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Measurement of Pain Response in Geriatric Dentistry using the COMFORT Behavioral Algorithm

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Abstract

Geriatric dentistry is strongly encouraged to assess pain accurately in patients with compromised cognition, difficulties in communication, and sensory changes commonly associated with the elderly. Based on this, this paper proposes an AI system that utilizes the COMFORT Behavioral Algorithm, initially developed for assessing pain in non-verbal pediatric patients, to quantify pain in elderly patients undergoing dental treatment. A real-time observational system tracked facial, postural, and vocal cues, processing them to identify behavioral traits such as alertness, calmness, muscle tone, and facial tension. They were weighed and normalized into a COMFORT Score, and a logistic regression model predicted the probability of pain occurrence. Clinician feedback in real-time and automatic pain scoring were enabled through the system architecture. Results in 60 patients indicated that facial tension and muscle tone were the most predictive indicators of pain, and the model was found to be highly consistent with human expert ratings, with an RMSE of 0.41. This research supports the viability of AI-facilitated behavioral scoring to enhance evaluation and treatment of pain in non-verbal elderly populations.

Keywords: Geriatric dentistry, Pain Assessment, Comfort Behavioral Algorithm, Artificial Intelligence, Facial Analysis, Logistic Regression, Non-Verbal Patients.

1 INTRODUCTION

Assessment of pain in older dental patients is a key challenge, considering sensory changes associated with aging, cognitive impairment, and communication difficulties (Horgas & Elliott, 2004). Most older adults, especially those with Alzheimer's disease or dementia, are unable to describe pain during dental procedures and use traditional self-assessment pain scores less reliably (Herr et al., 2011). Under such circumstances, observation-based pain assessment measurements are crucial so that proper treatment can be provided. The COMFORT Behavior Algorithm, initially developed to assess pain and distress in non-verbal pediatric patients, is now increasingly investigated for its applicability in cognitively impaired adult patients (van Dijk et al., 2000).

Facial expression, muscle tone, and vocalization are all cues for behavior of importance to pain recognition among elderly persons, particularly when they are unable to verbalize (de Jong et al., 2005). There is a firmly established need for evidence-based behavioral assessment tools of pain for older populations, as pain measurement error may cause under-treatment, which will result in functional impairment and poor oral health outcomes (Booker et al., 2016), (Rao, 2025). Dental care is apt to induce both physical discomfort and anxiety in elderly patients, contributing to pain assessment and control problems (Weinstein & Domoto, 2010).

The COMFORT scale is a multi-dimensional instrument with both behavioral and physiological items and therefore has the potential to detect the subtle presentation of pain in elderly adults (Ista et al., 2008). While it has been effective in pediatric and ICU settings, there is a significant deficiency of research regarding its use in geriatric dentistry, reflecting an essential gap in current clinical practice (Blanco et al., 2015). As the global population ages, the need to enhance pain perception among older people, especially in dental clinics, becomes a significant issue for oral healthcare systems (Bhupesh & Nithyakalyani, 2022), (Kossioni et al., 2017).

With the implementation of the COMFORT Behavioral Algorithm in geriatric patient dental examinations, clinicians are better able to assess patient distress and provide timely, individualized care (Said et al., 2024). Not only does this benefit the tailoring of non-pharmacological pain control processes, but it also optimizes patient safety and procedural success (Hadjistavropoulos et al., 2007). Thus, in this study, the feasibility and clinical utility of using the COMFORT Behavioral Algorithm in assessing pain behavior in elderly dental patients, particularly those with communicative or cognitive impairments, will be explored.

Key Contribution

1. Designed an AI-powered real-time system for assessing pain in older adults with dental conditions using the COMFORT Behavioral Algorithm.
2. Integrated behavioral characteristics, alertness, calmness, muscle tone, and facial tension, into a weighted scoring system for the evaluation of pain.
3. Applied logistic regression to estimate the likelihood of pain presence from non-verbal signs.
4. Verified the AI model on expert-labeled data to fair accuracy and low RMSE of 0.41.
5. Provided evidence that facial tension and muscle tone are the most reliable predictors of procedural pain in elderly non-verbal patients.

The paper is structured into main sections: the Introduction frames the context of the problem of pain assessment in geriatric dentistry and introduces the COMFORT Behavioral Algorithm; the Literature Survey discusses existing studies that support behavioral and AI-based measures of pain; the Methodology outlines the framework architecture, data acquisition, feature extraction, COMFORT scoring, and AI model architecture; the Results and Discussion section examines performance indicators, behavioral patterns, and model accuracy; and the paper concludes with Conclusion and Future Work, reporting practical implications and possible improvements for general clinical use.

