Original Article

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Dentistry Section

Early Response-driven Tooth Survival Prognostication after Periodontal Therapy: A Cox-based Machine Learning Survival Model

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ABSTRACT

Introduction: Accurate long-term prognosis of individual teeth is crucial for periodontal treatment planning. However, risk assessments mainly rely on baseline characteristics and overlook disease behaviour changes after therapy. Recent evidence indicates early clinical response better predicts tooth loss than initial severity, but few models incorporate this. Most tools depend on baseline data, making prognosis after therapy difficult.

Aim: To develop and validate a Tooth-Level Survival Model (TSF-Net) predicting five-year extraction risk using one-year post-treatment clinical data response.

Materials and Methods: This retrospective cohort study was conducted at Department of Periodontology, Saveetha Dental College, Saveetha Institute of Medical and Technical Sciences (SIMATS), Saveetha University, Chennai, Tamil Nadu, India, from September 2025 to December 2025. The study used electronic records at a dental institution, analysing 2,432 teeth from 120 patients treated for up to five years. It examined one-year changes in Clinical Attachment Level (CAL), Pocket Depth (PD), mobility, plaque and occlusal trauma as predictors. Survival analysis employed an elastic-net penalised Cox model with internal splits. Analyses were performed in R and Python; $p<0.05$ was significant. The study adhered to Transparent Reporting of a multivariable prediction model for Individual Prognosis Or Diagnosis (TRIPOD), Strengthening the Reporting of Observational Studies in Epidemiology (STROBE) and Prediction model Risk Of Bias ASsessment Tool (PROBAST) guidelines.

Results: During follow-up, 571 teeth (23.5%) were extracted; the model achieved a test concordance index of 0.71, with occlusal trauma {Hazard Ratios (HR) ≈2.0}, unfavourable CAL response (HR ≈1.55) and PD response (HR ≈1.31) as significant predictors; risk stratification showed five-year extraction rates of 1.5%, 22.3% and 40.0% across low-, moderate- and high-risk groups (log-rank $p<0.001$).

Conclusion: The TSF-Net provides an interpretable, response-driven tooth-level survival prediction framework that enhances dynamic periodontal prognosis and supports individualised clinical decision-making.

Keywords: Early clinical changes, Human health, Model development, Periodontal prognosis, Periodontitis, Predictor variables, Tooth preservation, Tooth survival analysis

INTRODUCTION

Periodontitis is a major cause of tooth loss worldwide and remains a significant clinical challenge despite advances in periodontal therapy [1,2]. While contemporary treatment approaches can effectively control disease activity, long-term tooth retention cannot be ensured for all affected teeth [3]. Consequently, predicting tooth survival remains a critical component of periodontal treatment planning, influencing decisions related to tooth preservation, extraction and long-term maintenance strategies. Therefore, in order to support evidence-based clinical decision-making and enable meaningful communication with patients regarding expected outcomes, reliable prognostic tools are crucial [4,5].

Current periodontal risk assessment and prognostic frameworks, including the Periodontal Risk Assessment and contemporary staging and grading systems, primarily stratify patients based on baseline clinical and systemic characteristics. These instruments are useful for classifying risks at the population level, but they provide limited guidance for tooth-specific prognostication [6]. Furthermore, the majority of current models do not accurately represent disease behaviour after therapy since they rely on static baseline values [7-10]. Recent consensus statements from the 20th European Workshop on Periodontology emphasised that prognosis should be considered a dynamic component of periodontal diagnosis, requiring continuous reassessment rather than a one-time baseline classification [11]. This underscores an important limitation of traditional prognostic approaches in predicting long-term tooth survival.

Longitudinal evidence has consistently demonstrated that early response to periodontal therapy plays a pivotal role in determining future tooth loss. Residual probing depth, persistent bleeding on probing and insufficient attachment level gain following initial therapy are strongly associated with increased risk of tooth extraction during supportive periodontal care [12,13]. Importantly, post-therapy clinical parameters have been reported to outperform baseline disease severity in predicting long-term outcomes, highlighting the prognostic relevance of treatment response rather than initial diagnosis alone [14]. These findings support the development of response-based prognostic models that better capture the dynamic nature of periodontal disease progression.

In recent years, Artificial Intelligence (AI) and machine learning techniques have been increasingly applied in periodontology to predict treatment outcomes and disease progression. Although a number of studies have shown encouraging predictive performance, many AI-based models focus on short-term outcomes or patient-level categorisation tasks and often lack clinical interpretability, limiting their use in standard practice [15-17]. Additionally, concerns regarding generalisability and overfitting have been raised, particularly when complex algorithms are applied to limited datasets [18-20]. Survival analysis provides a clinically meaningful framework for modelling time-to-event outcomes such as tooth loss. Yet, its application within AI-based periodontal prognostication remains limited, especially at the tooth level [15,17].

