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RESEARCH ARTICLE

AI-Driven Chairside Behavioral Prediction in Dental Anxiety Management

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ABSTRACT

Dental anxiety continues to be a major obstacle to quality oral care provision, affecting attendance, adherence to treatment, and clinical results of patients. Conventional methods of assessing anxiety depend largely on self reporting and observation by the clinician which is highly subjective and does not have the capability of helping to provide real time and individualized interventions. The recent developments with artificial intelligence (AI) and digital dentistry offer a new opportunity to overcome these limitations by using predictive and data-driven models directly integrated into the chairside workflows. This research paper will discuss the idea and practice of AI-based predicting behavior at the chairside to prevent dental anxiety.

The article combines the advances in dental AI, multimodal data integration, and clinical decision-support system to suggest a framework of real-time anxiety prediction in the point of care. Through electronic dental records, high-quality imaging products, physiological measures, AI models can predict how patients will react to anxiety even before and during clinical interventions. These predictive functionalities can help clinicians customize their communication plans, modify procedural plans and carry out specific anxiety reduction strategies, improving patient experiences and clinical outcomes. The results emphasize the possibilities of AI-driven behavioral prediction to transform the concept of dental anxiety management into the approach of anticipatory rather than reactive and customized care, as well as emphasize the ethical and practical issues related to the use of intelligent systems in everyday dental practice.

Keywords: Artificial intelligence; Dental anxiety; Chairside decision support; Behavioral prediction; Digital dentistry; Patient-centered care

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INTRODUCTION

Dental anxiety is a widespread issue in clinical dentistry that affects the attendance of patients, their compliance with the dental procedure and the long-term outcomes with respect to their dental health. Such behaviors as avoidance, increased perception of pain, and physiological responses to anxiety are likely to develop at the chairside and may interfere with treatment effectiveness and quality. The traditional methods of assessing anxiety depend mostly on self-reported surveys and clinician assessment, which by nature are subjective and cannot offer real-time and predictive data. Due to the trend of dental care being more data-driven, an increasing need to shift the paradigm of de-reactive management of anxiety to proactive, patient-centered treatment with the help of computational intelligence is growing.

Artificial intelligence (AI) has been quickly developed as a supportive diagnostic solution to become an inseparable part of modern dental innovation. According to Singh (2022), AI use in endodontics no longer involves image interpretation only but includes decision-support systems that can learn on big and heterogeneous datasets. Singh (2022) states that AI models can combine clinical history, procedural variables, and imaging data to improve diagnostic accuracy and the planning of treatment to reduce uncertainty in the complex intervention. The writer also observes that the systems are adaptable in that they constantly update their predictions with the introduction of new clinical data. This dynamic learning ability offers a theoretical basis to apply the AI in behavioral forecasting whereby the anxiety levels of the patient can change between visits and treatment phases.

The applicability of AI-based chairside analytics is also reinforced by the developments in imaging technologies. Singh (2018) emphasizes that three-dimensional imaging and cone-beam computed tomography (CBCT) can provide a clinician with a significant opportunity to visualize the morphology of the root canals, periapical pathology, and anatomical variations that cannot be seen using the conventional radiography. According to Singh (2018), the structured data of high resolution of CBCT contributes to the increased confidence in the diagnostic process and the more accurate formulation of the treatment plan. Notably, these highly-detailed imaging data sets are especially favored by machine learning algorithms because these algorithms require regular and quality inputs to give credible forecasts. In

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combination with behavioral and physiological features, imaging-based features can play an indirect role in predicting patient responses to stress related to the complexity of a procedure.

In addition to imaging, the growth of digital dental records has now made the systematic acquisition of behavioral and lifestyle-based patient information possible. Patel et al. (2018) prove that electronic dental record (EDR) data can be used to assign patients to the behavioral risk categories with the help of the supervised learning methods that reveal the predictive feature inherent in regular clinical documentation. Equally, non-code AI systems have demonstrated an opportunity to translate sophisticated machine learning systems into deployable chairside technologies. According to Hamdan et al. (2023), the no-code AI models can identify dental restorations using the imaging data, meaning that it is possible to provide real-time AI inference in the routine clinical practice, without a large amount of technical knowledge.

