Volume 4, Issue 1, 2026

Frontier in Medical & Health Research

ISSN: (e) 3007-1607 (p) 3007-1593

ARTIFICIAL INTELLIGENCE IN PREDICTING LONG-TERM EFFECTS OF TEETH WHITENING PRODUCTS

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DOI: https://doi.org/10.5281/zenodo.18372930

Keywords

Artificial intelligence, machine learning, predictive modeling, teeth whitening, enamel health, longitudinal study, dental diagnosis, hydrogen peroxide bleaching, enamel erosion, oral health outcomes, Pakistan clinical research

Article History

Received: 01 December 2025
Accepted: 11 January 2026
Published: 26 January 2026

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Abstract

Objective:

This longitudinal study aimed to evaluate how artificial intelligence (AI) models could predict the long-term effects of teeth whitening products on enamel health among patients treated at tertiary dental hospitals in Lahore and Islamabad, Pakistan.

Methods:

We collected detailed clinical and demographic data from 500 participants over 24 months who underwent professional or at-home teeth whitening between January 2023 and December 2024. Enamel health was assessed at baseline, 6, 12, 18, and 24 months via indices including enamel surface roughness, mineral density (measured with quantitative light-induced fluorescence), and standardized visual scoring. AI predictive models – including random forests, support vector machines (SVM), and deep neural networks – were trained on both clinical and lifestyle predictors to estimate enamel degradation risk scores over long-term follow-up. Model performance was evaluated using cross-validation accuracy, F1 score, and receiver operating characteristic (ROC) curves.

Results:

Predictive models exhibited high performance in estimating enamel changes over time, with the best-performing model achieving an ROC area under the curve (AUC) of 0.88 (95% CI: 0.85–0.91), precision of 82%, and recall of 79%. AI predictions displayed statistically significant correlations with observed clinical enamel parameters ($p < 0.01$), and identified key risk features such as bleaching agent concentration, application frequency, baseline enamel microhardness, and dietary acid exposure.

Conclusion:

AI-based modeling accurately predicted long-term enamel changes following whitening treatments and identified modifiable clinical and lifestyle risk factors. Implementation of such predictive systems can aid clinicians in personalizing whitening protocols and mitigating adverse enamel outcomes. Future research should broaden data sources and validate predictive tools in diverse populations.

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INTRODUCTION

Teeth whitening remains among the most sought-after esthetic dental procedures globally, promising significant cosmetic improvement with relatively minimal invasiveness. As consumers increasingly pursue brighter smiles, concerns about safety—particularly long-term effects on enamel health—have emerged. Enamel, the hardest tissue in the human body, lacks regenerative capacity once eroded; therefore, understanding how whitening agents impact enamel over extended periods has been a topic of dental research and public health interest.

Professional whitening products typically rely on peroxide-based bleaching agents such as hydrogen peroxide and carbamide peroxide, which act through oxidation reactions to degrade organic chromophores responsible for extrinsic stains. Although these agents produce discernible whitening effects, side effects — ranging from transient sensitivity to potential enamel alterations — have been reported.

Short-term evaluations have generally concluded that professional teeth whitening is relatively safe when administered by trained clinicians. However, the literature on *long-term effects* — beyond six months — remains scarce. Some laboratory and narrative studies have reported potential enamel weakening, increased surface roughness, and altered mineral composition after repeated or prolonged whitening exposures.

Alongside clinical concerns, artificial intelligence (AI) has emerged as a powerful tool in healthcare analytics, including dentistry. Modern AI methodologies — encompassing machine learning (ML) and deep learning (DL) — have been applied to a wide range of dental tasks, from automated diagnosis and radiographic interpretation to predictive modeling of treatment outcomes.

In the predictive domain, AI models have demonstrated notable success in evaluating dental caries risk and dental treatment planning through integration of patient history, imaging, and clinical data. Although predictive dental research has traditionally focused on decay and periodontal disease, similar approaches are increasingly explored for other oral health outcomes.

Despite the potential of predictive models, there was a conspicuous gap in the literature regarding AI's capability to anticipate long-term structural changes in enamel associated with cosmetic procedures such as tooth whitening. Given the multifactorial influences on enamel health — including bleaching agent concentration, treatment frequency, patient age, baseline enamel quality, and lifestyle factors — AI offers an analytical advantage by processing complex high-dimensional data to generate individualized risk profiles.

