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Article

AI-Based Prediction of Pulpal Recovery After Deep Caries Management Using Serial Clinical and Imaging Parameters

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ABSTRACT

The diagnosis of pulpal health and the ability to predict recovery after treatment is critical to achieving pulp vitality and care is a major clinical challenge. Traditional clinical evaluations and dental imaging can give valuable diagnostic information, but may not adequately detect changes in pulpal status over time. The aim of this study is to investigate an artificial intelligence (AI) based method to predict pulpal recovery using serial clinical examination and dental imaging parameters. The suggested framework incorporates patient symptoms, pulp vitality responses, caries depth, remaining dentine thickness, periapical findings and treatment-related variables to delineate patterns that are correlated with successful healing, delayed recovery, and pulpal failure. Longitudinal data can be analysed to estimate recovery probabilities and to detect clinically relevant factors that predict treatment outcomes, using machine learning and deep learning techniques. The performance of the model would be assessed with sensitivity, specificity, accuracy, and area under the receiver operating characteristic curve, which would be compared with the conventional clinical assessment methods. The concept is inspired by the latest use of AI in restorative dentistry, caries detection and dental image analysis. This framework could be used to inform earlier identification of pa-tients at risk of pulpal complications and to support individual treatment planning, as it provides for repeated observations as well as baseline findings. It will need to be clinically validated and tested elsewhere to prove its reliability, generalizability and usefulness in restorative dentistry.

INTRODUCTION

The condition of deep dental caries is still a major problem in the field of restorative dentistry, as the carious lesion's development into the dental pulp will elevate the likelihood of pulpal inflammation, pulp exposure, and loss of vitality. The goal of deep caries treatment is to arrest the caries, maintain the vitality of the pulp and preserve the function of the affected tooth for long-term use. The success of pulp healing following treatment is, however, difficult to predict due to the different responses of the pulp to various lesions, depending on the depth of the lesion, remaining dentine thickness, bacterial activity, preoperative symptoms, and the success of the restorative procedure. Therefore, it is crucial to be able to predict the recovery of the pulp to improve the treatment plan

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and avoid unnecessary endodontic treatment. With the progression of restorative dentistry, artificial intelligence (AI) has gained significant attention and promise in various clinical settings, such as the support of clinical assessment, diagnostic interpretation, and personalised treatment decision-making (Najeeb & Islam, 2025; Sajid et al., 2025).

Traditional methods for the assessment of pulpal health include clinical symptoms, pulp sensibility tests, percussion examination and dental imaging. While these methods are still of importance, they have some limitations in their ability to predict the biological healing potential of the pulp after deep caries management. The initial response of a tooth to treatment may be good but treatment may later fail due to continued inflammation, pulp necrosis or other issues. Likewise, one radiograph may give valuable information on caries depth and periapical status, but fail to reflect the changes that may take place during the healing process. The limitations highlight the need for serial clinical and imaging evaluations to track progression of treatment over time. The research findings of AI for pulp exposure prediction prior to caries removal before excavation have validated the use of deep learning and dental imaging analysis for the decision-making process in deep caries management (Ramezanzade et al., 2023). However, wider surveys have recommended that AI's use is growing in dentistry, such as in diagnostic support and image interpretation (Mallineni et al., 2024; Bagde, 2021). With recent advancements in AI, there are opportunities to incorporate clinical data, dental radiographs, intraoral images and treatment-related data into predictive models. Machine learning algorithms can discover relationships between several variables, and deep learning models can detect pertinent patterns in complicated dental images. These capabilities may support more comprehensive assessments of caries severity, restoration quality, and periapical changes. For example, AI-driven approaches to dental caries management have been discussed as potential tools for improving clinical decision-making, while research on AI-based evaluation of caries, periapical conditions, and restoration status highlights the relevance of automated image analysis in dental practice (Liang et al., 2025; Keskin et al., 2025). Furthermore, AI-based dental X-ray enhancement and deep learning applications for caries detection provide additional methodological foundations for developing integrated predictive systems (Khan et al., 2025; Noor Uddin et al., 2025).

Despite these developments, predicting pulpal recovery requires a broader approach than detecting caries or identifying the likelihood of pulp exposure. Successful prediction must account for changes in clinical symptoms, pulp vitality responses, and imaging findings across multiple follow-up periods. An AI model that incorporates these serial observations may identify early warning patterns associated with delayed healing or treatment failure and distinguish them from indicators of favorable recovery. The growing interest in evidence-based AI applications in endodontology further supports the need to evaluate the clinical reliability and practical limitations of such predictive technologies (Cagay Sevencan & Yavşan, 2025). Nevertheless, model performance, data quality, interpretability, and external validation remain important considerations before AI-generated predictions can be incorporated into routine patient care.

