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Review Article

Bayesian Hierarchical Modeling of Risk Factors Associated with Treatment Outcomes in Periodontal Therapy: A Conceptual Framework

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ABSTRACT

Periodontal treatment outcomes vary substantially across patients, teeth, and sites, even when similar therapeutic protocols are applied. This variation reflects differences in baseline disease severity, local anatomical conditions, behavioral exposures, systemic risk, and maintenance adherence. Conventional analytic approaches often simplify this structure and may therefore obscure clinically meaningful sources of heterogeneity. A major problem in periodontal outcome research is the absence of a coherent methodological framework for applying Bayesian hierarchical models to multilevel clinical data. Single-level models and conventional regression strategies may estimate average treatment effects but provide limited insight into how risk factors operate across nested biological and clinical units. This limitation is especially important when clinicians need individualized probabilities rather than only population-level associations. The objective of this article is to propose a conceptual framework for Bayesian hierarchical modeling of risk factors associated with periodontal treatment outcomes. The framework is designed for studies evaluating probing depth reduction, clinical attachment gain, pocket closure, residual pockets, and tooth survival after surgical or non-surgical periodontal therapy. It emphasizes how prior evidence, multilevel random effects, and posterior prediction can be integrated into a clinically interpretable analytic structure. This conceptual article is based on a critical synthesis of 30 peer-reviewed articles published between 2017 and 2026 in periodontology, evidence-based dentistry, and biostatistics. The synthesis focuses on periodontal treatment endpoints, patient-level and site-level risk factors, Bayesian multilevel modeling principles, prior elicitation, computational estimation, and posterior predictive interpretation. No new empirical dataset is analyzed. The proposed framework specifies the periodontal data hierarchy, relevant variance components, fixed and random effects, prior choices, model-checking procedures, and clinical translation pathways. It shows how Bayesian hierarchical modeling can support individualized treatment planning by estimating patient-specific and site-specific probabilities of success. The framework is intended to guide future empirical research and improve methodological rigor in periodontal outcome studies.

Keywords: Bayesian hierarchical modeling, Periodontal therapy, Risk factors, Treatment outcomes, Multilevel analysis, Conceptual framework

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Introduction

Periodontal therapy is evaluated through outcomes such as probing depth reduction, clinical attachment gain, residual pocket resolution, and tooth survival, yet these endpoints rarely vary at only one biological level. Consensus definitions of periodontitis and disease severity emphasize that clinical diagnosis integrates site-level findings, tooth-level involvement, and patient-level susceptibility [1], while staging and

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grading further recognize complexity, extent, progression, and risk modification [2]. This multilevel character makes periodontal outcome prediction inherently hierarchical rather than purely individual or purely site based [3-5].

The challenge is intensified because periodontal response depends on interacting clinical, behavioral, and systemic determinants. Diabetes and periodontal inflammation are linked through bidirectional biological pathways that affect disease progression and therapeutic response [6], while smoking cessation and lifestyle interventions influence the risk environment in which periodontal care occurs [7]. Behavioral change and oral hygiene improvement also shape treatment success because plaque control and adherence influence the persistence of residual inflammation after active therapy [8].

Traditional periodontal analyses often summarize data at the patient level or apply models that do not fully represent the nesting of sites within teeth and teeth within patients. Endpoint-focused guidance for active periodontal therapy has highlighted the importance of clinically meaningful outcomes rather than isolated measurements [9], but the statistical structure used to analyze these outcomes must also match the clinical structure of the data. When site-level observations are treated as independent, standard errors, risk estimates, and predictions may become misleading.

This article develops a conceptual framework for applying Bayesian hierarchical modeling to periodontal treatment outcome research. The framework draws on periodontal endpoint literature and Bayesian statistical methodology to show how prior knowledge, random effects, and posterior predictive distributions can be combined for individualized risk estimation [10]. The article first explains the rationale for a Bayesian hierarchical approach, then defines the data structure and heterogeneity sources, before later sections specify model components, prior elicitation, clinical translation, implementation challenges, and future research needs.

Rationale for a Bayesian hierarchical approach

Bayesian hierarchical modeling is well suited to periodontal research because it directly represents clustered data and separates variation across levels of analysis. In periodontal therapy, measurements are commonly repeated over time, sites are nested within teeth, teeth are nested within patients, and patients may be nested within clinicians, practices, or studies. A Bayesian hierarchical model can estimate treatment effects while simultaneously quantifying uncertainty at each level rather than collapsing the structure into a single average response [11].