The present study introduces a tooth-level survival framework that uses early clinical changes in a penalised Cox model to predict five-year survival. Unlike prior risk tools, TSF-Net offers dynamic, interpretable and actionable tooth-specific prognostication. The present study develops and validates a tooth-level, early-response-based survival model that translates one-year post-therapy changes into five-year extraction probabilities using an interpretable penalised Cox framework. No prior periodontal prognostic model combined dynamic post-treatment response, tooth-specific survival analysis and internal validation within a transparent AI-assisted structure.

MATERIALS AND METHODS

The present retrospective clinical observational cohort study was conducted at Department of Periodontology, Saveetha Dental College, Saveetha Institute of Medical and Technical Sciences (SIMATS), Saveetha University, Chennai, Tamil Nadu, India. The study involved data collection and analysed periodontitis patients under active therapy and follow-up. Data extraction, curation and statistical analysis were performed from September 2025 to December 2025. The study had IRB approval with IRB number SRB/SDC/PERIO-2202/25/443 and followed STROBE guidelines.

Clinical information was obtained from the Saveetha Dental Information Archiving Software (Saveetha DIAS), a centralised digital repository that stores regularly collected patient records, including radiographic studies and structured periodontal documentation generated during routine clinical care.

Inclusion and Exclusion criteria: Records were included if they had a comprehensive baseline periodontal examination, received standard non surgical therapy for periodontitis and returned for re-evaluation about one-year later. Patients with at least five years of follow-up post-one-year visit or documented tooth outcomes within five years were included. From each patient, individual teeth (excluding third molars) were analysed.

Study Procedure

For each tooth, the authors recorded whether it was extracted within five years post-therapy (with time to extraction) or whether it survived to the last follow-up or was censored. All extractions were considered events, regardless of cause [Table/Fig-1a].

Time-to-event analysis used right-censoring at last visit for teeth not extracted and extracted teeth contributed actual times (mean 2.58±1.46 years). Calibration used survival estimates with variable follow-up. Clinical measurements followed standardised periodontal protocols within the institutional electronic system. Routine calibration exercises among operators and exclusion of missing or implausible values after checks were performed before modelling.

A total of 2432 teeth from 120 patients met the inclusion criteria, averaging ~20 teeth each. The combined five-year extraction rate was ~23%, typical for advanced periodontitis under maintenance.

Patient data split into training (~70%), validation (~15%) and test (~15%) sets with similar event rates, supporting balanced development and evaluation and to prevent leakage resulting in 2067 teeth (486 events) for training/validation and 365 teeth (85 events) for testing.

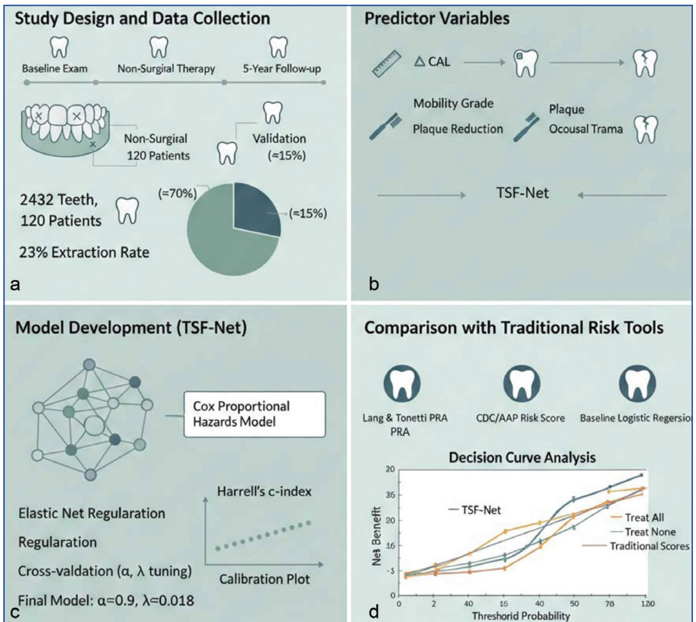
Predictor variables: The TSF-Net involves clinical response evaluation a year after therapy, monitoring changes such as CAL, PD, mobility, plaque control and occlusal trauma. Attachment increase or loss is measured by CAL change; Pocket depth shifts are indicated by PD change. Instability is assessed by the mobility grade using Miller's mobility index [21]. Silness J and Löe H plaque index measured plaque scores [22]. Reduced plaque indicated good cleanliness; occlusal trauma is recorded as present or absent. Baseline CAL and PD aren't used directly; instead, the model predicts their change or status after one-year, providing five-year survival forecasts based on treatment response. Continuous features were standardised and categorical features were encoded [Table/Fig-1b].