This study therefore focuses on AI-based prediction of pulpal recovery after deep caries management using serial clinical and imaging parameters. It proposes integrating patient symptoms, pulp vitality findings, caries depth, remaining dentine thickness, radiographic changes, and treatment characteristics into a longitudinal predictive framework. The central objective is to investigate whether combining repeated clinical observations with imaging information can improve the prediction of successful pulpal recovery, delayed healing, and pulpal failure compared with conventional assessment approaches. By emphasizing longitudinal data integration, the study aims to contribute to the development of evidence-informed, individualized restorative treatment planning. Any proposed model would require prospective clinical evaluation and independent validation to establish its predictive accuracy, generalizability, and clinical usefulness.

Literature Review

Artificial Intelligence in Restorative Dentistry

Artificial intelligence (AI) is increasingly being applied in restorative dentistry to improve diagnostic accuracy, support treatment planning, and facilitate evidence-based clinical decision-making. Machine learning and deep learning algorithms can analyze dental images, identify pathological changes, and assist clinicians in evaluating caries severity and restoration outcomes. Najeeb and Islam (2025) discussed current trends and future prospects of AI in restorative dentistry, highlighting its potential to improve diagnostic processes and support more individualized dental care. Similarly, Sajid et al. (2025) described applications of AI across dental specialties, demonstrating its relevance to clinical assessment, treatment planning, and outcome prediction.

Mallineni et al. (2024) provided a descriptive review of AI applications in dentistry, emphasizing the expanding role of computational approaches in dental diagnosis and clinical practice. These developments provide a foundation for investigating whether AI can predict pulpal recovery following deep caries management. However, accurate prediction requires more than identifying carious lesions; it requires integrating clinical findings, treatment characteristics, and changes in pulpal status over time.

AI-Based Caries Detection and Pulp Exposure Prediction

The assessment of deep caries is important because the proximity of a lesion to the dental pulp influences treatment decisions and the risk of pulp exposure. Ramezanzade et al. (2023) investigated the prediction of pulp exposure before caries excavation by comparing deep learning-based image data with standard dental radiographs. Their work provides a relevant foundation for applying AI to preoperative risk assessment and treatment planning in deep caries management.

Noor Uddin et al. (2025) reviewed applications of AI-based deep learning models for detecting dental caries on intraoral images, reflecting the growing interest in automated image interpretation. Khan et al. (2025) also examined dental X-ray enhancement and caries detection using a novel computational approach. These studies are relevant to extracting imaging features such as lesion depth, lesion boundaries, and the relationship between caries and the pulp.

Nevertheless, predicting pulp exposure before excavation differs from predicting pulpal recovery after treatment. The former primarily concerns the anatomical risk associated with caries removal, whereas the latter requires assessing biological responses, symptom progression, pulp vitality, and possible treatment failure. Consequently, imaging-based predictions should be combined with serial clinical observations to develop a more comprehensive model of pulpal recovery.

Clinical and Imaging Parameters for Assessing Pulpal Recovery

Pulpal recovery following deep caries management depends on several interacting factors, including the initial condition of the pulp, the extent of carious tissue, the remaining dentine thickness, the treatment approach, and the quality of the final restoration. Clinical parameters such as spontaneous pain, sensitivity, responses to pulp sensibility tests, and percussion findings provide information about the patient's condition. Imaging parameters, including caries depth, dentine thickness, restoration integrity, and periapical changes, provide complementary anatomical and pathological information. Keskin et al. (2025) investigated AI applications in evaluating periapical conditions, caries, and restoration status. Their work is relevant to the potential integration of radiographic findings into automated assessment systems. Liang et al. (2025) examined AI-driven dental caries management strategies across clinical practice, professional education, and public self-care, illustrating the broader relevance of AI to structured caries assessment and management.

For pulpal recovery prediction, these parameters should be collected at baseline and at predefined follow-up intervals. A single examination may not adequately represent changes in symptoms or pulp status. Serial assessments can help identify improvement, persistent inflammation, or deterioration. However, pulp sensibility tests measure neural responses rather than directly measuring pulpal blood flow, and no single clinical or imaging indicator should be interpreted as definitive evidence of histological recovery. An integrated assessment is therefore necessary.

Longitudinal AI Prediction and Evidence-Based Endodontology

Longitudinal AI prediction involves analyzing observations collected from the same patient at multiple time points. Unlike models based exclusively on baseline data, longitudinal models can identify changes in clinical symptoms, vitality responses, and radiographic features that may indicate different recovery trajectories. In deep caries management, this approach could support the estimation of recovery probabilities and the early identification of patients who may require additional intervention.

Cagay Sevencan and Yavşan (2025) examined the use of AI in evidence-based endodontology through bibliometric and scientometric analysis, providing context for understanding the development of AI research within endodontic practice. Junaid et al. (2022), in their systematic review of AI for cephalometric landmark identification and diagnosis, addressed the development and performance of AI in dental imaging-related applications. Although cephalometric analysis differs from pulpal recovery assessment, it demonstrates the wider use of automated image analysis in dentistry.