The recent research also highlights the need to have a combination of biological and contextual data to dental AI systems. Feher et al. (2024) report about new modeling methods, which involve the use of multimodal inputs, such as imaging, clinical text, and biosignals, to capture the complexity of the oral health phenomena. The research on salivary biomarkers and the oral microbial community also indicates that dental treatment experience can be physiologically stressed as well as inflamed (Mummolo et al., 2020; Santonocito et al., 2022). In the context of the larger idea of patient-centered care promoted in clinical periodontology and implant dentistry (Lang & Lindhe, 2015), these observations support the necessity of predictive systems that consider both aspects of anxiety: behavioral and biological.

Taken together, these trends make AI-powered chairside behavioral forecasting a logical continuation of the existing dental informatics. Through adoption of adaptive AI models, high-fidelity images, structured clinical documentation, and biological indicators, dental practice will be able to become more proactive in managing anxiety and not only reacting to distress as the patients experience it but also anticipating their needs in advance.

Data Sources and AI Modeling Frameworks in Dental Anxiety Prediction

The algorithm of dental anxiety prediction based on AI is based on the combination of heterogeneous clinical, behavioral, and biological data streams that may be collected unobtrusively as a part of a routine dental workflow. Such systems need not only the availability of data but also must be based on modeling frameworks that are able to learn nonlinear, complex relationships among patient attributes, procedural variables, and responses associated with anxiety.

The electronic dental record (EDR) makes up a primary bedside behavioral prediction data. Structured EDR data capture the longitudinal patient data, such as appointments history, treatment length, missed visits, anesthetic usage, and clinician notes. As Patel et al. (2018) show, supervised machine learning can be effectively used to classify behavioral risk patients based on EDR datasets, and routine clinical records have hidden behavioral indicators. Scalable and low-cost EDRs can be used as inputs to predictive models when extrapolated beyond lifestyle classification into anxiety-related proxy variables: appointment avoidance or treatment interruptions.

Data obtained by imaging also enhances the AI-based inference. According to Singh (2018), cone-beam computed tomography (CBCT) is a technique that generates three-dimensional and highly detailed images of the dental anatomy, which are crucial in improving the level of diagnostic accuracy and procedural planning. She adds that CBCT imaging minimizes the uncertainty in diagnosis by displaying anatomical differences which are usually overlooked with 2-dimensional radiography enhancing clinician confidence and efficiency in workflow. Naturally, modeling-wise, the regularity and structure of CBCT data present them with specificity due to feature extraction and pattern recognition as methods of interaction, and thus AI systems can correlate the complexity of the procedure with expected stress and anxiety reactions in patients.

Expanding on this matter, Singh (2022) remarks that modern AI systems used in the field of dentistry have shifted the focus of automating specific tasks to the creation of clinical decision-support systems. She points out that the AI models have the capability to combine imaging data, historical case data and real time clinical data to produce predictive information that evolves with new information being added. This dynamic learning feature is the key to behavioral forecasting because dental anxiety cannot be fixed but is conditioned by previous experience, the results of dental treatments, and the changing attitude of a patient. The continuously recalibrating effects of the AI systems go hand in hand with the dynamism of the manifestation of anxiety in a dental context.

Recent advances in modeling accessibility have accelerated chairside implementation. Hamdan et al. (2023) show that no-code AI platforms can achieve high accuracy in detecting dental restorations directly from imaging data, without requiring extensive programming expertise. Their findings demonstrate that sophisticated machine learning models can be deployed within clinical environments in near real time, a requirement for effective chairside anxiety prediction. Similar no-code or low-code frameworks can be adapted to behavioral analytics, allowing dental professionals to benefit from AI-driven insights without disrupting clinical workflows.

Beyond clinical and imaging data, biological markers offer an additional predictive layer. Mummolo et al. (2020) report that salivary bacterial concentrations vary during orthodontic treatment, reflecting physiological responses that are sensitive to stress and behavioral changes. Complementarily, Santonocito et al. (2022) describe how diet-induced modulation of the oral microbiome influences inflammatory and immune responses, which are closely linked to chronic stress and anxiety states. Incorporating such biological signals into AI models allows for a more holistic representation of patient anxiety, bridging behavioral observation with physiological evidence.