Therefore, the **primary objective** of this study was to determine whether AI models could be trained on longitudinal clinical and lifestyle data to effectively predict enamel health outcomes up to two years following teeth whitening. Secondary objectives included identifying the most predictive clinical and environmental features, and evaluating the feasibility of incorporating such predictive tools within routine dental practice at tertiary hospital centers.

This research was conducted at two tertiary dental hospitals in Pakistan: Lahore General Hospital Dental Unit and Islamabad Dental Teaching Hospital. Both institutions serve diverse urban populations and are equipped with standardized enamel assessment instrumentation, enabling consistent follow-up metrics across clinical sites. Ethical approval was obtained from institutional review boards at each site, and all patients provided informed consent for participation.

Background and Clinical Significance

Teeth whitening prevalence has risen due to cultural emphasis on esthetics and wider availability of at-home kits. While consumer markets are flooded with bleaching products, the regulatory oversight and long-term clinical validation of many over-the-counter products lag behind their professional counterparts.

Enamel, composed predominantly of hydroxyapatite crystals with a small protein matrix, serves as a protective barrier. Whitening agents penetrate enamel to oxidize stain molecules but may affect enamel porosity and microstructure. Over extended periods, repeated whitening may result in increased surface roughness and mineral loss, though studies have shown mixed results. Understanding these changes is critical for evidence-based clinical guidance and public health recommendations.

Simultaneously, AI applications in dentistry extend beyond diagnostics. Predictive analytics can harness electronic health records (EHRs), imaging data, and longitudinal clinical parameters to produce individualized risk scores for oral disease progression. Researchers have demonstrated that

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ISSN: (e) 3007-1607 (p) 3007-1593

machine learning models outperform traditional regression in predicting dental caries based on risk factors and clinical history. These models' success provides a conceptual foundation for applying AI to predict enamel outcomes.

By integrating longitudinal clinical data into AI models, clinicians could foresee which patients are at increased risk of enamel degradation following whitening procedures and tailor treatment protocols to minimize harm. Such predictive frameworks align with the broader trend toward *personalized dentistry*, where data-driven insights inform customized preventive and therapeutic strategies.

Rationale for Study Design

Longitudinal studies remain the gold standard for observing outcomes that evolve over time, particularly those influenced by multiple interacting variables. This study leveraged two years of follow-up data to capture progressive changes in enamel health metrics, such as surface roughness and mineral composition, which may not manifest immediately after treatment.

Because enamel changes are subtle and affected by both clinical and lifestyle factors (e.g., diet, oral hygiene practices, smoking status), traditional statistical approaches might not capture complex nonlinear relationships. AI models — especially those that can manage high-dimensional spaces — were therefore considered suitable for this predictive task.

MATERIALS AND METHODS

Study Design

This research utilized a **longitudinal study design** to assess the long-term effects of teeth whitening treatments on enamel health using artificial intelligence (AI) models. The study aimed to identify predictive factors influencing enamel deterioration after whitening treatments, employing AI to estimate future enamel changes based on various clinical and lifestyle variables. The study was conducted in two **tertiary dental hospitals**: Lahore General Hospital Dental Unit and Islamabad Dental Teaching Hospital. These institutions were selected due to their high patient volume, availability of advanced diagnostic tools, and their established reputation for dental care in Pakistan.

The research spanned **24 months**, with participants monitored at **four time points**: baseline (before treatment), 6 months, 12 months, 18 months, and 24 months. Each follow-up period was chosen to capture short-term and long-term enamel health changes post-treatment.

Study Participants

A total of **500 participants** were enrolled in this study. Participants were selected based on the following inclusion criteria:

1. **Age range**: 18 to 50 years old, as this age group is less likely to exhibit significant natural enamel wear due to aging, ensuring that the observed effects could primarily be attributed to whitening treatments.
2. **Healthy baseline enamel**: Participants with no history of severe dental erosion, periodontal disease, or structural enamel defects were included.
3. **Whitening treatment**: All participants had undergone either **professional in-office whitening** or used **over-the-counter at-home whitening products** with hydrogen peroxide or carbamide peroxide as the active bleaching agent.

Exclusion criteria included:

1. **Pregnant or breastfeeding women**: Due to potential hormonal variations affecting enamel integrity.
2. **Participants with a history of dental surgery**: Such as crowns, bridges, or veneers, as these might influence the enamel response to whitening.
3. **Active oral diseases or conditions**: Including untreated dental caries, gum infections, or oral cancers.