Bagde (2021) addressed AI applications across dentistry, while Ismail et al. (n.d.), whose supplied reference lacks publication details, may be relevant to digital dentistry depending on the specific article intended. Mosobi (2023) and Aggarwal (2023) published e-poster abstracts in the Journal of Conservative Dentistry and Endodontics. These abstract collections may offer supplementary context, but individual findings should only be attributed to them after the relevant abstracts have been verified. Khanagar et al. (2021) reviewed AI applications in forensic odontology, demonstrating the wider methodological relevance of AI in dentistry, although forensic applications do not directly establish its effectiveness in predicting pulpal healing.

Overall, the literature supports the investigation of AI for dental image analysis, caries assessment, and clinical decision support. Nevertheless, evidence concerning AI-based prediction of pulpal recovery specifically through the integration of serial clinical and imaging parameters remains an important area for further investigation.

Research Gap and Conceptual Framework

Existing research provides a foundation for automated caries detection, pulp exposure prediction, dental radiograph analysis, and AI-assisted clinical decision-making. However, these applications do not necessarily

Table 1: Summary of Relevant Literature and Its Application to AI-Based Pulpal Recovery Prediction

Author(s)	*Research focus*	*Relevance to the present study*
Najeeb and Islam (2025)	AI in restorative dentistry	Provides the restorative dentistry context for AI-assisted prediction.
Sajid et al. (2025)	AI applications across dental specialties	Supports the broader clinical application of AI in dentistry.
Ramezanzade et al. (2023)	AI prediction of pulp exposure before caries excavation	Provides a foundation for preoperative risk assessment in deep caries.
Mallineni et al. (2024)	Descriptive review of AI in dentistry	Establishes the wider diagnostic and clinical applications of AI.
Liang et al. (2025)	AI-driven caries management strategies	Supports AI-assisted caries assessment and treatment planning.
Keskin et al. (2025)	AI evaluation of periapical, caries, and restoration status	Supports integration of radiographic and restoration-related features.
Cagay Sevencan and Yavşan (2025)	AI in evidence-based endodontology	Provides context for AI adoption in endodontic research.
Khan et al. (2025)	Dental X-ray enhancement and caries detection	Supports image preprocessing and automated feature detection.
Noor Uddin et al. (2025)	Deep learning for caries detection on intraoral images	Supports AI-based extraction of caries-related imaging features.
Junaid et al. (2022)	AI for cephalometric identification and diagnosis	Provides methodological context for automated dental image analysis.
Bagde (2021)	AI applications across dentistry	Provides broader context for dental AI applications.
Khanagar et al. (2021)	AI in forensic odontology	Offers methodological context for AI applications in dentistry.
Mosobi (2023); Aggarwal (2023)	E-poster abstracts in conservative dentistry and endodontics	Potential supplementary sources, subject to verification of relevant abstracts.
Ismail et al. (n.d.)	Digital dentistry; full publication details not supplied	Potential background source, pending bibliographic verification.

Source: Literature synthesized from the references supplied for this study.

establish whether AI can reliably predict pulpal recovery after deep caries management. A key research opportunity is the development of a longitudinal predictive framework that combines baseline clinical status, serial symptoms, pulp sensibility responses, imaging characteristics, and treatment-related variables.

The proposed framework would use these data to classify recovery trajectories and estimate the likelihood of successful pulp preservation, delayed or uncertain recovery, and pulpal failure. Its performance should be compared with conventional clinical assessment and evaluated using independent patient data. Because predictive accuracy alone does not establish clinical usefulness, the model should also be assessed for calibration, generalizability, and potential clinical benefit. The central contribution of this research would therefore be the integration of repeated clinical and imaging observations into a unified AI-based prediction model. Such a model could support risk stratification and follow-up planning while retaining the clinician's responsibility for diagnosis and treatment decisions.

In summary, the reviewed literature establishes the relevance of AI to dental image analysis, caries detection, restorative treatment planning, and endodontic decision support. The principal research gap is the need to evaluate whether integrating serial clinical and imaging parameters can improve prediction of pulpal recovery after deep caries management. Addressing this gap could contribute to more individualized monitoring and better-informed decisions about pulp preservation, subject to rigorous clinical validation.

Methodology

Study Design and Setting

This study will adopt a prospective longitudinal observational design to investigate the application of artificial intelligence (AI) in predicting pulpal recovery following deep caries management. The study will follow patients over scheduled clinical and radiographic assessments to identify changes in pulpal status and determine which baseline and follow-up parameters are

most predictive of successful recovery. A longitudinal approach is appropriate because pulpal health may evolve after treatment, making repeated observations valuable for evaluating outcomes. The proposed methodology builds on developments in AI-assisted restorative dentistry and dental diagnostic decision-making described by Najeeb and Islam (2025), Sajid et al. (2025), and Mallineni et al. (2024).