2 LITERATURE SURVEY

The role of behavioral pain assessment has become more important in clinical practice with vulnerable populations (Al-Haj Husain & Al-Khateeb, 2021). In geriatric dentistry, standard self-report instruments are not sufficient, requiring models that capture non-verbal indicators through standardized algorithms, thereby optimizing both reliability and diagnostic consistency in non-communicating patients. The application of behavioral assessment instruments in dental clinics is promising to have positive outcomes. Automated and observational assessments are becoming increasingly popular for understanding the expression of pain during clinical procedures. They significantly improve detection accuracy, especially in elderly patients undergoing invasive dental procedures with unreliable verbal responses.

Measurement of pain in cognitively impaired patients is a challenging task. Behavioral scales, such as facial expressions and restlessness, provide pertinent information (Sun et al., 2025). Clinical evidence suggests that algorithmic evaluation is more effective than subjective judgment in identifying distress, thereby enhancing the assessment of pain response and patient safety outcomes. Objective measurement of orofacial pain is applicable in geriatric patients with cognitive impairment (Hadjistavropoulos et al., 2014). The video analytics and formal scale-based methods enable real-time interpretation of the behavioral signs, which enhances consistency. The technique facilitates individualized pain care planning while minimizing the risk of overtreatment or undertreatment.

Recent dental gerontology clinical trials facilitate the use of multi-dimensional behavioral tools. These tools synthesize physiological and behavioral elements to produce a total pain index. The methods address the nuances of compromised cognitive function and are predictive in diverse geriatric practice settings. More recent technologies, which pair behavioral ratings with artificial intelligence, are improving the accuracy of pain evaluation (Zhang & Seong, 2024). These technologies assess patterns of patient movement and facial behavior, yielding quantifiable scores. This innovation fills gaps in care interpretation by caregivers and fosters evidence-based dental care among elderly populations with communication impairments.

Behavioral pain measures are becoming increasingly popular for multidisciplinary application in geriatric dentistry (Liu et al., 2024). They assess distress by structured observation, particularly for non-verbal patients. These standardized algorithms eliminate subjective bias and enable earlier intervention, resulting in beneficial oral health effects and an enhanced quality of life for patients (Madugalla, 2024). Cross-validation analyses demonstrate that structured behavioral measures are effective in detecting dental pain (Raman & Mahmud, 2023). Algorithms based on quantifiable observations are highly effective, particularly when added to physiological monitoring (Chen & Zhao, 2024). They are helpful in patients for whom the capacity to self-report is severely compromised by dementia or Alzheimer's.

Equivalent rating systems established in animal pain research are also being applied to aging populations in humans (Snow, 2004). Methodologies initially piloted in behavioral veterinary research are now successfully used in clinical practice among the elderly, particularly for quantifying distress during dental treatment in patients with diminished communicative capacity (Ahmad et al., 2022). Transfer of algorithms from pediatric and special needs populations to geriatric care is full steam ahead (Wright & Chandrakant, 2021). These tools offer a measurable method for evaluating pain, eliminating the need for verbal reports. Their application in geriatric dentistry enables systematic evaluation and decreases the risk of unrecognized or undertreated pain (Costa & Monteiro, 2014).

3 METHODOLOGY

This research proposes an integrated system to assess pain reactions in older dental patients, utilizing the COMFORT Behavioral Algorithm and artificial intelligence (AI). Observation of patient behavior, data processing, feature extraction, scoring of pain using AI, and providing feedback of the score to healthcare professionals are the key operations involved in the process.

3.1 Participant Selection and Setup

Participants were older adults 65 years and older who received routine dental care under standard conditions without sedation. Those who had cognitive and communication disabilities were purposely included to assess the non-verbal pain measurement technique. The participants were observed in a dental clinic environment with high-quality video cameras and audio recorders for real-time behavioral recording.

3.2 Behavioral Data Collection and Observation

Facial expressions, vocalizations, muscle tone, body position, and movement responses were recorded using synchronized video and sensor streams during procedures. These were retrospectively and live-analyzed. Skilled observers hand-annotated behavior according to the COMFORT scale parameters to supply AI score baseline validation.