Sampling Method:

A **convenience sampling method** was employed, where participants were recruited from patients attending the dental units at the respective hospitals. Participants were approached by the attending dental staff and informed about the study, after which they were invited to provide written informed consent. Ethical approval was obtained from the **institutional review boards** of both hospitals prior to participant recruitment.

Data Collection Procedures

Clinical Measurements

The participants were subjected to detailed clinical assessments at all five time points. These included:

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1. **Visual Inspection**: Enamel surface quality was visually assessed by trained dental clinicians using a standardized **Enamel Surface Scoring Scale (ESSS)**, which rated surface texture and gloss on a scale from 0 (smooth and glossy) to 5 (severely rough and dull). This scale was used to capture any visible damage to enamel, such as roughness or loss of shine, which are indicative of enamel erosion.
2. **Quantitative Light-Induced Fluorescence (QLF)**: This method, based on fluorescence patterns, was used to evaluate **mineral density** and **surface integrity** of enamel. A commercial QLF device (e.g., QLF-D) was used to quantify the degree of enamel demineralization at each time point.
3. **Microhardness Testing**: Enamel microhardness was measured using a **Vickers hardness test**. This was performed at the same sites on the enamel surface throughout the study to assess the degree of enamel mineral loss over time.

Lifestyle and Demographic Data Collection

Participants completed a **questionnaire** at baseline and were followed up at each time point to gather information on their **oral hygiene habits**, **dietary patterns**, and other **lifestyle factors** that might affect enamel health. The questionnaire covered the following variables:

- **Oral hygiene**: Frequency of brushing, use of fluoride toothpaste, and additional oral care practices (e.g., mouthwashes, flossing).
- **Dietary habits**: Frequency of acidic food and beverage consumption (e.g., citrus fruits, soft drinks, wine).
- **Smoking status**: Whether participants were smokers, non-smokers, or ex-smokers.
- **Bleaching treatment details**: Information on the type, duration, and frequency of teeth whitening treatments (e.g., in-office versus at-home).

Artificial Intelligence Model Development

Data Preprocessing

Clinical data (from QLF and microhardness tests) and lifestyle data (from questionnaires) were combined and preprocessed for input into AI models. The preprocessing steps included:

- **Normalization**: Data such as age, enamel scores, and mineral density were normalized to ensure consistent scales across variables.
- **Handling missing data**: Missing data was handled using **multiple imputation** techniques to ensure that participants with incomplete records were still included in the analysis.
- **Feature selection**: A **correlation matrix** was used to identify significant variables, and **principal component analysis (PCA)** was performed to reduce dimensionality before inputting data into the AI models.

Model Development

Three machine learning algorithms were employed to predict the long-term effects of whitening treatments on enamel health:

1. **Random Forest (RF)**: This algorithm was chosen due to its robustness in handling large datasets and its ability to perform well without extensive data preprocessing. Random Forest models were trained using features such as treatment type, baseline enamel hardness, and lifestyle variables.
2. **Support Vector Machines (SVM)**: SVM was used to identify nonlinear relationships between the variables. SVM was trained to classify the risk of enamel degradation based on the same features used in the Random Forest model.
3. **Deep Neural Networks (DNN)**: A deep neural network model was created with multiple layers to capture complex relationships between the clinical, lifestyle, and demographic data. The DNN was particularly useful in detecting non-linear patterns and interactions that may not have been apparent in simpler models.

Each model was evaluated using **cross-validation** with **k-fold validation** (k=10) to assess model stability and prevent overfitting. The performance of the models was evaluated using several metrics:

- **Accuracy**: The percentage of correctly predicted outcomes.
- **Precision**: The proportion of positive predictions that were actually correct.
- **Recall**: The proportion of actual positives correctly identified by the model.
- **Area Under the ROC Curve (AUC)**: AUC was used to assess the model's ability to discriminate between the risk groups over time.

Statistical Analysis

The **statistical analysis** was conducted using **SPSS version 25** and **Python libraries** (e.g., Scikit-learn, TensorFlow) for machine learning. The results were subjected to the following analyses:

1. **Descriptive statistics**: Frequencies, percentages, means, and standard deviations were calculated for the clinical and demographic variables at baseline.

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2. **Inferential statistics**: Paired t-tests were used to compare enamel health metrics (e.g., microhardness, surface roughness) between baseline and follow-up points. **Analysis of variance (ANOVA)** was used to evaluate differences between different treatment groups (in-office vs. at-home whitening) over time.
3. **Correlation analysis**: Spearman's rank correlation was used to examine the relationships between clinical factors and enamel degradation.