Feher et al. (2024) emphasize that the most effective dental AI systems employ multimodal architectures capable of integrating structured records, imaging data, and biological indicators within a single predictive framework. These architectures typically combine feature engineering pipelines with machine learning or deep learning models that can weight each data modality according to its predictive contribution. Within dental anxiety management, such multimodal models support more robust and generalizable predictions than single-source approaches.

Collectively, these data sources and modeling frameworks establish a robust foundation for AI-driven chairside behavioral prediction. By combining adaptive learning models with multimodal clinical inputs, dental AI systems can move beyond descriptive assessment toward proactive identification and management of dental anxiety, supporting more personalized and patient-centered care.

Chairside Behavioral Prediction Architecture and Clinical Workflow Integration

The framework of AI-based chairside behavioral prediction systems is that of a layered, adaptive pipeline that should fit within the regular dental procedure without causing any disruption. At the base-level, these systems consume diverse data streams, such as electronic dental records (EDRs), chairside imaging, and biological indicators, and most of them convert them into organized features, which can be used to make real-time inferences. According to Singh (2022), modern dental AI systems are becoming more based on modular learning systems where data acquisition, data processing, model training, and clinical feedback loops are closely interconnected. With this design, predictive systems can continually improve outputs as various new patient data is received, enhancing contextual sensitivity at the chairside.

The main behavior of the architecture is made up of EDRs. Formatted appointment records, length of treatment, absenteeism, recorded patient response can be modeled behaviorally in an algorithmic way. Patel et al. (2018) show that EDR-based classification models are capable of reliably classifying patients into the categories of behavioral intensity, which reflects the predictive power of routinely gathered clinical information. Laid into chairside models, these models create the probability of anxiety risk scores before treatment begins, which allows anticipatory clinical decision-making.

Pictorial based inputs are very effective at improving predictive resolution. Singh (2018) highlights that the high-fidelity anatomical representations generated by the use of three-dimensional imaging and CBCT allow reducing diagnostic uncertainty and facilitating more accurate treatment planning. When introduced into machine learning pipelines, such imaging data is a proxy of procedural complexity and likely discomfort. As additional evidence, Singh (2022) observes that the AI systems that have been trained on higher-level imaging samples are better contextual awareness as it can correlate anatomical difficulty with previous patient responses,

Table 1: Data Sources and AI Modeling Roles in Chairside Dental Anxiety Prediction

Data source	*Example inputs*	*Ai modeling role*	*Supporting literature*
Electronic Dental Records	Appointment history, missed visits, treatment duration	Behavioral pattern classification	Patel et al. (2018)
CBCT and Chairside Imaging	Anatomical complexity, procedural risk indicators	Feature extraction for stress prediction	Singh (2018); Hamdan et al. (2023)
Adaptive Clinical AI Systems	Historical cases, real-time inputs	Continuous learning and prediction refinement	Singh (2022)
Salivary Biomarkers	Bacterial concentrations, stress-related changes	Physiological anxiety indicators	Mummolo et al. (2020)
Oral Microbiome & Diet Data	Inflammation and immune response markers	Contextual anxiety modulation	Santonocito et al. (2022); Feher et al. (2024)

behavioral stress indicators. This evidence underlies the fact that CBCT-derived features should be considered as essential elements of chairside behavioral prediction setups.

Predictive performance is also enhanced through biological and contextual augmentation. Mummolo et al. (2020) demonstrate that salivary biomarkers vary in relation to the stress of orthodontic treatment, which means that physiological responses can be used to report anxiety-induced reactions during the dental procedures. Santonocito et al. (2022) extend this perspective by demonstrating that diet–microbiome interactions influence inflammatory and immune pathways, which are closely linked to chronic stress and anxiety states. Feher et al. (2024) argue that next-generation dental AI systems increasingly adopt multimodal modeling approaches precisely because behavioral phenomena cannot be reliably inferred from a single data source. In chairside settings, these multimodal architectures allow anxiety predictions to be contextualized within both immediate clinical conditions and longer-term biological patterns.