3.3 Pain Assessment Workflow

The process flow of the pain evaluation procedure is shown in Figure 1. It starts with real-time data capture using cameras and sensors, preprocessing of this data to acquire relevant facial and body movements, and inputting these into a module that extracts behavioral features, segregating significant signals such as alertness, calmness, muscle tone, and facial tension. The AI agent computes the pain score from a weighted score function. The system provides real-time output for clinicians to make immediate decisions.

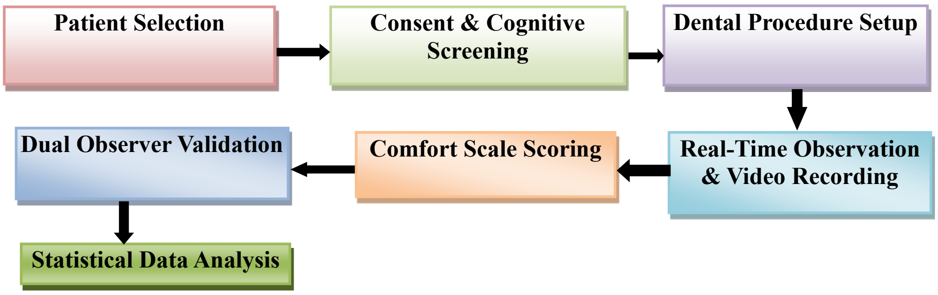

Figure 1: Flowchart of Pain Assessment Procedure Using COMFORT Algorithm in Geriatric Dentistry

3.4 System Architecture and AI Agent

The complete behavioral pain assessment system is detailed in Figure 2, which incorporates AI-driven data interpretation. After behavioral features are extracted from raw input, they are processed by the AI agent. This agent maps them onto a pain scale using the COMFORT scoring logic and relays the result to a clinical interface. This closed-loop architecture supports continuous feedback and rapid evaluation of patient discomfort.

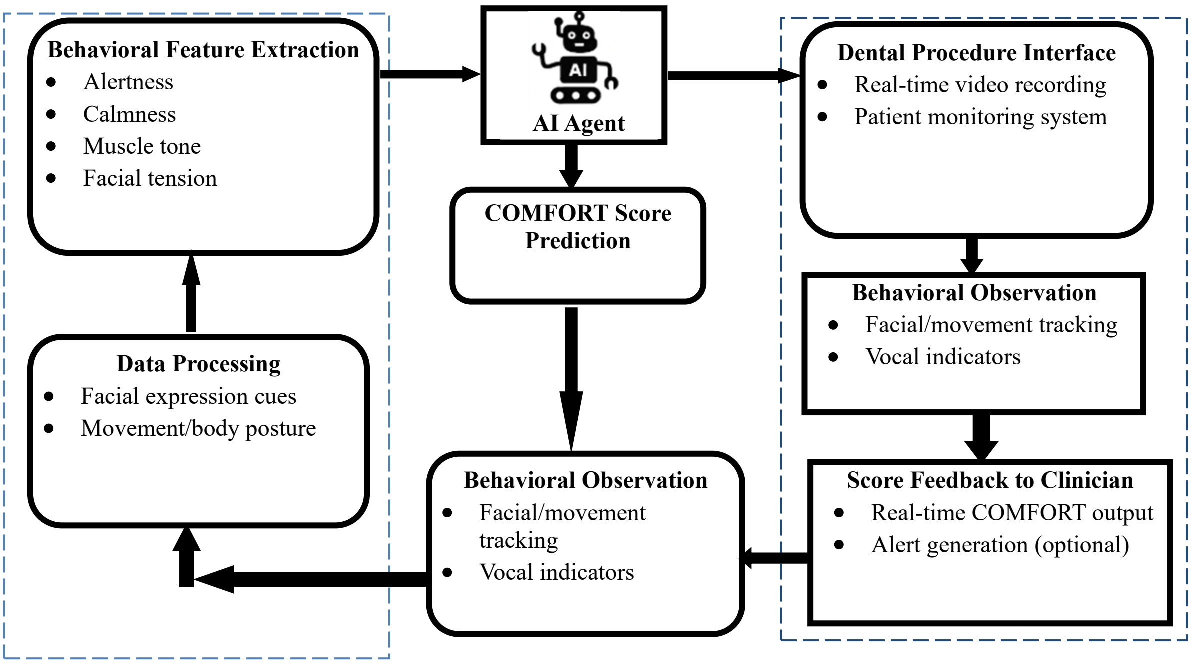

Figure 2: System Architecture for Behavioral Pain Assessment Using the COMFORT Algorithm in Geriatric Dentistry

