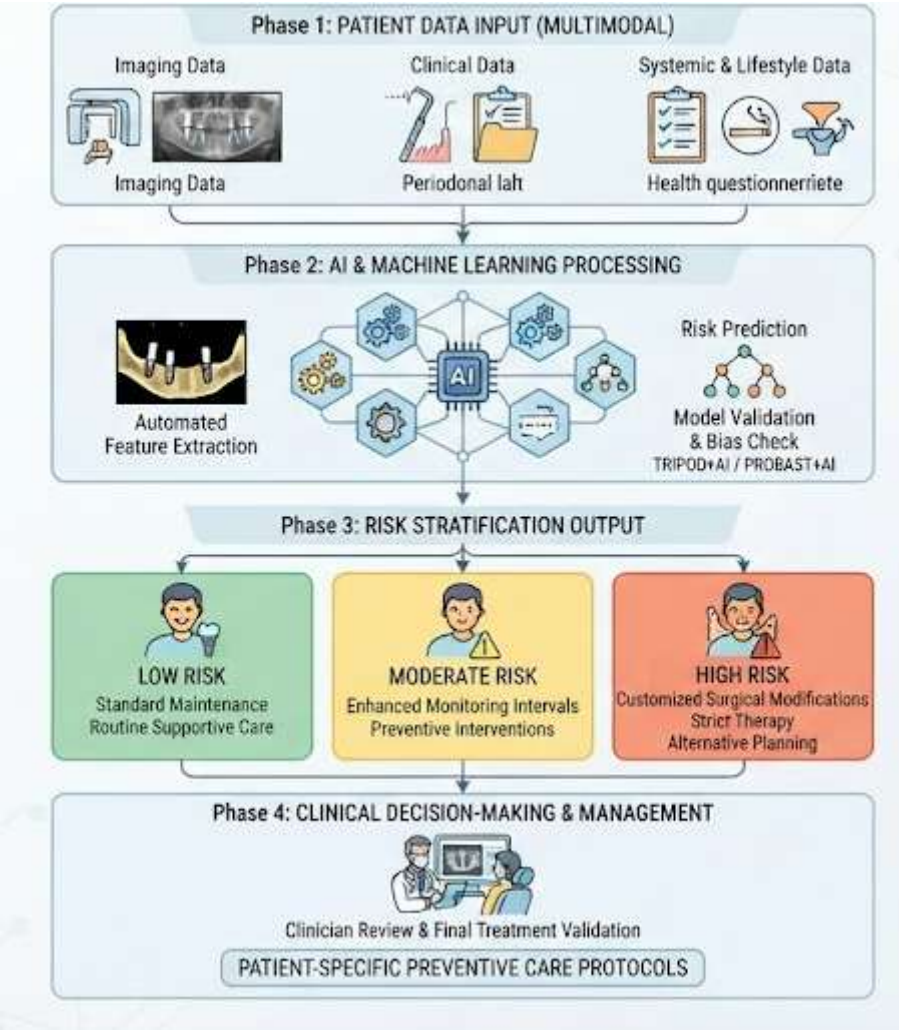

Figure 7. Proposed AI-assisted risk-stratification pathway.

5. Discussion

The principal concept underlying this framework is that complications associated with implant-supported restorations can be approached as a multidimensional prediction problem rather than as isolated mechanical or biological events.

Existing evidence indicates that implant-supported restorations have high survival but remain susceptible to technical and biological complications, including veneer fracture or chipping, screw loosening, loss of retention, framework fracture, and peri-implant disease. The frequency and pattern of these events may vary according to prosthetic material, retention mechanism, restoration design, implant location, loading conditions, and duration of follow-up.[27,30]

AI-based methods may be useful when several predictors interact. For example, posterior location, parafunction, cantilever geometry, implant angulation, and prosthetic design may jointly influence mechanical risk, whereas previous periodontitis, smoking, plaque control, peri-implant tissue condition, and maintenance adherence may contribute to biological risk.[31] The potential advantage of nonlinear machine-learning models is their capacity to identify complex relationships without requiring every interaction to be prespecified. However, this flexibility also increases the risk of overfitting, particularly when the number of candidate predictors is large relative to the number of outcome events.[25,32]