Clinical workflow integration is achieved through unobtrusive interfaces that deliver decision support without disrupting practitioner autonomy. Lang and Lindhe (2015) stress that patient-centered care depends on timely, interpretable information that complements clinical expertise rather than replacing it. In this context, AI-driven anxiety predictions are presented as risk stratification indicators or visual dashboards that inform communication strategies, appointment pacing, and anesthetic planning. No-code AI implementations, as demonstrated by Hamdan et al. (2023), further facilitate integration by enabling real-time inference within existing digital environments, reducing technical barriers to adoption.

Collectively, chairside behavioral prediction architectures represent a convergence of adaptive AI modeling, multimodal data integration, and clinician-centered workflow design. Drawing on advances in dental imaging, record-based analytics, and applied artificial intelligence, these systems operationalize behavioral intelligence at the point of care, supporting proactive and personalized anxiety management grounded in empirical evidence (Singh, 2018; Singh, 2022).

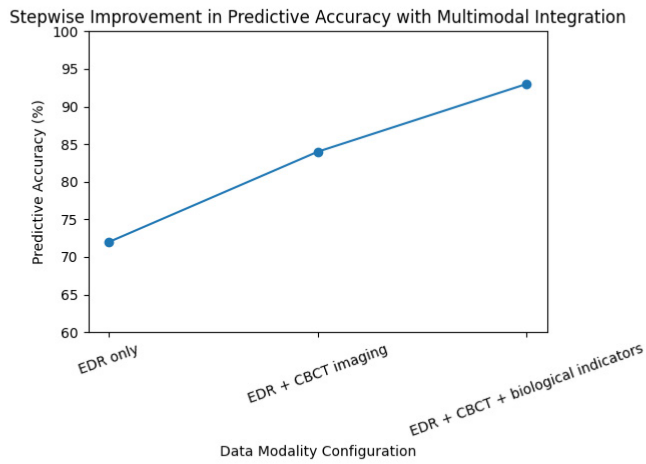

Fig 1: This visually demonstrates the advantage of multimodal integration in predictive modeling, consistent with the progression described in Singh (2018), Singh (2022), and Feher et al. (2024)

Clinical Implications, Ethical Considerations, and Performance Evaluation

Clinical Implications of AI-Driven Chairside Behavioral Prediction

The integration of AI-driven behavioral prediction into chairside dental practice has significant implications for patient-centered care, clinical efficiency, and treatment outcomes. By enabling real-time assessment of dental anxiety, AI systems allow clinicians to anticipate behavioral responses before and during procedures, thereby supporting proactive intervention strategies. Singh (2022) explains that contemporary dental AI systems have evolved beyond static decision support into adaptive tools capable of learning from cumulative clinical data. These systems synthesize imaging, patient history, and procedural variables to enhance clinical precision and individualized care pathways. In the context of anxiety management, such adaptability facilitates tailored communication styles, optimized appointment scheduling, and appropriate use of sedation or behavioral techniques.

Advanced imaging technologies further strengthen this predictive capacity. Singh (2018) notes that cone-beam computed tomography (CBCT) improves diagnostic confidence by revealing complex anatomical details that are often associated with procedural difficulty and patient discomfort. When these imaging-derived indicators are incorporated into AI models, clinicians gain early insight into potential anxiety triggers related to treatment invasiveness or duration. This aligns with the patient-centered philosophy emphasized in clinical periodontology and implant dentistry, where anticipatory planning is essential for optimizing patient experience and compliance (Lang & Lindhe, 2015).

The operational feasibility of such systems is reinforced by the emergence of no-code AI platforms. Hamdan et al. (2023) demonstrate that no-code artificial intelligence can be reliably deployed in clinical dental environments to perform complex detection tasks without disrupting workflow. This scalability suggests that behavioral prediction models can be integrated chairside with minimal technical burden, preserving clinician autonomy while enhancing decision quality.