Patient Selection and Data Collection

Patients presenting with deep carious lesions requiring vital pulp-preserving treatment will be recruited according to predefined inclusion and exclusion criteria. Eligible participants will undergo baseline clinical examination, appropriate pulp vitality testing, and standardized dental imaging before treatment. Clinical information will include age, presenting symptoms, pain characteristics, sensitivity responses, percussion findings, and relevant dental history. Imaging variables will include caries depth, remaining dentine thickness where measurable, proximity to the pulp, and periapical status.

Treatment-related information, including caries management technique, pulp protection procedures, and restorative materials, will also be recorded. Follow-up assessments will be conducted at predefined intervals, for example, 3, 6, and 12 months after treatment, subject to the approved study protocol. This approach will enable the investigation of temporal changes in clinical and imaging indicators. Previous research on AI-based pulp exposure prediction supports the relevance of dental imaging for caries-related assessment (Ramezanzade et al., 2023), while studies examining caries, periapical conditions, and restoration status demonstrate additional opportunities for AI-assisted interpretation of dental records (Keskin et al., 2025).

Clinical and Imaging Parameter Integration

The collected data will be organized into clinical, radiographic, treatment-related, and longitudinal categories. Clinical findings will be combined with imaging features to develop a comprehensive dataset for predicting pulpal recovery. Dental images will undergo quality checks, standardization, and preprocessing to reduce inconsistencies caused by image quality, acquisition settings, or differences between imaging devices. Where image-based deep learning is applied, relevant features may be extracted automatically, while structured clinical variables will be encoded for machine learning analysis.

The integration of clinical and imaging information is consistent with the broader direction of AI-supported caries management and restorative dentistry (Liang et al., 2025; Najeeb & Islam, 2025). Evidence from reviews of deep learning in dental caries detection also provides methodological context for selecting appropriate image-processing and classification approaches (Noor Uddin et al., 2025).

AI Model Development and Validation

The study will evaluate suitable supervised machine learning algorithms, such as random forest, support vector machines, and gradient boosting, alongside deep learning approaches for dental images where the sample size and data quality permit. The models will use clinical measurements, imaging features, treatment characteristics, and changes observed during follow-up to estimate the probability of successful pulpal recovery or subsequent pulpal failure.

The dataset will be divided into training, validation, and independent testing sets at the patient level to prevent observations from the same patient appearing across different partitions. Where feasible, external validation using data from another clinical setting will be considered. Model performance will be evaluated using accuracy, sensitivity, specificity, precision, F1-score, and the area under the receiver operating characteristic curve. Calibration and explainability analyses will also be conducted to assess whether predicted probabilities are reliable and which variables contribute most to the predictions. These procedures reflect established methodological considerations in dental AI research and the wider evaluation of AI diagnostic systems (Mallineni et al., 2024; Cagay Sevencan & Yavşan, 2025).

Outcome Definition and Statistical Analysis

The primary outcome will be pulpal recovery following deep caries management, determined using predefined clinical criteria and follow-up findings. Successful recovery will be characterized by the absence of persistent symptoms, clinically acceptable pulp vitality responses, and no evidence of progressive periapical disease. Pulpal failure will be defined according to documented evidence of pulp necrosis, irreversible pulpal disease, or the need for endodontic intervention. Cases with inconclusive findings will be classified separately or managed according to predefined adjudication rules.

Statistical analyses will summarize participant characteristics, treatment variables, follow-up findings, and outcome distributions. Regression and machine learning analyses will investigate associations between candidate predictors and pulpal outcomes. Missing data, class imbalance, and potential confounding variables will be addressed using appropriate prespecified procedures. AI predictions will be compared with conventional clinical assessments to determine whether combining serial observations improves predictive performance. Ethical approval, informed consent, confidentiality safeguards, and transparent reporting will be incorporated throughout the research process.

Overall, this methodology will establish a structured framework for assessing whether serial clinical and imaging parameters can improve AI-based prediction of pulpal recovery. The prospective design, patient-level

Table 2: Major Clinical and Imaging Variables for AI-Based Prediction of Pulpal Recovery

Variable category	*Parameters collected*	*Purpose in prediction*
Patient characteristics	Age, relevant medical and dental history	Identify patient-level factors associated with recovery
Clinical indicators	Pain history, sensitivity, percussion response, pulp vitality tests	Assess clinical evidence of pulpal health
Imaging indicators	Caries depth, remaining dentine thickness, pulp proximity, periapical findings	Characterize lesion severity and surrounding tissue status
Treatment variables	Caries management technique, pulp protection, restorative material	Account for differences in treatment approaches
Serial follow-up data	Changes in symptoms, vitality responses, and radiographic findings	Detect evolving recovery patterns
Outcome variables	Successful recovery, uncertain recovery, or pulpal failure	Provide reference labels for model development and evaluation

Source: Proposed study framework informed by Ramezanzade et al. (2023), Keskin et al. (2025), Liang et al. (2025), and Najeeb and Islam (2025).

model validation, and clinically defined outcomes will help determine the potential value of AI as a decision-support tool in restorative dentistry. As the study is proposed, any improvement in predictive accuracy must be demonstrated using collected patient data rather than assumed in advance.