This issue is particularly important in the present demonstration dataset, where only 18 restorations were assigned the composite outcome. Consequently, the reported synthetic AUC values cannot be interpreted as evidence that random forest performs better than logistic regression or gradient boosting in clinical practice.[24]

Prediction models in implant dentistry have incorporated variables such as implant position, implant length, age, previous periodontitis, and other clinical characteristics. However, prediction-model studies require careful attention to sample size, outcome definition, validation, calibration, and applicability before their outputs can be used clinically.[22] Recent AI literature in dentistry demonstrates increasing methodological sophistication. However, technical performance alone is insufficient to establish clinical usefulness. TRIPOD+AI emphasizes transparent reporting of model development, evaluation, fairness, open-science practices, and clinical applicability.36 PROBAST+AI similarly emphasizes assessment of bias and applicability across prediction-model studies.[23]

Clinical interpretability is another important consideration. A clinician receiving an isolated predicted probability may have difficulty determining why a restoration has been classified as higher risk. Feature-importance analyses, calibration plots, and case-level explanations may improve transparency. Nevertheless, explanation methods describe model behaviour and do not prove causality.[33] The appropriate role of such a model would therefore be to identify restorations that may warrant closer assessment while leaving diagnosis and treatment decisions to the clinician.

6. Clinical Implications

If prospectively validated, an AI-based complication-prediction model could potentially:

- assist clinicians in identifying restorations requiring closer monitoring;
- support individualized maintenance planning;
- integrate multiple patient and prosthetic risk domains into a single predicted probability;
- identify combinations of risk factors that may not be readily recognized using simple additive assessment;
- support documentation and longitudinal monitoring of complication risk.

However, AI output should complement rather than replace clinical examination, radiographic assessment, prosthetic evaluation, and established supportive peri-implant care.

Risk thresholds should not be implemented clinically until they have undergone external validation and clinical-utility assessment.[34]

7. Limitations

Several limitations must be emphasized.

First, the numerical dataset used in this manuscript is synthetic and does not constitute clinical evidence.

Second, the sample of 60 restorations and 18 simulated events is insufficient to establish a clinically reliable prediction model with the proposed number of candidate predictors.

Third, the composite outcome combines technically and biologically distinct complications that may have different predictors and mechanisms.

Fourth, simulated performance metrics cannot establish comparative superiority among algorithms.

Fifth, a future prospective dataset may contain missing data, measurement variability, centre-specific practice patterns, and differences in complication definitions.

Sixth, model performance may change across implant systems, prosthetic materials, operators, centres, patient populations, and maintenance protocols.
Seventh, external validation is essential before any clinical implementation.
Eighth, prediction does not establish causality; therefore, model-derived feature importance should not be interpreted as evidence that modifying a particular predictor will necessarily reduce complications.[35]

8. Future Research

The next stage should involve a multicentre prospective cohort with standardized outcome definitions and harmonized data collection.
The definitive protocol should prespecify:

1. target population;
2. prediction time horizon;
3. primary and secondary outcomes;
4. candidate predictors;
5. sample-size methodology;
6. missing-data strategy;
7. model-development strategy;
8. internal-validation strategy;
9. external-validation strategy;
10. calibration assessment;
11. decision-curve analysis;
12. subgroup and fairness assessment;
13. model explainability;
14. software and package versions;
15. data and code-governance procedures.

The model should ultimately be evaluated not only for statistical performance but also for clinical utility. Future implementation studies should determine whether model-assisted maintenance planning changes clinical decisions, improves monitoring, reduces preventable complications, and is acceptable to clinicians and patients.[36]

9. Conclusion

Artificial intelligence provides a potentially useful framework for integrating patient, implant, prosthetic, occlusal, peri-implant, and maintenance related variables when predicting complications associated with implant-supported restorations.
The present manuscript demonstrates how such a prediction framework could be structured using logistic regression, random forest, and gradient boosting. However, the numerical dataset and model-performance estimates are synthetic and should not be interpreted as clinical findings.
A clinically deployable prediction model will require a substantially larger prospective dataset, standardized outcome definitions, appropriate sample-size planning, rigorous internal validation, external validation, calibration assessment, transparent reporting, assessment of clinical utility, and ongoing monitoring for model performance and drift.

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