A central advantage of this approach is partial pooling, which allows information to be shared across related units while preserving local differences. For example, a site with limited observations can borrow strength from other sites in the same tooth or patient, while still retaining its own posterior estimate. This property is clinically important because periodontal studies often include many correlated sites but relatively fewer patients, making purely independent estimates unstable.

Bayesian models also permit the formal incorporation of prior information from previous clinical evidence. In periodontal therapy, systematic reviews have synthesized evidence on subgingival instrumentation [12], access flap procedures [13], regenerative treatment of intrabony defects [14], and furcation regeneration [15]. These evidence sources can inform weakly informative or clinically informed priors for expected treatment effects, variance parameters, and risk factor coefficients, provided that prior assumptions are made transparent.

Compared with frequentist mixed-effects models, Bayesian hierarchical models provide full posterior distributions rather than only point estimates and confidence intervals. This distinction matters because clinicians often need probabilities of clinically meaningful outcomes, such as the probability that a residual pocket will close or that a tooth will survive under supportive periodontal therapy. Bayesian analysis is therefore aligned with clinical decision-making because it expresses uncertainty in probabilistic terms that can be updated when new evidence becomes available [16].

The Bayesian workflow also supports model criticism, sensitivity analysis, and predictive validation. Tools for Bayesian computation and probabilistic programming, including Stan [17] and brms [18], make it feasible to estimate complex multilevel models with varying intercepts and slopes. Visualization and model evaluation methods, including posterior predictive checks, leave-one-out cross-validation, and WAIC, provide a structured way to assess whether the model adequately represents periodontal outcome data [19, 20].

Data structure and sources of heterogeneity

The first step in the proposed framework is to define periodontal data according to its natural hierarchy. Repeated observations over time form the lowest temporal layer, followed by site-level measurements such as probing depth, bleeding on probing, plaque presence, and clinical attachment level. These sites are

nested within teeth, which differ by tooth type, mobility, furcation involvement, root anatomy, and baseline defect morphology.

Tooth-level factors contribute additional heterogeneity because different teeth have different prognostic profiles. Long-term studies of periodontally compromised patients show that tooth loss after active periodontal therapy is not distributed uniformly across dentitions [21], and updated evidence identifies multiple predictors of tooth loss during maintenance care [22]. These findings justify tooth-level random effects and, when appropriate, tooth-level slopes for variables such as furcation involvement or baseline mobility.

Patient-level determinants represent another major source of variation in periodontal outcomes. Smoking exposure can reduce the effectiveness of non-surgical periodontal therapy [23], while diabetes-related mechanisms and glycemic status may alter inflammatory burden and healing potential [6]. Compliance, oral hygiene behavior, and maintenance attendance further shape outcomes because supportive periodontal therapy depends on repeated risk control rather than a single treatment episode [24-27].

Treatment-level and clinician-level factors should also be considered when data are collected across procedures, operators, centers, or studies. Evidence comparing surgical access, subgingival debridement, pocket reduction, and regenerative approaches shows that treatment effects may differ by procedure type, defect characteristics, and therapeutic objective [13, 28]. In a hierarchical framework, these factors can be modeled as fixed effects when they are primary explanatory variables or as random effects when the purpose is to account for unexplained variability across clinicians or centers.

For a Bayesian periodontal model to be clinically useful, each level of the hierarchy must be linked to plausible risk factors and measurable outcomes. Site-level inflammation, tooth-level prognosis, patient-level risk status, and center-level treatment variation can each contribute to the posterior probability of treatment success. **Table 1** outlines the hierarchical data structure and the risk factors typically assessed at each level.

Table 1. Hierarchical Data Structure in Periodontal Treatment Studies: Levels, Units of Analysis, and Associated Risk Factors