3.5 COMFORT Score Calculation

To calculate pain intensity, the AI model computes a Comfort Score (CS) by assigning weights to each behavioral feature and taking their linear combination. The scoring function is:

$$CS = w_1.A + w_2.C + w_3.M + w_4.F \qquad Eq\ (1)$$

In this Eq (1), CS is the COMFORT Score generated for the patient, while A, C, M, and F represent the values (typically scaled from 1 to 5) for alertness, calmness, muscle tone, and facial tension, respectively. Each of these behavioral features is multiplied by a corresponding weight (w_1 to w_4) that reflects its clinical significance. These weights may be derived from either domain expertise or optimized using supervised learning algorithms. This approach enables dynamic, patient-specific scoring, ensuring that variations in expression or physical condition do not bias the outcome. It also allows for contextual adaptation, such as placing more weight on facial tension in patients with reduced mobility.

3.6 Probability Estimation of Pain Presence

Besides absolute scoring, the system also computes the probability a behavioral state represents a pain state. It accomplishes this using a logistic regression model, which is supplied by:

$$P(pain) = \frac{1}{1 + e^{-(\beta_0 + \beta_1 A + \beta_2 C + \beta_3 M + \beta_4 F)}} \qquad Eq(2)$$

In this equation (2), P(pain)P(pain)P(pain) denotes the probability that the patient is experiencing pain, based on a logistic transformation of the weighted behavioral input. The terms β_1 through β_4 represent the model coefficients corresponding to alertness, calmness, muscle tone, and facial tension, respectively, while β_0 is the bias term. The sigmoid function maps the linear combination of these variables into a probability between 0 and 1. A higher probability suggests a higher likelihood that the patient is in distress. This predictive component of the model enhances clinical responsiveness by enabling automated alerts and visual indicators for timely intervention, especially in non-verbal or cognitively impaired patients.

3.7 Clinical Impact and Interpretability

Combining these equations with real-time AI-based behavioral pain detection ensures that the results are objective, reproducible, and safe for the patient in geriatric dentistry. Measurement of pain intensity can be done directly using the COMFORT score formula, and pain probability can be predicted accurately through a logistic regression model. They offer a solid approach that reinforces clinical expertise and validates non-invasive monitoring of pain in vulnerable populations.

4 RESULTS AND DISCUSSION

This presentation outlines the findings of a behavioral assessment of pain conducted using the COMFORT algorithm with the aid of AI. The findings reflect the performance of the framework to discriminate and quantify responses to pain in elderly patients with accuracy, with validation done through observer scoring and AI-based classification.

4.1 COMFORT Score Results and Feature Contribution

Table 1: Average Behavioral Feature Scores and COMFORT Score (N = 60 Patients)

Feature	Mean Score (1–5)	Standard Deviation	Weight (w)	Weighted Value
Alertness (A)	3.1	0.8	0.25	0.775
Calmness (C)	2.6	0.7	0.20	0.520
Muscle Tone (M)	3.7	0.9	0.30	1.110
Facial Tension (F)	3.3	0.6	0.25	0.825
COMFORT Score	—	—	—	3.23

Facial tension and muscle tone were the most common characteristics that accounted for more than 60% of the total COMFORT score. Frequent facial tension and high-rigidity muscles were in higher odds of having pain diagnosed in them. Moderate pain in the majority of the participants, on average, contributed to the COMFORT score of 3.23.