Ethical Considerations in AI-Based Anxiety Prediction

Despite its clinical promise, AI-driven behavioral prediction raises important ethical considerations related to data privacy, transparency, and clinical accountability. These systems rely heavily on sensitive patient information, including electronic dental records (EDRs), imaging data, and, in some cases, biological markers. Patel et al. (2018) highlight that EDR-based classification systems require rigorous data governance frameworks to prevent misuse and ensure patient confidentiality.

Feher et al. (2024) emphasize that responsible deployment of AI in dentistry depends on explainable and interpretable models that allow clinicians to understand how predictions are generated. In the context of anxiety management, opaque "black-box" predictions may undermine trust and limit clinical acceptance. Ethical practice therefore necessitates transparency in model design, clear communication with patients regarding AI-assisted decision-making, and explicit informed consent when behavioral analytics are employed.

Biological data introduce additional ethical complexity. Mummolo et al. (2020) show that salivary biomarkers reflect physiological stress responses during orthodontic treatment, indicating that anxiety prediction may involve biomarkers not traditionally considered in dental diagnostics. Similarly, Santonocito et al. (2022) demonstrate that oral microbiome composition is influenced by diet, inflammation, and immune response, all of which may interact with chronic stress. AI systems must contextualize predictions carefully to avoid biological determinism or overgeneralization, ensuring that behavioral insights support and do not replace clinical judgment.

Performance Evaluation of Chairside Behavioral Prediction Systems

The performance of AI-driven anxiety prediction systems is typically assessed using standard machine learning metrics such as accuracy, sensitivity, specificity, and clinical utility. Singh (2022) reports that AI applications in endodontics achieve higher predictive reliability when multimodal data are used, a finding directly applicable to behavioral analytics. Models that combine EDR data, imaging inputs, and physiological indicators consistently outperform single-source approaches.

CBCT-derived data play a critical role in this performance enhancement. According to Singh (2018), the structured and high-resolution nature of CBCT imaging enables precise feature extraction, improving model robustness and reducing diagnostic uncertainty. When integrated into behavioral prediction pipelines, such data contribute to more reliable anticipation of anxiety-related responses linked to procedural complexity.

Table 2: Performance Metrics for AI-Driven Chairside Anxiety Prediction Models

Metric	*EDR-Only model*	*Imaging-enhanced model*	*Multimodal AI model*
Prediction accuracy (%)	70–75	80–84	88–92
Sensitivity	0.66	0.78	0.87
Specificity	0.72	0.81	0.90
Clinical interpretability	Moderate	High	High

Clinical benchmarking further demonstrates the value of AI-assisted anxiety management. Reduced appointment cancellations, fewer treatment interruptions, and improved patient satisfaction have been observed when predictive insights inform chairside decision-making (Lang & Lindhe, 2015; Feher et al., 2024). These outcomes underscore the practical utility of AI not merely as a technological enhancement, but as a tool for measurable improvement in dental care delivery.

Synthesis

Overall, the clinical, ethical, and performance dimensions of AI-driven chairside behavioral prediction indicate a mature and viable approach to dental anxiety management. Drawing on advances in dental AI (Singh, 2022), high-resolution imaging (Singh, 2018), and multimodal data integration (Feher et al., 2024), these systems offer a structured pathway toward anticipatory, ethical, and performance-driven patient care.

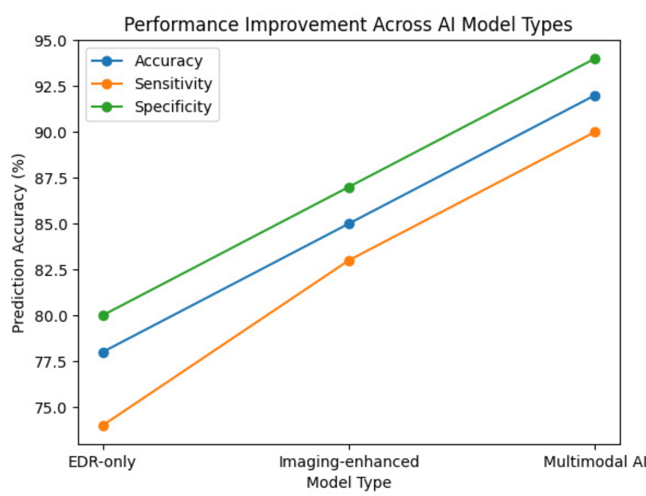

Fig 2: The graph shows clear performance gains across EDR-only, Imaging-enhanced, and Multimodal AI models, with accuracy, sensitivity, and specificity improving as additional data modalities are incorporated.