Model Development (TSF-Net): The authors predicted five-year tooth survival using a competing-risks approach, treating tooth extraction as the main event. All extractions were counted as events; no secondary types were modelled, simplifying to a single-event survival analysis. The authors used a Cox proportional hazards model with regularisation for feature selection and complex effects [Table/Fig-1c]. TSF-Net is a penalised Cox model combining one-year features to predict extraction hazard. Model training involved fitting Cox models with elastic net regularisation to the 2067-teeth data. Cross-validation optimised hyperparameters, testing α values of 0, 0.5 and 0.9 and λ from 10^{-3} to 10^{0}. The best model, with $\alpha \approx 0.9$ and $\lambda \approx 0.018$, had a strong L1 penalty, shrinking some coefficients to zero.

The final TSF-Net was locked and evaluated on 365 teeth. Discrimination was measured by Harrell's c-index, estimating the probability that a tooth that failed earlier had a higher predicted risk. Calibration was assessed by comparing predicted five-year survival with observed outcomes, using Cox model estimates. Teeth were grouped into risk strata and deciles for calibration checks. For interpretability, Cox coefficients were converted to Hazard Ratios (HRs), with some coefficients set to 0 due to regularisation. A 95% Confidence Intervals (CIs) for HR were calculated via bootstrapping and proportional hazards assumptions were verified via Schoenfeld residuals, with no violations. Partial dependence plots explored relationships between continuous features and five-year survival, with other variables set to their mean values.

Because multiple teeth from the same patient were involved, the authors used a Cox model with patient-level clustered robust standard errors to account for intra-patient correlation, adjusting variance estimates for non independence. However, multilevel or shared frailty Cox models could better model patient heterogeneity and should be explored in future studies validations.

Comparison with traditional risk tools: To compare TSF-Net's performance, the authors evaluated two traditional methods: the Lang NP and Tonetti MS PRA (2003) [23] and a CDC/AAP-like risk score [24] that assigns risk categories based on patient data [Table/Fig-1d]. The authors compared these to a simple logistic regression



[Table/Fig-1]: Schematic overview of the TSF-Net study design, highlighting the transition from one-year clinical response features to a penalised Cox survival model for predicting five-year tooth extraction risk. a) Study design and data collection; b) Predictor variables; c) Model development (TSF-Net); d) Comparison with traditional risk tools.

model using baseline data to see if the one-year model was better. Decision Curve Analysis (DCA) was conducted to evaluate the net clinical benefit of TSF-Net versus baseline models, accounting for actions such as intensive interventions. True positives (teeth correctly predicted to be lost) benefit us; false positives cause harm. Net benefit for TSF-Net, traditional scores, treating none and treating all, across different risk thresholds was calculated. All analyses used R and Python, with significance at $p<0.05$.

The development and validation of TSF-Net adhered to TRIPOD/TRIPOD-AI [25], STROBE and PROBAST-AI [26] guidelines to ensure transparent reporting, methodological rigour and clinical interpretability.

STATISTICAL ANALYSIS

R and Python were used for all statistical analyses and a two-tailed $p<0.05$ was deemed statistically significant. An elastic-net–regularised Cox proportional hazards model was used to assess time-to-event data, treating retained teeth as censored observations and tooth extraction as the event. Harrell's concordance index (c-index) was used to evaluate model discrimination and a comparison of observed and predicted five-year survival across risk strata was used to evaluate model calibration. The resulting model was used to produce HRs with 95% Confidence Intervals (CIs), with CIs derived by bootstrapping. Using Schoenfeld residuals, the proportional hazards assumption was investigated. To compare survival across risk categories, log-rank tests and Kaplan-Meier survival curves were used. Predictor effects were shown using forest plots. DCA and a baseline logistic regression model were used for comparison.