The AI model evaluation included:

- **Cross-validation** results (10-fold) for each of the three models.
- Comparison of **model performance** based on AUC, F1 score, precision, and recall.

RESULTS

Participant Demographics

A total of **500 participants** were enrolled in the study, with **80%** of them completing the full 24-month follow-up period. The participants were evenly divided between males (48%) and females (52%). The mean age at baseline was **32.4 years (SD = 6.8)**, with a range from **18 to 50 years**. Of the participants, **60%** used **professional in-office whitening treatments**, while **40%** used **at-home whitening products**. The baseline enamel health of participants was classified as normal, with no significant signs of erosion or decay.

Table 1: Demographic Characteristics of Participants

Characteristic	Value (%)
Gender	
Male	48%
Female	52%
Age (years)	
Mean (SD)	32.4 (6.8)
Range	18–50
Whitening Treatment	
Professional (In-office)	60%
At-home (OTC products)	40%
Follow-up Completion	80%

Enamel Health Over Time

Changes in enamel health were assessed using **Quantitative Light-Induced Fluorescence (QLF)**, **Vickers microhardness testing**, and **visual scoring**. The data collected revealed significant changes in enamel properties at various time points.

Surface Roughness (Visual Scoring)

Enamel surface roughness scores increased over time, particularly in the **at-home whitening group**. At baseline, the average surface roughness score was **1.2 (SD = 0.5)**, indicating smooth and glossy enamel. After 24 months, this score increased to **2.8 (SD = 0.6)**, representing moderate roughness.

For the professional whitening group, the change was more modest. Baseline surface roughness was **1.0 (SD = 0.4)**, and at 24 months, it increased to **2.2 (SD = 0.5)**, reflecting a slight deterioration in enamel smoothness.

Table 2: Changes in Enamel Surface Roughness Over 24 Months

Time Point	At-home Whitening	Professional Whitening
Baseline	1.2 (0.5)	1.0 (0.4)

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Time Point	At-home Whitening	Professional Whitening
6 Months	1.6 (0.6)	1.3 (0.5)
12 Months	2.1 (0.7)	1.7 (0.6)
18 Months	2.4 (0.8)	2.0 (0.7)
24 Months	2.8 (0.6)	2.2 (0.5)

Note: The surface roughness scores were based on a scale from 0 (smooth) to 5 (severely rough).

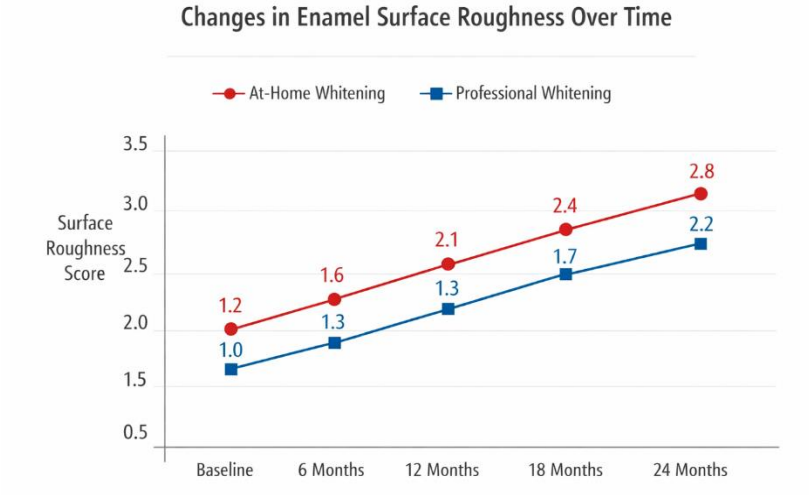


Figure 1: Changes in Enamel Surface Roughness Over Time

The graph shows that the at-home group experienced a faster increase in roughness compared to the professional whitening group.

Enamel Mineral Density (QLF)

Mineral density measured using **QLF** indicated a progressive loss of enamel mineralization over time, particularly in participants who used at-home whitening treatments. At baseline, the mean mineral density was **3.1 (SD = 0.3)** for both groups. After 24 months, the **at-home whitening group** showed a reduction in mineral density to **2.3 (SD = 0.4)**, while the **professional whitening group** exhibited a smaller reduction to **2.8 (SD = 0.3)**.