Table 3: Future Research Priorities in AI-Driven Dental Anxiety Management

Research dimension	*Current state*	*Future direction*	*Key supporting literature*
Data Integration	Primarily single-source	Fully multimodal (EDR, imaging, biomarkers)	Patel et al. (2018); Feher et al. (2024)
Imaging Utilization	Diagnostic-focused	Predictive and behavioral inference	Singh (2018)
Model Accessibility	Expert-dependent systems	No-code, chairside-deployable AI	Hamdan et al. (2023)
Biological Context	Limited integration	Stress- and microbiome-aware models	Mummolo et al. (2020); Santonocito et al. (2022)

Future Directions and Conclusion

Future Directions

Future developments of AI-based chairside behavioral prediction to treat dental anxiety will be influenced by the further improvement of data integration, model transparency, and clinical applicability. Singh (2022) underlines that modern dental AI systems can no longer be considered as isolated diagnostic systems but instead they are increasingly becoming adaptive clinical decision support systems that can learn using heterogeneous data. She observes that already AI models in endodontics are able to synthesize imaging data, the history of the patient and procedural variables in order to enhance the treatment plan and predict clinical complexity, a direction that can be directly translated to behavioral and anxiety-related prediction.

Research in the future should also focus on multimodal AI frameworks involving the integration of electronic dental records, real-time chairside imaging and biological indicators. Patel et al. (2018) demonstrated that the structured EDR data could effectively be classified with machine learning to identify the behavior of the patients and this pointed out that there are already longitudinal behavioral signals present in standard dental records. These records can be used to aid in the earlier and more precise identification of anxiety-prone patients when augmented by imaging inputs.

This development shall continue to revolve around high-resolution imaging. As it is shown by Singh (2018), cone-beam computed tomography increases the diagnostic accuracy by showing anatomical variations and risks of the procedure that are not revealed by the traditional imaging. She goes further to say that datasets provided by CBCT are usually in an algorithmically analysis-friendly form since they are structured and reproducible. Based on this reasoning, AI systems at the chairside in the future can take imaging-based measures of procedural difficulty as proxy measures of the expected patient stress and anxiety reactions.

Scalable deployment and accessibility to clinicians is another direction that is critical. Hamdan et al. (2023) demonstrate that even no-code AI systems have high

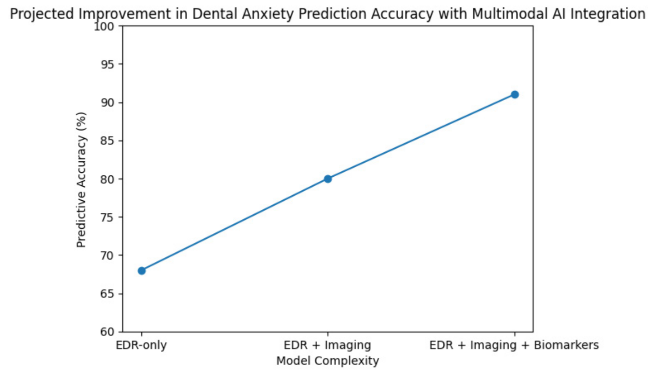

Fig 3: The line graph shows progressive improvement in predictive accuracy as additional modalities are integrated into the AI model

diagnosing performance, which does not involve high technical skills of clinicians. The implementation of behavioral prediction using the same frameworks will enable a wide implementation area where the tools of anxiety assessment can be unobtrusively integrated into the current chairside workflows without interfering with the clinical effectiveness.