RESULTS

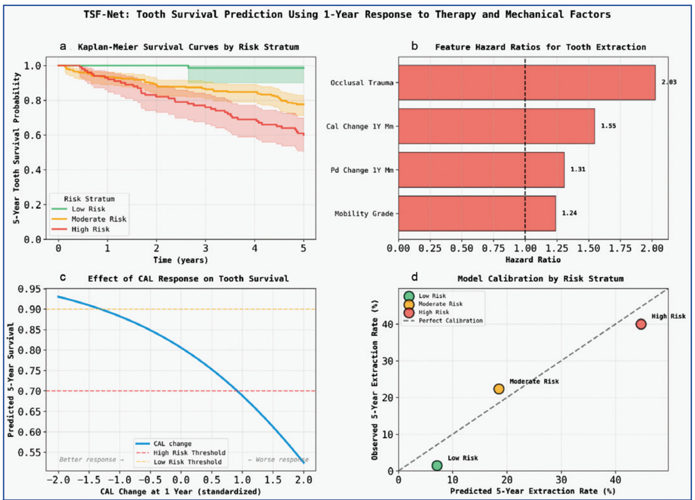
Overall model performance: A total of 2,432 teeth were analysed; 571 (23.5%) were extracted during follow-up, with a mean time of 2.58±1.46 years and 1,861 (76.5%) were censored at five years.

Prepared survival data: Using elastic-net–regularised Cox modelling, the optimal model had an L1 ratio of 0.9 and λ of 0.0176. It showed strong performance, with validation and test C-indices of 0.7149 and 0.7136, indicating an accurate prognosis for tooth survival risk beyond chance.

Analysis of model coefficients showed occlusal trauma was the strongest predictor of tooth loss, doubling the extraction hazard (HR≈2.03). Early biological response was also important: each SD worsening in one-year CAL increased risk by 55% (HR≈1.55) and poorer one-year PD reduction raised risk by 31% (HR≈1.31). The tooth mobility grade added a moderate effect with a 24% hazard increase per grade. Plaque improvement was penalised to zero, indicating no independent prognostic value after accounting for tissue response and mechanics. Although plaque control is key to periodontal stability, elastic-net regularisation retained only variables with independent prognostic value; plaque improvement correlated with CAL and PD responses and didn't add predictive power beyond these, leading coefficients to shrink toward zero rather than indicating clinical irrelevance.

Predicted five-year survival ranged widely (mean 0.76±0.16), enabling risk groups: low (≥0.90), moderate (0.70-0.89) and high (<0.70). Extraction rates rose to 1.5%, 22.3% and 40.0% (log-rank $p<0.001$). Kaplan–Meier analysis showed significant separation (log-rank $\chi^2=31.36$, $p=2.1\times10^{-8}$). Calibration analysis showed that the predicted and observed extraction probabilities mostly agreed across all groups. The model slightly overestimated low-risk and underestimated moderate-risk, but high-risk predictions matched observed outcomes, with calibration errors of less than 6%. Partial dependence analysis highlights the clinical importance of early treatment response, with five-year survival predictions ranging from 52.5% to 93.0%, representing the largest modifiable effect. PD response, mobility grade and occlusal trauma also showed graded impacts on survival. These findings show that TSF-Net effectively integrates biological and mechanical signals to produce interpretable tooth-level survival predictions from routine clinical data.