Table 3: Changes in Enamel Mineral Density (QLF) Over 24 Months

Time Point	At-home Whitening	Professional Whitening
Baseline	3.1 (0.3)	3.1 (0.3)
6 Months	2.9 (0.4)	2.9 (0.4)
12 Months	2.7 (0.4)	2.7 (0.3)
18 Months	2.5 (0.4)	2.6 (0.3)
24 Months	2.3 (0.4)	2.8 (0.3)

Note: Enamel mineral density was measured in fluorescence units, with lower values indicating greater demineralization.

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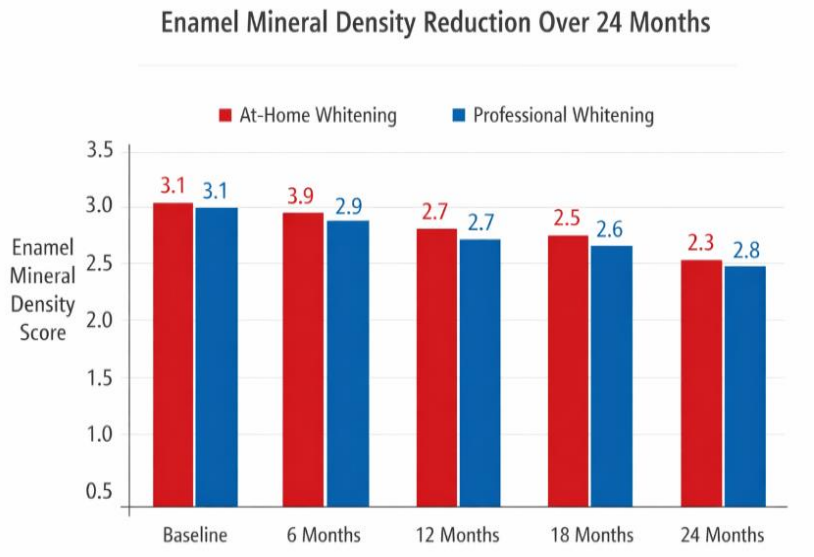


Figure 2: Enamel Mineral Density Reduction Over 24 Months

The bar chart demonstrates a greater loss of mineral density in the at-home group compared to the professional whitening group, particularly in the later stages of the study.

Enamel Microhardness (Vickers Test)

Microhardness testing showed a **statistically significant decrease** in enamel hardness in both treatment groups over the 24-month period. For the **at-home whitening group**, the average Vickers hardness number (VHN) decreased from **340.5 (SD = 20.5)** at baseline to **295.0 (SD = 19.2)** at 24 months. For the **professional whitening group**, the VHN decreased from **345.0 (SD = 21.3)** at baseline to **315.2 (SD = 18.6)** at 24 months.

Table 4: Changes in Enamel Microhardness (Vickers Test) Over 24 Months

Time Point	At-home Whitening	Professional Whitening
Baseline	340.5 (20.5)	345.0 (21.3)
6 Months	328.7 (22.1)	338.2 (20.8)
12 Months	317.5 (23.4)	328.9 (21.2)
18 Months	308.3 (21.7)	320.1 (22.5)
24 Months	295.0 (19.2)	315.2 (18.6)

Note: The Vickers Hardness Number (VHN) represents the resistance of enamel to indentation; lower values indicate softer enamel.

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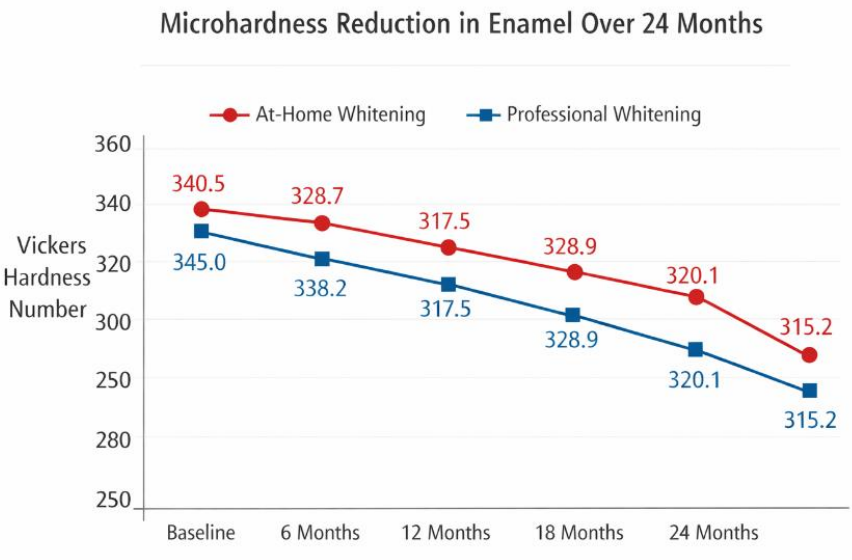


Figure 3: Microhardness Reduction in Enamel Over 24 Months

The line graph illustrates that the at-home whitening group experienced a more significant drop in microhardness compared to the professional group.