AI Model Development and Outcome Assessment

The development of an artificial intelligence (AI) model for predicting pulpal recovery after deep caries management requires the integration of clinical, radiographic, and treatment-related information collected at multiple time points. Unlike conventional assessments that primarily rely on individual clinical examinations, an AI-based framework can analyze longitudinal patterns to identify changes associated with pulp healing, persistent inflammation, and treatment failure. Artificial intelligence is increasingly being explored in restorative dentistry for diagnostic support, treatment planning, and the interpretation of dental imaging, providing a foundation for the development of predictive models for pulpal outcomes (Najeeb & Islam, 2025; Sajid et al., 2025).

Data Integration and Feature Selection

The first stage involves collecting standardized patient data before treatment and during scheduled follow-up visits. Clinical parameters should include spontaneous pain, sensitivity to thermal stimuli, percussion responses, and pulp sensibility test results. Imaging parameters may include caries depth, remaining dentine thickness, the proximity of the lesion to the pulp, and changes in periapical tissues. Treatment-related variables, including the caries removal technique, pulp-protective materials, and restoration type, should also be incorporated into the dataset.

The selection of imaging features is particularly important because previous research has investigated AI-based prediction of pulp exposure before caries excavation using deep learning and conventional dental radiographs (Ramezanzade et al., 2023). Similarly, AI applications for detecting caries on intraoral images demonstrate the relevance of automated image interpretation to dental diagnosis (Noor Uddin et al., 2025). These approaches provide methodological support for developing a model that combines imaging findings with serial clinical observations rather than relying on radiographic features alone.

Data preprocessing should include missing-data assessment, image standardization, removal of duplicate records, and appropriate coding of clinical variables. Where serial observations are used, each patient's records must be linked across follow-up visits while maintaining patient confidentiality. Feature selection should prioritize variables with clinical relevance and predictive value to minimize unnecessary model complexity. The broader potential of AI to support caries management and individualized clinical decision-making has also been discussed by Liang et al. (2025).

Model Architecture and Training

The proposed framework may combine machine learning algorithms for structured clinical data with deep learning models for dental images. Algorithms such as logistic regression, random forest, and gradient boosting can be evaluated for predicting categorical outcomes, including successful recovery, uncertain recovery, and pulpal failure. Convolutional neural networks may be considered for extracting relevant features from standardized radiographs, while longitudinal models can assess changes in clinical findings across follow-up visits.

The integration of these techniques would allow the model to estimate the probability of pulpal recovery by considering interactions between baseline disease severity, treatment characteristics, imaging findings,

and subsequent clinical responses. AI research in dental imaging has examined the evaluation of caries, periapical conditions, and restoration status, supporting the potential value of automated radiographic assessment in this framework (Keskin et al., 2025). Improvements in dental X-ray enhancement and caries detection may also contribute to image preprocessing and feature extraction (Khan et al., 2025).

The dataset should be divided into training, validation, and testing subsets at the patient level to prevent observations from the same patient appearing across different subsets. Model selection and hyperparameter tuning should be performed using the training and validation data, while the independent test set should be reserved for final performance assessment. External validation across different clinical settings would be necessary before the model could be considered suitable for routine use.

Outcome Classification and Clinical Interpretation

Pulpal recovery should be defined using prespecified clinical criteria and appropriate follow-up periods. Successful recovery may be characterized by the absence of persistent or worsening symptoms, supportive pulp sensibility findings, and no evidence of developing apical disease. Uncertain or delayed recovery may involve persistent symptoms or inconclusive clinical findings requiring additional observation. Pulpal failure may be indicated by findings consistent with pulp necrosis, irreversible pulp disease, or the subsequent need for endodontic treatment.

These categories should be established through a predefined clinical assessment protocol rather than determined solely by the AI model. Pulp sensibility tests do not directly measure pulpal blood flow, and no single symptom or imaging feature should automatically determine the outcome. Where appropriate, expert clinical adjudication should be used to establish reference outcomes.

The proposed approach is consistent with the broader investigation of AI across dental specialties and its potential to assist clinical decision-making (Mallineni et al., 2024; Bagde, 2021). Nevertheless, AI predictions should be interpreted as decision-support estimates rather than definitive diagnoses. Evidence-based endodontic assessment remains essential when determining whether a pulp is recovering or requires further intervention (Cagay Sevencan & Yavşan, 2025).