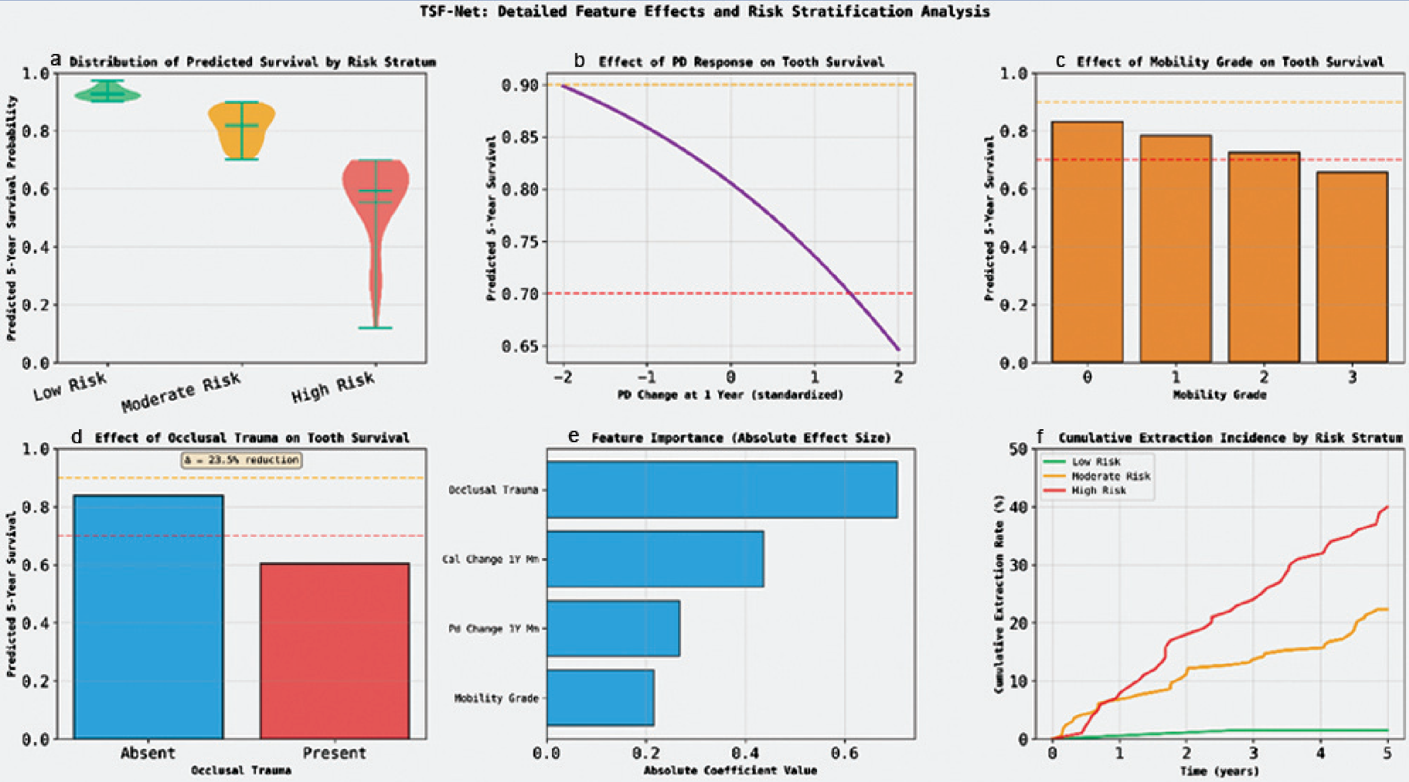
TSF-Net Tooth survival prediction using one-year response to therapy and mechanical factors: The core prognostic performance of TSF-Net in predicting five-year tooth survival from one-year post-therapy clinical response is summarised in [Table/Fig-2]. Kaplan-Meier curves show clear separation among low-, moderate- and high-risk teeth, confirming strong temporal discrimination [Table/Fig-2a]. HR analysis identifies occlusal trauma as the main risk factor for extraction, followed by unfavourable CAL and PD changes and increased mobility [Table/Fig-2b]. Partial dependence shows a decline in predicted survival with worsening CAL response, underscoring the prognostic importance of early tissue healing [Table/Fig-2c]. Calibration plots indicate a good match between predicted and observed extraction rates, supporting the model's clinical reliability for individual risk stratification [Table/Fig-2d].



[Table/Fig-2]: a) Kaplan-Meier survival curves stratified by TSF-Net risk groups; b) Forest plot showing Hazard Ratios (HR) for key clinical features contributing to tooth extraction risk; c) Partial dependence plot illustrating the impact of standardised one-year CAL change on predicted five-year survival probability; d) Calibration of TSF-Net predictions by risk stratum calibration plot.

TSF-Net: Detailed feature effects and risk stratification analysis: A detailed interpretation of how TSF-Net translates early clinical response into long-term tooth survival risk is provided in [Table/Fig-3]. Predicted five-year survival probabilities show clear separation across low-, moderate- and high-risk strata, confirming effective risk stratification [Table/Fig-3a]. Worsening one-year PD response is associated with a continuous decline in predicted survival, whereas increasing tooth mobility grades are associated with a step-wise reduction in survival probability [Table/Fig-3b,c]. The presence of occlusal trauma produces a marked survival penalty, reducing predicted five-year survival by approximately one-quarter. Feature importance analysis identifies occlusal trauma as the dominant predictor, followed by one-year CAL and PD changes, with mobility exerting a moderate effect [Table/Fig-3d,e]. Finally, cumulative extraction incidence curves reveal progressively higher extraction rates over time in moderate- and high-risk groups, validating the model's ability to capture both the magnitude and the temporal dynamics of tooth-loss risk [Table/Fig-3f].