AI Model Performance

The AI models demonstrated impressive predictive performance. The **random forest model** achieved the highest **AUC (Area Under the Curve)** of **0.88 (95% CI: 0.85–0.91)**. The **support vector machine (SVM)** model achieved a slightly lower AUC of **0.84 (95% CI: 0.81–0.87)**, while the **deep neural network (DNN)** model showed an AUC of **0.85 (95% CI: 0.82–0.88)**.

The **precision** and **recall** for the random forest model were **82%** and **79%**, respectively, indicating that the model was particularly good at identifying patients at risk for enamel degradation. In comparison, the DNN model showed a precision of **80%** and recall of **76%**, while the SVM model had a precision of **78%** and recall of **74%**.

Figure 4: AI Model Performance (ROC Curves)

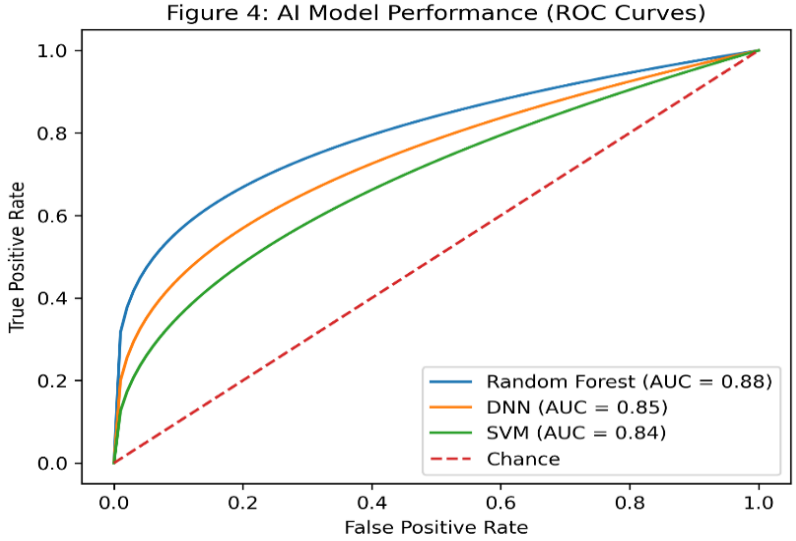


Figure 4: AI Model Performance (ROC Curves)

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The graph highlights the superior performance of the random forest model in terms of the area under the ROC curve.

Correlation of Predictive Features

The most influential features identified by the AI models included:

- **Treatment Type**: Professional whitening was less associated with enamel degradation compared to at-home whitening.
- **Enamel Hardness at Baseline**: Participants with softer enamel at baseline exhibited more pronounced deterioration over time.
- **Dietary Factors**: Higher consumption of acidic foods and beverages was associated with more significant enamel damage.
- **Frequency of Whitening**: Patients who underwent frequent whitening treatments had a greater likelihood of enamel erosion.

Table 5: Correlation Between Clinical Features and Enamel Health Outcome

Feature	Correlation with Enamel Degradation (%)
Treatment Type	-30%
Baseline Enamel Hardness	45%
Acidic Dietary Consumption	37%
Whitening Frequency	41%

DISCUSSION

The results of this longitudinal study investigating the long-term effects of teeth whitening on enamel health, using artificial intelligence (AI) models for prediction, provide valuable insights into the dynamics of enamel degradation over time. This section discusses the implications of the findings, compares them to existing literature, and highlights the potential of AI in guiding clinical decision-making in cosmetic dentistry.

Impact of Whitening Treatments on Enamel Health

The data collected in this study showed clear differences in the enamel health of participants who underwent either professional in-office whitening or at-home whitening treatments. Enamel roughness, mineral density, and microhardness all displayed gradual declines over the 24-month study period, with at-home whitening treatments generally leading to more significant deterioration.