Model Performance Evaluation

The predictive performance of the model should be assessed using accuracy, sensitivity, specificity, precision, F1-score, and the area under the receiver operating characteristic curve. Calibration should also be evaluated to determine whether predicted recovery probabilities correspond to observed outcomes. Where the study includes multiple follow-up periods, performance should be examined across those periods to establish whether serial data improve prediction compared with baseline measurements alone.

The model should be compared with conventional clinical assessment and, where feasible, a model based only on baseline clinical and imaging variables. This comparison would help establish whether longitudinal data provide meaningful additional predictive value. AI

Table 3: Proposed AI Model Components and Assessment of Pulpal Recovery

Model component	*Variables or methods*	*Purpose*
Clinical data	Pain, thermal sensitivity, percussion responses, pulp sensibility tests	Identify clinical patterns associated with recovery
Imaging data	Caries depth, remaining dentine thickness, periapical findings	Characterize lesion severity and radiographic changes
Treatment variables	Caries removal approach, pulp-protective materials, restoration type	Assess the relationship between treatment and outcomes
Longitudinal integration	Serial clinical examinations and imaging findings	Identify changes in pulpal status over time
Predictive algorithms	Logistic regression, random forest, gradient boosting, and selected deep learning models	Estimate the probability of recovery or failure
Validation	Patient-level data separation, independent testing, and external validation	Assess generalizability and reduce data leakage
Performance assessment	Sensitivity, specificity, F1-score, discrimination, and calibration	Evaluate predictive reliability and clinical usefulness
Clinical interpretation	Recovery, uncertain recovery, and pulpal failure	Support individualized monitoring and treatment planning

Source: Proposed framework informed by Najeeb and Islam (2025), Ramezanzade et al. (2023), Keskin et al. (2025), and Noor Uddin et al. (2025).

evaluation should also consider interpretability, subgroup performance, data quality, and the potential consequences of false-positive and false-negative predictions. Systematic evaluation of AI performance is important for determining whether promising technical results translate into clinically useful applications (Junaid et al., 2022; Khanagar et al., 2021).

Expected Clinical Contribution

The principal contribution of the proposed AI model is its potential to support earlier identification of patients who may experience delayed pulpal recovery or treatment failure after deep caries management. By integrating serial clinical and imaging parameters, the framework may provide a more comprehensive assessment than approaches based exclusively on a single examination. It could also assist clinicians in prioritizing follow-up appointments, identifying patients requiring further investigation, and evaluating alternative restorative management strategies.

However, these benefits remain to be demonstrated through prospective clinical studies. The model's effectiveness will depend on the representativeness of the training data, consistency of clinical assessments, quality of dental images, and validation across different patient populations. Evidence supporting AI-assisted dental caries management provides a relevant foundation for further investigation, but does not by itself establish the accuracy of AI-based pulpal recovery prediction (Liang et al., 2025; Mosobi, 2023; Aggarwal, 2023).

Ultimately, a validated model could contribute to more personalized restorative dentistry by combining clinical expertise with longitudinal predictive analytics. Its implementation should preserve clinician oversight, protect patient data, and ensure that AI-generated risk estimates complement rather than replace established diagnostic procedures.

Results and Discussion

The integration of artificial intelligence (AI) with serial clinical and imaging parameters offers a promising approach to predicting pulpal recovery following deep caries management. By combining patient symptoms, pulp vitality responses, caries depth, remaining dentine thickness, and radiographic findings over time, an AI-based model could provide a more comprehensive assessment of pulpal status than isolated clinical observations. However, because no original patient dataset or model outputs have been provided, the results discussed in this section represent anticipated findings and evidence-informed interpretation rather than experimentally established outcomes.

Predictive Value of Serial Clinical and Imaging Parameters

Serial clinical assessments are important for identifying changes in pulpal condition following deep caries management. Symptoms such as spontaneous pain, prolonged sensitivity, and discomfort during functional activities may provide useful information about recovery, although individual symptoms cannot independently establish pulpal status. Similarly, pulp sensibility tests, percussion findings, and radiographic examinations contribute complementary diagnostic evidence.

Artificial intelligence can support the integration of these variables by identifying patterns across multiple observations. Najeeb and Islam (2025) discussed emerging AI applications in restorative dentistry, highlighting the potential of computational methods to support diagnosis and treatment planning. Likewise, Sajid et al. (2025) described applications of AI across dental specialties, supporting its potential role in data-assisted clinical decision-making.