Hierarchical level	Unit of analysis	Typical periodontal variables	Associated risk factors	Modeling implication
Level 1	Repeated observations over time	Baseline, post-treatment, maintenance, and follow-up measurements	Time since therapy, recall interval, maintenance adherence, disease recurrence	Supports longitudinal change modeling and time-varying outcome estimation
Level 2	Periodontal site	Probing depth, clinical attachment level, bleeding on probing, plaque presence, suppuration	Local plaque retention, residual inflammation, baseline pocket depth, bleeding status	Requires site-level random effects or correlated residual structures
Level 3	Tooth	Tooth type, mobility, furcation involvement, intrabony defect morphology, tooth survival	Molar status, furcation grade, root anatomy, mobility, defect depth	Supports tooth-level random intercepts and tooth-specific prognosis estimation
Level 4	Patient	Smoking, diabetes, age, oral hygiene behavior, systemic health, adherence	Tobacco exposure, glycemic status, compliance, behavioral risk, baseline severity	Allows patient-specific effects and individualized posterior prediction
Level 5	Clinician, center, practice, or study	Treatment protocol, operator, maintenance system, study design	Surgical versus non-surgical therapy, regenerative material, center experience, recall organization	Accounts for practice-level and study-level heterogeneity in multicenter datasets

Model specification and prior elicitation

A Bayesian hierarchical model for periodontal treatment outcomes should begin by defining the clinical endpoint and the scale on which it is measured. Continuous outcomes such as probing depth reduction or clinical attachment gain may be modeled with Gaussian or robust likelihoods, whereas binary outcomes such as pocket closure, residual pocket presence, or tooth survival may require Bernoulli, binomial, or survival-oriented extensions [9, 29]. The likelihood should therefore be chosen according to the periodontal outcome, not imposed as a generic regression form.

The fixed-effect component should represent clinically interpretable risk factors at the site, tooth, patient, and treatment levels. Site-level predictors may include baseline probing depth, plaque, bleeding, or suppuration, while tooth-level predictors may include molar status, mobility, furcation involvement, and defect morphology [30, 31]. Patient-level predictors should include systemic and behavioral determinants such as diabetes, smoking, oral hygiene behavior, and compliance, because these factors modify both disease susceptibility and treatment response [23, 32].

The random-effect component should represent unexplained heterogeneity across nested periodontal units. A basic model may include random intercepts for sites, teeth, and patients, whereas a more flexible model may allow random slopes when the effect of a risk factor differs across patients or clinical centers [11]. Bayesian periodontal applications such as biclustering models demonstrate that periodontal data can contain structured dependence that is difficult to capture with simple independent-error assumptions [33].

Prior elicitation should be transparent, clinically justified, and matched to the level of available evidence. Weakly informative priors may stabilize estimation when evidence is limited, while informative priors may be derived from systematic reviews of subgingival instrumentation, surgical access, regenerative therapy, and furcation treatment [12, 14, 15]. For heterogeneity parameters, penalized complexity priors and weakly informative random-effects priors can reduce implausible variance estimates while preserving uncertainty [34, 35].

Posterior estimation can be performed through MCMC or related Bayesian computation methods implemented in probabilistic programming environments. Stan provides a general platform for fitting customized hierarchical models [17], while brms enables accessible specification of Bayesian multilevel models and advanced distributional structures [18, 36]. Convergence diagnostics, posterior predictive checks, and sensitivity analyses should be treated as essential parts of the model rather than optional technical appendices [19, 20].

Output interpretation and clinical translation

The primary output of the proposed framework is not only a regression coefficient but a posterior distribution for each risk factor and variance component. For example, the effect of smoking on probing depth reduction can be summarized by its posterior mean, credible interval, and probability of exceeding a clinically meaningful threshold [23]. This interpretation is more directly useful than a binary significance test because it communicates both direction and uncertainty.

Posterior predictive distributions translate model parameters into individualized clinical probabilities. A clinician could estimate the probability that a deep molar site with furcation involvement in a patient with diabetes will achieve pocket closure after therapy, while accounting for uncertainty at the site, tooth, and patient levels [6, 29]. This approach connects statistical inference to practical questions about prognosis, maintenance intensity, and patient communication.

Bayesian outputs can also support treatment planning by comparing predicted outcomes under alternative clinical strategies. Evidence comparing non-surgical instrumentation, access flap surgery, pocket reduction, and regenerative approaches provides plausible prior information and clinically relevant contrasts for prediction [12, 13, 28]. A posterior predictive framework could therefore estimate whether a given patient profile is more likely to benefit from one treatment pathway than another.

Clinical translation requires outputs that are interpretable to periodontists and patients rather than only statisticians. Probability statements such as “the posterior probability of pocket closure is 0.72 under this treatment plan” are more intuitive than abstract model coefficients, especially when paired with uncertainty intervals and risk explanations [10, 16]. Such outputs could eventually be embedded into decision support systems that combine periodontal charting, systemic risk assessment, and maintenance planning.