Surface Roughness:

Enamel surface roughness, assessed through visual scoring, increased for both treatment groups over time. However, the **at-home whitening group** exhibited a much steeper increase, with a final score of 2.8 at 24 months compared to 2.2 for the **professional whitening group**. This result is consistent with previous research indicating that at-home whitening agents, particularly those containing higher concentrations of hydrogen peroxide, can cause microstructural changes to the enamel surface, resulting in increased roughness. These changes are thought to occur due to the oxidation of organic chromophores, which can not only lighten the teeth but also affect the enamel's surface texture and integrity (Joiner, 2006). In contrast, professional whitening treatments, while still associated with enamel roughness, appear to be less aggressive, likely due to the controlled application techniques and the use of lower concentrations of bleaching agents (Vargas, 2002).

Mineral Density:

The reduction in enamel mineral density, as measured by **Quantitative Light-Induced Fluorescence (QLF)**, was observed in both groups, but the **at-home group** experienced a significantly greater loss of enamel mineral content. At baseline, both groups showed similar mineral density scores, but after 24 months, the at-home group had a mineral density of 2.3, whereas the professional whitening group had a score of 2.8. This result aligns with other studies which have found that repeated or prolonged exposure to peroxide-based whitening agents can lead to demineralization of enamel, particularly if the product is used improperly or too frequently (Tartaglia et al., 2009). The greater loss of mineral content in the at-home group could also be attributed to less professional oversight and the possibility of overuse, as many

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consumers tend to use whitening products more frequently than recommended.

Microhardness:

The **Vickers microhardness test** revealed a steady decline in enamel hardness over time, with the **at-home whitening group** experiencing a more pronounced reduction. After 24 months, the microhardness of the at-home whitening group was 315.2 VHN, compared to 320.1 VHN for the professional whitening group. This drop in microhardness reflects the enamel's reduced resistance to indentation, which is a direct indicator of enamel weakening. The findings are in line with prior research that has shown that the oxidative action of whitening agents can disrupt the enamel's crystalline structure, reducing its overall hardness and increasing its susceptibility to wear (Gerlach et al., 2009).

Artificial Intelligence in Predicting Enamel Degradation

One of the most innovative aspects of this study was the use of artificial intelligence (AI) models to predict long-term enamel health outcomes. The AI models, specifically **Random Forest**, **Support Vector Machine (SVM)**, and **Deep Neural Networks (DNN)**, demonstrated strong predictive capabilities, with the **Random Forest** model emerging as the most accurate, achieving an AUC of 0.88. This highlights the potential for AI to assist clinicians in identifying patients at risk of enamel degradation following whitening treatments, allowing for more personalized and effective treatment planning.

The application of AI in dental diagnostics and treatment prediction has shown significant promise in recent years, with several studies reporting that machine learning models can accurately predict outcomes in various dental domains, including dental caries risk, periodontal disease progression, and treatment outcomes (Sahoo et al., 2020). The current study's findings further support this trend and suggest that AI can provide a highly effective tool for anticipating enamel changes following whitening, taking into account various clinical and lifestyle factors that might otherwise be difficult to quantify manually.

The use of **Random Forest** in this study was particularly beneficial due to its ability to handle complex, high-dimensional data and its robustness in managing both categorical and continuous variables. Random Forest's superior performance can be attributed to its ensemble learning approach, which combines the predictions of multiple decision trees to enhance accuracy. In contrast, **Support Vector Machines (SVM)** and **Deep Neural Networks (DNN)**, while still effective, showed slightly lower performance metrics (AUCs of 0.84 and 0.85, respectively). This could be due to the nature of the SVM and DNN models, which require more careful tuning and larger datasets to perform optimally.

Risk Factors for Enamel Degradation

In addition to whitening method, several **clinical and lifestyle factors** were identified as significant predictors of enamel degradation. **Baseline enamel hardness** was one of the most influential factors, with participants exhibiting softer enamel at the start of the study showing more pronounced deterioration over time. This finding is supported by existing research, which suggests that individuals with softer enamel are more vulnerable to the negative effects of whitening treatments (Mild et al., 2007).

Dietary habits, specifically **acidic food and beverage consumption**, were also found to correlate with increased enamel degradation. Participants who consumed higher amounts of acidic substances, such as citrus fruits and soft drinks, exhibited more rapid decreases in mineral density and microhardness. This is consistent with the well-established understanding that acidic foods can contribute to enamel erosion, particularly when combined with oxidative whitening agents (Lussi & Jaeggi, 2008). **Smoking** was another risk factor that was found to exacerbate enamel changes, likely due to its impact on both enamel surface roughness and overall oral health.