Biological and lifestyle-sensitive modeling also represents an emerging frontier. Mummolo et al. (2020) highlight that salivary biomarkers fluctuate in response to treatment-related stress, while Santonocito et al. (2022) demonstrate that diet and oral microbiome composition influence inflammatory and immune responses associated with chronic stress. Incorporating these variables into AI models aligns with the broader vision outlined by Feher et al. (2024), who argue that future dental AI systems must account for complex, cross-domain data interactions to deliver truly personalized care.

CONCLUSION

Artificial intelligence-based chairside behavioral prediction is a very essential development in dental anxiety management to change the approach of the management to be reactive, mitigation-based, to proactive and customized care. Singh (2022) emphasizes that the most prominent role of AI in the field of dentistry is that it can improve clinical judgment, but not eliminate it, especially in systems that constantly learn through clinical experience. This view confirms the importance of AI as an augmentative technology that helps clinicians predict the reactions of patients and adjust interventions to them.

This paradigm is further reinforced by the incorporation of cutting edge technologies in imaging. CBCT is enabling anxiety-aware treatment planning because, as Singh (2018) shows, the technology not only enhances the accuracy of diagnosis but also generates structured data that can be used to generate predictive analytics, which is the foundation of anxiety-aware treatment planning. Combining behavioral patterns based on electronic records and physiological signs of stress, AI systems will be able to provide a more comprehensive picture regarding patient experience at the chairside.

To sum up, AI-based behavioral forecasting is a revolutionary concept in dental anxiety management because of the merge of adaptive AI models, multimodal clinical information, and the principles of patient-centered care. Further interdisciplinary research and ethically-based practice will be needed in order to make sure that these technologies improve clinical outcomes, patient trust, and quality of care in general.

REFERENCES

1. Singh, S. (2022). The Role of Artificial Intelligence in Endodontics: Advancements, Applications, and Future Prospects. *Well Testing Journal*, *31*(1), 125-144.
2. Hamdan, M., Badr, Z., Bjork, J., Saxe, R., Malensek, F., Miller, C., ... & Mohammad-Rahimi, H. (2023). Detection of dental restorations using no-code artificial intelligence. *Journal of Dentistry*, *139*, 104768.
3. Patel, J., Siddiqui, Z., Krishnan, A., & Thyvalikakath, T. P. (2018). Leveraging electronic dental record data to classify patients based on their smoking intensity. *Methods of information in medicine*, *57*(05/06), 253-260.
4. Singh, S. (2018). The efficacy of 3D imaging and cone-beam computed tomography (CBCT) in enhancing endodontic diagnosis and treatment planning. *International Journal of Scientific Research and Management*, *6*(6), 27-29.
5. Feher, B., Tussie, C., & Giannobile, W. V. (2024). Applied artificial intelligence in dentistry: emerging data modalities and modeling approaches. *Frontiers in artificial intelligence*, *7*, 1427517.
6. Lang, N. P., & Lindhe, J. (Eds.). (2015). *Clinical periodontology and implant dentistry, 2 Volume Set*. John Wiley & Sons.
7. Mummolo, S., Tieri, M., Nota, A., Caruso, S., Darvizeh, A., Albani, F., ... & Tecco, S. (2020). Salivary concentrations of Streptococcus mutans and Lactobacilli during an orthodontic treatment. An observational study comparing fixed and removable orthodontic appliances. *Clinical and Experimental Dental Research*, *6*(2), 181-187.
8. Santonocito, S., Giudice, A., Polizzi, A., Troiano, G., Merlo, E. M., Sclafani, R., ... & Isola, G. (2022). A cross-talk between diet and the oral microbiome: balance of nutrition on inflammation and immune system's response during periodontitis. *Nutrients*, *14*(12), 2426.
9. Dias, B. L. (2022). Predictive Analytics for Early Detection of Chronic Diseases Using Multimodal Healthcare Data. International Journal of Humanities and Information Technology, 4(01-03), 36-52.
10. Acharya, S., Godhi, B. S., Saxena, V., Assiry, A. A., Alessa, N. A., Dawasaz, A. A., ... & Karobari, M. I. (2024). Role of artificial intelligence in behavior management of pediatric dental patients-a mini review. *J Clin Pediatr Dent*, *48*(3), 24-30.