Proposed conceptual framework

The proposed conceptual framework begins with study design and data harmonization. Periodontal researchers should first define the target outcome, the follow-up interval, the treatment context, and the hierarchical units of analysis. This step is consistent with endpoint-focused periodontal guidance, which emphasizes that outcome definitions must be clinically meaningful before statistical modeling begins [9].

The complete analytical pathway, from periodontal data hierarchy to Bayesian posterior prediction and clinical translation, is summarized in **Figure 1**.

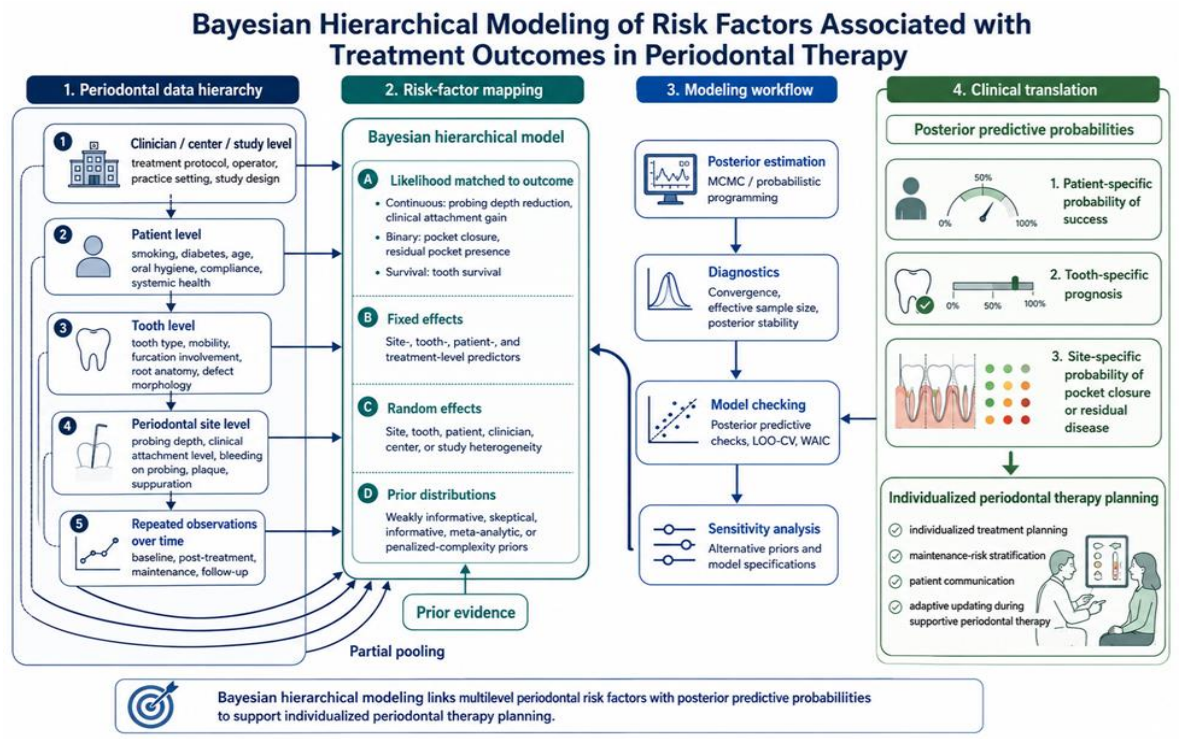


Figure 1. Bayesian hierarchical framework for individualized prediction of periodontal treatment outcomes

The second stage is risk factor mapping across hierarchy levels. Site-level inflammatory indicators, tooth-level anatomical prognosis, patient-level systemic and behavioral exposures, and center-level treatment variation should be identified before model estimation [1, 2]. This mapping prevents clinically important predictors from being misplaced at the wrong level of analysis.

The third stage is Bayesian model construction, including likelihood selection, fixed effects, random effects, and prior specification. Priors may be weakly informative when evidence is sparse or more informative when supported by periodontal systematic reviews and meta-analyses [14, 15]. **Table 2** presents the core components and modeling steps of the proposed Bayesian hierarchical framework.