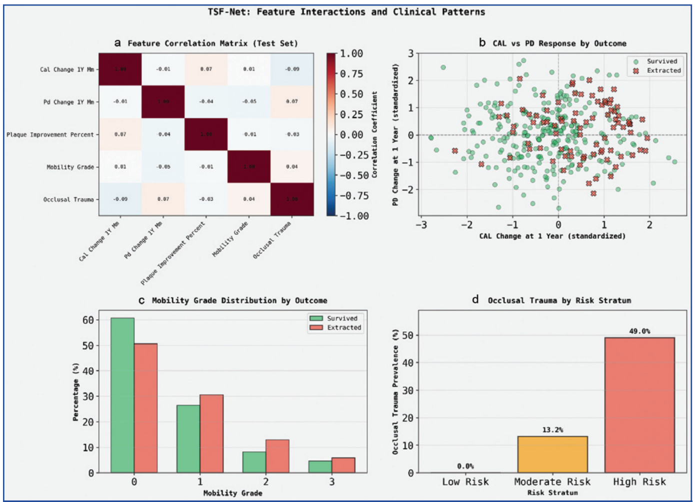
TSF-Net: Feature interactions and clinical patterns: The feature correlation matrix in the test set, demonstrating minimal multicollinearity among predictors, with low pair-wise correlations between CAL change, PD change, plaque improvement, mobility grade and occlusal trauma, supporting the stability and interpretability of the survival model is shown in [Table/Fig-4a]. The relationship between one-year CAL and PD responses stratified by outcome, where extracted teeth cluster toward poorer CAL and PD responses, while surviving teeth predominantly exhibit favourable tissue changes, indicating that early healing trajectories strongly



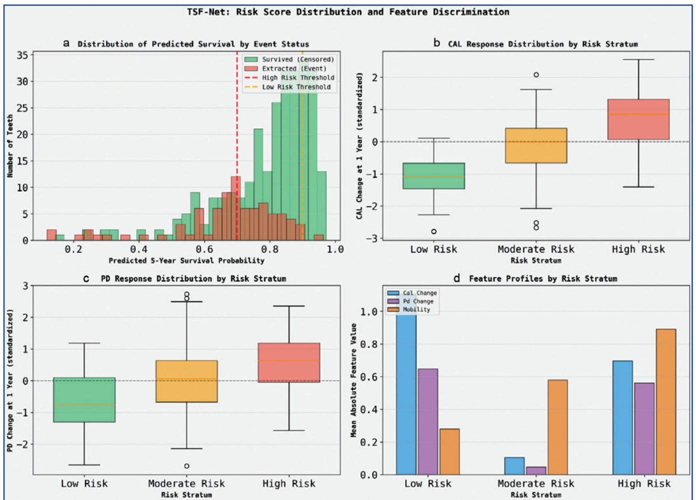
[Table/Fig-3]: a) Distribution of predicted five-year tooth survival by TSF-Net risk strata; b) Effect of one-year Probing Depth (PD) response on predicted tooth survival; c) Impact of tooth mobility grade on predicted survival; d) Bar chart comparing predicted survival probabilities between teeth with and without occlusal trauma. e) Chart ranking the relative importance of clinical features in TSF-Net's survival predictions; f) Cumulative tooth extraction incidence by risk stratum.

differentiate long-term outcomes is illustrated in [Table/Fig-4a]. The distribution of mobility grades by outcome, showing a higher prevalence of advanced mobility (grades 2-3) in extracted teeth than in surviving teeth, underscoring the prognostic relevance of mechanical instability is presented in [Table/Fig-4c]. The occlusal trauma prevalence across risk strata, showing a step-wise increase from low-risk to high-risk groups, with nearly half of high-risk teeth exhibiting occlusal trauma, reinforcing its central role as a modifier of tooth survival risk is depicted in [Table/Fig-4d].

PD response distributions by risk group, revealing progressively poorer probing depth reduction from low- to high-risk strata, reinforcing the prognostic role of early pocket response is presented in [Table/Fig-5c]. The mean absolute feature profiles across risk strata, demonstrating that high-risk teeth exhibit worse CAL and PD responses and higher mobility is summarised in [Table/Fig-5d]. In contrast, low-risk teeth exhibit favourable tissue responses and minimal mechanical instability, supporting the clinical interpretability of TSF-Net risk scores.



[Table/Fig-4]: a) Feature Correlation Matrix (Test Set); b) Scatterplot of one-year CAL and PD responses by outcome; c) Mobility grade distribution by outcome; d) Occlusal trauma by risk strata.



[Table/Fig-5]: a) Distribution of predicted five-year survival probabilities by event status; b) CAL response distribution by risk stratum; c) PD response distribution by risk stratum; d) Feature profiles by risk stratum.