Imaging parameters may provide additional predictive

Table 4: Clinical and Imaging Parameters and Their Expected Contributions to Pulpal Recovery Prediction

Parameter	*Expected predictive contribution*	*Clinical interpretation*
Spontaneous pain and symptom progression	May help identify persistent pulpal inflammation	Requires interpretation alongside other findings
Pulp sensibility responses	Provides information about neural response	Does not directly measure pulpal blood flow or guarantee tissue recovery
Caries depth	Indicates the extent of carious tissue involvement	Greater depth may increase the risk of pulpal complications
Remaining dentine thickness	Indicates the amount of dentine separating the lesion from the pulp	May help estimate the risk of pulpal injury
Periapical radiographic findings	Identifies changes in surrounding tissues	New or progressive abnormalities may indicate complications
Restoration integrity	Indicates the quality of the coronal seal	Restoration failure may increase the risk of recurrent contamination
Serial follow-up measurements	Captures changes over time	May improve prediction compared with baseline-only assessment

Table 5: Proposed Evaluation of AI-Based Pulpal Recovery Prediction

Evaluation component	*Recommended approach*	*Purpose*
Predictive accuracy	Accuracy and balanced accuracy	Evaluates overall classification performance
Sensitivity	Proportion of pulpal failures correctly identified	Assesses the model's ability to recognize high-risk cases
Specificity	Proportion of successful recoveries correctly identified	Assesses the model's ability to distinguish lower-risk cases
Discrimination	Area under the receiver operating characteristic curve	Measures the model's ability to separate outcome groups
Calibration	Comparison of predicted and observed probabilities	Determines whether estimated risks reflect actual outcomes
Temporal validation	Testing on patients assessed during a later period	Evaluates performance over time
External validation	Testing using data from another clinical setting	Assesses generalizability across populations and institutions

information. Caries depth, remaining dentine thickness, and changes in periapical tissues can contribute to evaluating the clinical condition of the tooth. Ramezanzade et al. (2023) investigated AI-based prediction of pulp exposure before caries excavation, demonstrating the relevance of AI to preoperative caries assessment. Although predicting pulp exposure differs from predicting subsequent pulpal recovery, this work provides a methodological foundation for investigating AI-assisted pulpal risk assessment. Furthermore, Keskin et al. (2025) examined AI applications in evaluating periapical conditions, caries, and restoration status, illustrating the potential value of automated dental image analysis.

The expected advantage of combining these parameters lies in their complementary nature. Clinical symptoms provide information about patient experience, while imaging characterizes structural changes and the condition of surrounding tissues. Restoration-related variables may further clarify whether treatment has maintained an adequate protective seal. Mallineni et al. (2024) reviewed the broader applications of AI in dentistry, supporting the rationale for integrating different sources of dental information within computational decision-support systems.

Nevertheless, the contribution of each parameter must be established empirically. A variable that appears clinically relevant may offer limited additional predictive value once other variables are included. Accordingly, feature importance analysis and appropriate statistical testing would be required to determine which clinical and imaging indicators contribute most strongly to reliable prediction.

AI Model Performance and Longitudinal Prediction

A longitudinal AI model could estimate the probability of successful pulpal recovery at defined follow-up intervals. Unlike a model based exclusively on pretreatment information, a serial-data model could update its predictions when new symptoms, vitality responses, or imaging findings become available. This approach may be particularly valuable when the initial clinical presentation does not clearly establish the likelihood of recovery.

Potential model architectures include gradient-boosting algorithms for structured clinical data, recurrent neural networks for sequential observations, and multimodal deep learning models for combining clinical records with dental images. Model selection should depend on the available sample size, data structure, and clinical prediction objective rather than on algorithmic complexity alone.

Liang et al. (2025) discussed AI-driven strategies for dental caries management, providing relevant context for integrating computational methods into preventive and restorative care. Khan et al. (2025) investigated dental X-ray enhancement and caries detection, while Noor Uddin et al. (2025) reviewed deep learning applications for detecting caries in intraoral images. These studies support the relevance of image-processing techniques to caries assessment, although their findings should not be interpreted as direct evidence of predictive accuracy for pulpal recovery.

The evaluation should prioritize sensitivity for clinically important pulpal failures while maintaining adequate specificity to avoid unnecessary interventions. Calibration is equally important because a model that ranks patients correctly may still provide inaccurate estimates of their actual recovery probabilities. Decision-curve analysis could additionally assess whether using model predictions offers a meaningful clinical benefit compared with existing assessment strategies.

Cagay Sevencan and Yavşan (2025) examined AI use in evidence-based endodontology through bibliometric and scientometric analysis, providing a relevant overview of research activity in this area. However, the existence of growing research interest does not establish that a particular AI model is clinically effective. Prospective validation, transparent reporting, and comparison with

conventional clinical assessment remain necessary before implementation.

Clinical Implications and Comparison with Conventional Assessment

Conventional pulpal assessment depends on clinical history, examination, sensibility testing, and radiographic interpretation. These methods remain essential, but interpretation can be challenging when findings are inconsistent or when early pulpal changes are not clearly apparent. An AI-assisted framework could combine these findings into a structured risk estimate, helping clinicians identify patients who may require closer monitoring.

The proposed system should function as a decision-support tool rather than an autonomous diagnostic authority. For example, a patient with improving symptoms, reassuring vitality responses, and stable imaging findings may receive a different predicted risk profile from a patient with persistent pain and deteriorating clinical findings. These examples illustrate the intended application of the framework and are not evidence of validated model outputs.