Table 2. Proposed Bayesian Hierarchical Framework for Periodontal Treatment Outcome Modeling: Components, Prior Types, and Analytical Steps

Framework component	Main purpose	Bayesian modeling element	Possible prior type	Analytical step
Outcome definition	Identify the clinical endpoint to be predicted	Likelihood function for continuous, binary, count, or survival outcome	Weakly informative prior on intercept and residual scale	Select probing depth reduction, attachment gain, pocket closure, or tooth survival
Hierarchical data mapping	Represent periodontal nesting structure	Random intercepts for sites, teeth, patients, clinicians, or centers	Weakly informative or penalized complexity prior for variance terms	Specify site-within-tooth-within-patient structure
Risk factor selection	Link clinical predictors to the correct level	Fixed effects and possible random slopes	Informative priors from prior clinical studies when justified	Assign plaque, furcation, smoking, diabetes, and treatment variables to levels
Prior elicitation	Incorporate previous evidence transparently	Prior distributions for coefficients and heterogeneity	Weakly informative, skeptical, informative, or meta-analytic priors	Justify prior means, scales, and sensitivity alternatives
Posterior estimation	Estimate uncertainty in all parameters	MCMC or equivalent posterior simulation	Computational defaults checked by diagnostics	Assess convergence, effective sample size, and posterior stability

Model checking	Evaluate model adequacy and prediction	Posterior predictive checks, LOO-CV, WAIC	Alternative priors for sensitivity analysis	Compare observed and predicted outcomes
Clinical translation	Generate individualized predictions	Posterior predictive probabilities	Patient-updated priors in future learning systems	Report probability of success for patient-, tooth-, and site-specific profiles

The fourth stage is posterior inference and predictive validation. Bayesian workflow principles require that the fitted model be checked against observed periodontal patterns and compared with alternative specifications using predictive criteria [19, 20]. When the model fails to reproduce residual pocket distributions or tooth-level heterogeneity, the framework requires revision rather than uncritical reporting.

The final stage is clinical translation through individualized prediction. Posterior predictive probabilities should be expressed for patient-specific, tooth-specific, and site-specific profiles, allowing clinicians to communicate uncertainty and tailor maintenance strategies. Because long-term periodontal stability is influenced by recall intervals and residual probing depths, prediction should also be updated over time as new maintenance observations become available [22, 24].

Implementation challenges and future directions

The first implementation challenge is the need for well-structured multilevel datasets. Many periodontal studies contain rich site-level data but may not preserve complete information on tooth-level anatomy, patient-level risk, treatment protocol, and maintenance adherence. Future registries should therefore be designed around the hierarchy required for modeling rather than forcing hierarchical models onto incomplete datasets [21, 27].

The second challenge is computational and statistical expertise. Bayesian hierarchical models require careful prior specification, convergence assessment, posterior checking, and sensitivity analysis, which may be unfamiliar to many clinical research teams [8, 17]. User-friendly platforms such as brms can lower the technical barrier, but interdisciplinary collaboration remains essential for valid implementation [18, 36].

The third challenge is acceptance in periodontal and dental journals. Reviewers may be more familiar with frequentist regression, mixed-effects models, and conventional meta-analysis than with posterior distributions or Bayesian predictive checks. Clear reporting standards, transparent prior justification, and comparison with simpler models can help demonstrate that Bayesian methods improve rather than obscure clinical interpretation [10, 35].

Future research should test this framework through simulation studies, retrospective periodontal datasets, and prospective multicenter cohorts. Simulation can clarify when Bayesian hierarchical models outperform single-level or frequentist alternatives, while real-world validation can assess whether posterior predictions improve treatment planning, maintenance scheduling, and patient communication. Ultimately, the framework should evolve into open-source templates that allow periodontology researchers to specify clinically grounded Bayesian models without sacrificing statistical rigor [33, 34].

Conclusion

This conceptual framework presents Bayesian hierarchical modeling as a rigorous and clinically meaningful approach for analyzing risk factors associated with periodontal treatment outcomes. By aligning the statistical model with the biological and clinical hierarchy of periodontal data, it offers a more faithful representation of how treatment response varies across sites, teeth, patients, and care settings.

The framework also advances periodontal outcome research by showing how prior evidence, variance decomposition, posterior inference, and individualized prediction can be integrated into one coherent analytical pathway. Instead of treating uncertainty as a limitation, the Bayesian approach makes uncertainty explicit and clinically interpretable.

Operationalizing this framework will require collaboration among periodontists, biostatisticians, epidemiologists, informaticians, and clinical decision support developers. With careful implementation, Bayesian hierarchical modeling can strengthen evidence-based periodontics and support more individualized, transparent, and adaptive periodontal therapy planning.

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