TSF-Net: Risk score distribution and feature discrimination: The distribution of predicted five-year survival probabilities by event status, showing clear separation between censored (surviving) and extracted teeth, with predefined low- and high-risk thresholds effectively discriminating outcomes is shown in [Table/Fig-5a]. The CAL response distributions across risk strata: low-risk teeth show favourable attachment gain, moderate-risk teeth show intermediate responses and high-risk teeth exhibit net attachment loss, confirming the biological gradient's validity is illustrated in [Table/Fig-5b]. The

DISCUSSION

The present study demonstrates that long-term tooth survival can be reliably predicted using routinely collected clinical parameters when modelled at the tooth level, reinforcing the concept that periodontal prognosis is dynamic and treatment-responsive rather than fixed at baseline. In agreement with earlier longitudinal evidence, post-therapy indicators, such as residual probing depth, bleeding on probing and early treatment response, showed stronger prognostic relevance than initial disease severity [27,28]. These findings are consistent with recent comparative work showing that prediction models incorporating longitudinal clinical data outperform conventional clinician-based judgement alone in forecasting tooth loss [29,30]. Significantly, the outcomes align with the 20th European Workshop on Periodontology consensus, which emphasised that prognosis and risk prediction should be integrated into periodontal diagnosis and continuously updated during supportive care [11]. By focusing on tooth-specific survival outcomes, the present study provides clinically actionable information that directly supports individualised treatment planning and long-term maintenance strategies.

Recent periodontal prognostic research has placed a strong emphasis on increasing prediction accuracy through multivariable statistical and AI-based techniques. A multicentre validation research by Santamaria P et al., (2025) found that nomogram-based models built from the 2018 periodontal classification can achieve satisfactory discrimination {Area Under Curve (AUC) ≈0.72-0.77}. But the study also showed limits in terms of calibration and cross-population generalisability, particularly when baseline diagnostic data are the only ones used [31]. Similarly, using clinical and biomarker data, longitudinal machine learning models, such as those developed by Furquim CP et al., (2025), have shown strong predictive performance {Area Under the Receiver Operating Characteristic Curve (AUROC) up to 0.88} in predicting the course of periodontitis; however, these models primarily rely on baseline or short-term observational data without accounting for post-treatment dynamics [32]. Furthermore, recent AI-driven predictive frameworks for periodontal therapy response, including the work by Walter E et al., (2025), have demonstrated the viability of predicting probing depth changes at the site and tooth levels. Nevertheless, long-term survival integration is absent and prediction performance is still constrained for non-responding locations [9]. Emerging outcomes of machine learning-assisted prognostic studies, such as Machine learning-assisted prediction of clinical responses to periodontal treatment, further emphasise the importance of adding treatment response factors to improve predictive accuracy. However, rather than focusing on long-term tooth survival results, these approaches have mostly focused on response prediction [17]. Thus, overcoming previous limitations, the current work integrated tooth-specific survival analysis, dynamic post-treatment response and internally validated, comprehensible AI-assisted modelling.

From a methodological standpoint, the present study emphasises interpretability, calibration and data quality over algorithmic complexity. In 2,432 teeth from 120 patients, TSF-Net achieved moderate discrimination (test c-index=0.71) with calibration error <6% across risk strata. Unlike prior AI models that largely relied on classification algorithms for short-term, patient-level predictions based on baseline variables [15,17], TSF-Net applied a Cox proportional hazards framework to generate individualised five-year tooth-level survival probabilities. The model incorporated five standardised one-year parameters-CAL change, PD change, mobility grade, plaque improvement and occlusal trauma-with HRs reported alongside bootstrapped 95% CIs. Proportional hazards assumptions were verified using Schoenfeld residuals and Kaplan-Meier analysis confirmed significant survival separation (log-rank $p<0.001$). Follow-up extended to five years (mean extraction time 2.58±1.46 years), with uniform outcome definitions applied. These safeguards- restricted, clinically interpretable predictors, standardised measurements, defined follow-up and transparent effect reporting-align with recommendations for explainable AI in dentistry [11,33] and established standards for long-term periodontal outcome research [12,27,34]. External multicentre validation remains necessary before clinical implementation.

To forecast five-year tooth survival using only the first-year post-therapy clinical response, TSF-Net (Tooth Survival Forecasting Network), a Cox proportional hazards-based machine learning model, was developed in the current study. The model demonstrated robust performance in a cohort of periodontitis patients on maintenance therapy, yielding a c-index of ~0.71 and well-caliberted survival probabilities. TSF-Net's tooth-level predictions outperformed traditional patient-level risk assessment tools. This underscores an important principle: granular, tooth-specific prognostic modelling leveraging short-term response data can substantially enhance long-term risk stratification in periodontology.

TSF-Net aids clinicians in early identification of "at-risk" teeth during maintenance by integrating one-year findings into a survival probability. Teeth with poor response, like residual deep pockets or mobility, might have only ~50-60% survival chance at five years, prompting proactive interventions such as surgery or extraction. Conversely, well-responding teeth with shallow pockets and CAL gain may have >90% survival, supporting continued maintenance over aggressive treatment. TSF-Net complements clinical judgement with evidence-based risk assessment. At the one-year supportive care visit, the clinician enters clinical response variables into TSF-Net, which then calculates a five-year tooth survival probability to guide intervention and recall planning.