Sajid et al. (2025) and Bagde (2021) provide broader contexts for examining AI applications across dentistry. Junaid et al. (2022), although focused on cephalometric landmark identification and diagnosis, offer a related example of AI-supported dental image interpretation. Their work is methodologically relevant to automated image analysis but does not directly establish performance in pulpal recovery prediction.

Other sources require more cautious interpretation. Mosobi (2023) and Aggarwal (2023) published collections of conference e-poster abstracts, which may offer preliminary insights but provide less detailed evidence than fully reported clinical studies. Khanagar et al. (2021) reviewed AI applications in forensic odontology, a different dental specialty; its findings may inform general methodological considerations but cannot directly demonstrate effectiveness in restorative endodontic care. The supplied reference by Ismail et al. is bibliographically incomplete, so its specific contribution cannot be confidently assessed without the article title, publication year, and other publication details.

Limitations and Future Research Directions

Several challenges may affect the development of reliable pulpal recovery prediction models. First, clinical records and radiographic images may vary in quality, acquisition technique, and interpretation across practitioners and institutions. Second, inconsistent follow-up schedules and missing observations may introduce bias into longitudinal analyses. Third, differences in patient characteristics, caries severity, treatment methods, and restoration quality may influence outcomes and limit model generalizability. A further challenge is the definition of successful recovery. The outcome should be based on prespecified clinical criteria and follow-up procedures, distinguishing maintained pulp vitality and symptom resolution from persistent inflammation, pulp necrosis, or subsequent need for endodontic treatment. Where feasible, outcome assessment should be conducted independently of the model's predictions to reduce assessment bias.

Liang et al. (2025) and Najeeb and Islam (2025) provide relevant foundations for considering AI within broader caries management and restorative dentistry. Nevertheless, future research should move beyond image-based detection to evaluate longitudinal clinical outcomes directly. Studies should recruit sufficiently diverse patient populations, use prespecified model-development procedures, address class imbalance, and perform independent external validation. Explainability methods may also help clinicians understand which variables contribute to a prediction and identify potentially inappropriate recommendations.

Patient privacy, informed consent, data security, and equitable performance across demographic groups must be addressed throughout model development. If these requirements are met, AI-assisted longitudinal prediction could eventually support individualized monitoring and more timely clinical reassessment following deep caries management.

In summary, integrating serial clinical and imaging parameters into an AI-based prediction framework offers a plausible direction for improving risk assessment after deep caries treatment. Its principal potential advantage is the ability to interpret evolving clinical information rather than relying solely on a single examination. However, its clinical value will depend on demonstrated predictive accuracy, calibration, external validity, and evidence that model-assisted decisions improve patient outcomes without increasing unnecessary treatment.

Conclusion and Future Directions

Artificial intelligence offers promising opportunities to improve the prediction of pulpal recovery following deep caries management by integrating serial clinical assessments with dental imaging parameters. Unlike conventional approaches that rely primarily on individual examinations, AI-based predictive models can analyze changes in symptoms, pulp vitality responses, caries depth, remaining dentine thickness, and periapical findings over time. These capabilities may support earlier identification of patients at risk of persistent pulpal inflammation or treatment failure and facilitate more individualized restorative treatment planning. The growing application of AI in restorative dentistry and endodontics highlights its potential to enhance diagnostic consistency and clinical decision-making (Najeeb & Islam, 2025; Sajid et al., 2025; Mallineni et al., 2024).

Previous investigations into AI-based prediction of pulp exposure, dental caries detection, and radiographic

assessment provide a relevant foundation for developing longitudinal pulpal recovery models (Ramezanzade et al., 2023; Noor Uddin et al., 2025; Keskin et al., 2025). Furthermore, AI-driven caries management strategies may contribute to improved treatment planning and patient-centered care (Liang et al., 2025). However, predicting pulpal recovery requires additional evidence because accurate identification of caries or pulp exposure does not necessarily establish the ability to predict subsequent biological healing. Accordingly, future studies should prioritize prospective longitudinal datasets, standardized follow-up protocols, and clinically meaningful outcome definitions.

Future directions should include multicenter validation, comparisons between different machine learning and deep learning algorithms, and assessments of model interpretability, fairness, and generalizability across diverse patient populations. Improvements in dental image enhancement and automated radiographic interpretation may further strengthen the integration of imaging features into predictive systems (Khan et al., 2025). Evidence-based evaluation will also be necessary to determine whether AI predictions improve clinical decisions and patient outcomes (Cagay Sevencan & Yavşan, 2025). Ultimately, AI should complement rather than replace professional judgment, clinical examination, and patient preferences. With appropriate validation, data protection, and clinical oversight, AI-based prediction of pulpal recovery could become a valuable component of precision restorative dentistry, supporting timely interventions and the long-term preservation of natural teeth.

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