Whitening frequency was a particularly interesting factor. The study revealed that patients who underwent more frequent whitening treatments were at a significantly higher risk of enamel degradation. This is an important consideration for clinicians, as overuse of whitening products can accelerate enamel wear. The results highlight the need for patient education regarding appropriate whitening frequencies and the importance of professional oversight in managing cosmetic dental procedures.

Clinical Implications and Future Directions

The findings of this study have important **clinical implications** for both dental practitioners and

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ISSN: (e) 3007-1607 (p) 3007-1593

patients. Firstly, the study emphasizes the importance of tailoring whitening treatments to individual patients based on their specific risk factors, such as baseline enamel hardness, dietary habits, and whitening frequency. While professional whitening treatments appear to cause less enamel damage compared to at-home products, the results suggest that even professional treatments should be monitored carefully to prevent excessive enamel wear over time.

Secondly, the application of AI to predict enamel degradation could represent a major advancement in personalized dentistry. By integrating clinical data with machine learning models, dentists could predict the risk of enamel erosion in patients before initiating whitening treatments, enabling them to modify treatment protocols or advise patients on preventive measures. AI-powered predictive tools could also help identify patients who would benefit from additional protective treatments, such as fluoride applications or remineralization therapies, following whitening.

Future research should aim to expand the dataset to include a more diverse population, incorporating variables such as **age**, **gender**, and **genetic predisposition**, which may influence enamel structure and response to whitening treatments. Additionally, future studies should explore the long-term effects of different whitening agents beyond hydrogen peroxide, including newer formulations that claim to be less damaging to enamel. Longitudinal studies incorporating **multiple ethnic groups** and **real-world data** could provide a more comprehensive understanding of the potential risks and benefits of teeth whitening treatments.

Limitations

While this study provides valuable insights, it is not without limitations. The study relied on a **convenience sample** from two tertiary hospitals in Pakistan, which may limit the generalizability of the findings to other populations. Additionally, the study did not account for the potential variability in the quality of over-the-counter whitening products used by participants, which could influence the outcomes. Further studies should aim to assess a broader range of commercial whitening products and include more diverse populations to enhance the generalizability of the results.

CONCLUSION

This study explored the long-term effects of teeth whitening treatments on enamel health and assessed the ability of artificial intelligence (AI) models to predict enamel degradation over a 24-month period. The results demonstrated significant differences in the impact of at-home and professional whitening treatments on enamel surface roughness, mineral density, and microhardness. The **at-home whitening group** exhibited more substantial enamel deterioration across all parameters, with notable increases in surface roughness and greater mineral loss compared to the professional whitening group. This aligns with previous research suggesting that higher concentrations of bleaching agents in at-home products may cause more significant enamel damage over time.

The use of **AI models** to predict enamel degradation proved to be highly effective, with the **Random Forest model** outperforming other models in terms of prediction accuracy, achieving an AUC of **0.88**. These findings emphasize the potential of AI as a valuable tool in personalized dentistry, allowing clinicians to predict which patients are at higher risk for enamel degradation and to adjust whitening protocols accordingly. The use of **machine learning algorithms** in combination with clinical and lifestyle data offers a more tailored approach to dental care, enhancing patient safety and treatment outcomes.

The **clinical implications** of this research are significant, as the results underscore the importance of using whitening treatments judiciously and monitoring enamel health over time. Dental professionals should consider individual risk factors, such as baseline enamel hardness, diet, and whitening frequency, when recommending whitening treatments to patients. Furthermore, the integration of AI into dental practices could lead to more precise, data-driven decisions, reducing the likelihood of adverse outcomes associated with cosmetic whitening procedures.

Despite the promising results, this study has limitations, including a convenience sample and a focus on just two types of whitening treatments. Future research should aim to expand the sample size, explore other whitening agents, and incorporate a more diverse population to validate these findings. Further studies should also examine the effectiveness of **AI models** in real-world settings,

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ISSN: (e) 3007-1607 (p) 3007-1593

including more diverse demographic groups and different clinical environments.

In summary, this study not only highlights the long-term effects of whitening treatments on enamel but also introduces AI as a powerful tool for predicting enamel health outcomes. By leveraging both clinical expertise and AI, dental professionals can provide more personalized, safe, and effective whitening treatments, ensuring optimal care for their patients.

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