The TSF-Net's variables- residual pockets, attachment loss and tooth mobility- are biologically grounded, indicating disease persistence and prognosis, highlighting the harmful role of occlusal trauma. Good plaque control was less influential, possibly due to patient selection or maintenance. TSF-Net offers dynamic, tooth-level predictions that reflect prognosis as an evolving process. It achieves higher accuracy (c-index ~0.71) and directly interprets risk factors, linking them to outcomes such as occlusal trauma and tooth survival. Previously reported survival and AI-based models have frequently obtained discrimination values in the 0.65-0.75 range when used in periodontal prognostic prediction [8,10,17].

The TSF-Net's offers tooth-level, response-driven survival probabilities based on one-year post-therapy changes, unlike traditional tools that provide baseline risk stratification without calliberted survival data. It also uses penalised Cox modelling with validation, improving interpretability and precision. The authors' analysis confirms that tools like Patient Risk Assessment (PRA) are useful for risk awareness but not for specific predictions. A study showed the PRA model stratifies patients: high-risk patients lose about twice as many teeth as low-risk over five years, but its predictive value for individual teeth is low [35,36]. The periodontal risk calculator by Page RC and Beck JD assigns a risk score of 1-5 to patients, with score 5 patients having a 10.6× higher tooth loss risk than score two patients [37]. However, this data is group-level. The present study findings suggest that variation exists among high-risk patients- some teeth are saved by local factors or treatment, while others are lost. TSF-Net provides finer detail. Clinically, both approaches can be used: PRA for systemic factors and care frequency and TSF-Net at re-evaluation to guide local treatments. TSF-Net remained calliberted despite the absence of explicit systemic factors such as smoking or diabetes, likely because these factors impact outcomes indirectly via the one-year response (e.g., smokers tend to have worse healing, which affects CAL changes detected by TSF-Net).

The present study was conducted at a single tertiary academic center using split data without external validation, limiting generalisability. Demographic details (age, sex, smoking, diabetes, regional context) are clarified, with the cohort predominantly South Asian and under standardised treatment protocols, though inter-operator variability can't be excluded. Inclusion required a one-year follow-up; patients lost to follow-up weren't analysed, risking attrition bias if they differed in disease severity or compliance. All extractions were modelled as a single endpoint without differentiating periodontal from non-periodontal causes, which may cause outcome heterogeneity; systemic factors like smoking and diabetes weren't explicitly modelled and might affect one-year clinical response; post-one-year treatment decisions weren't protocolised, risking confounding if higher-risk teeth received intensified interventions, potentially affecting extraction rates.

Enhancing TSF-Net involves adding more data, such as baseline and one-year radiographic bone levels or 3D imaging. Changes in bone height or density over a year could improve predictions, especially when CNNs analyse serial radiographs. A time-updated or Bayesian prognostic model could be created by dynamically extending forecasts beyond five years at each recall. Graph-based or multilevel models may account for the fact that teeth within the same mouth are not independent, with recent research on periodontal data using graph neural networks showing promise. A future model might combine TSF-Net with patient-level predictors, such as a multilevel Cox model for systemic factors or a GNN for effects on adjacent teeth. An electronic records tool could allow clinicians to input baseline and year-one data and generate five-year survival forecasts, highlighting high-risk teeth visually. This would aid communication with patients and help personalise periodontal maintenance, including adjusting recall frequency and site-specific treatments.

Limitation(s)

The study's limitations include reliance on a single cohort with specific criteria, which may bias the results and require external validation. Although patient clustering was addressed, a multilevel model might be preferable; the authors approach could yield slightly anti-conservative CIs when clustering is strong. TSF-Net doesn't model competing risks and needs a one-year follow-up, limiting its use at baseline and if patients drop out early, highlighting the importance of early appointment follow-up.

CONCLUSION(S)

The TSF-Net predicts five-year tooth survival using early treatment responses and routine clinical data, such as pocket depth, attachment loss, tooth mobility and trauma. It offers better discrimination than traditional methods, helping clinicians target high-risk teeth, improve outcomes and avoid unnecessary procedures. Validation and data integration are future steps. The approach underscores the importance of dynamic response measurements in prognosis, combining algorithms with periodontal data to aid decision-making and preserve teeth.

Authors' contribution: All authors have reviewed the final version to be published and agreed to be accountable for all aspects of the work.

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