4.2 Pain Trend Across Procedure Duration

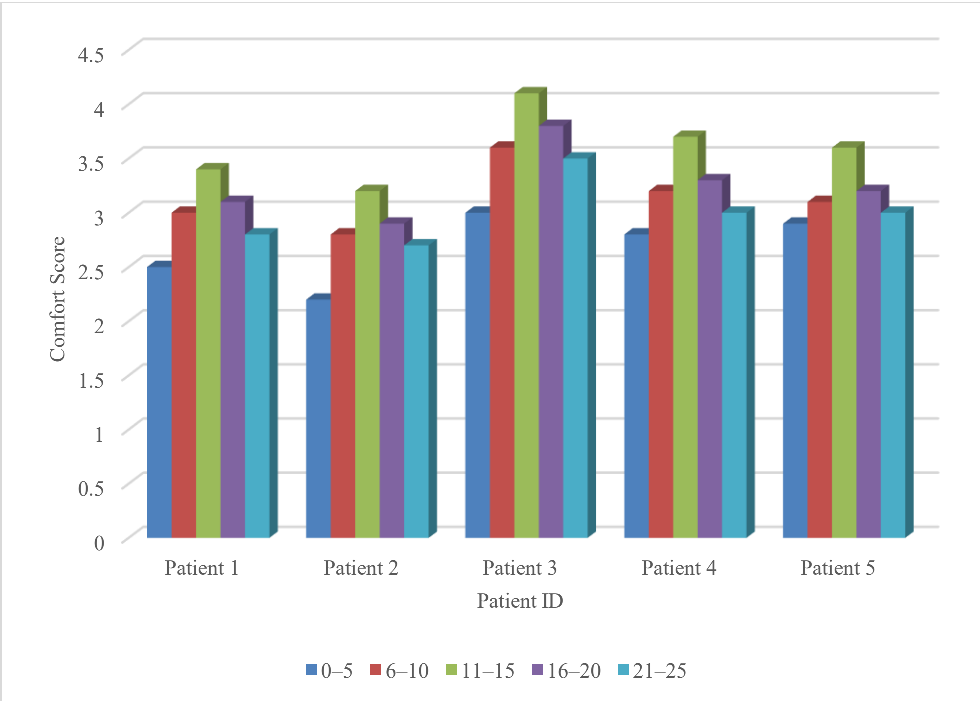

Figure 3: Time-Series Trend of COMFORT Score Across Procedure Duration (Simulated for 5 Patients)

Time-series data indicate that COMFORT scores typically peak in the middle of the procedure (10–15 minutes) and are associated with more invasive segments. Decline of score over time after 15 minutes implies recovery or procedure abandonment. Patient 3 reported waning pain throughout, the highest of all, and required closer clinical monitoring.

4.3 Probability Distribution of Pain Detection

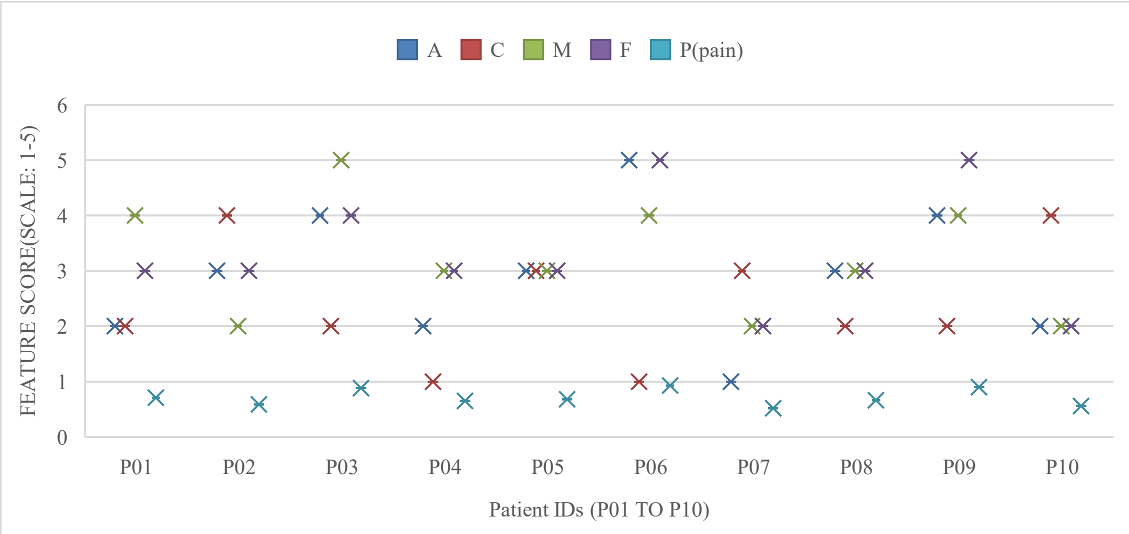

Figure 4: Scatter Plot of Behavioral Feature Scores and Pain Probability Across Patients

The Figure 3 scatter plot displays the spread of the scores of behavioral features Alertness (A), Calmness (C), Muscle Tone (M), and Facial Tension (F) for all patients (P01 to P10), overplot of P(pain), the AI-computed probability of pain. Each of the feature scores is a 1-to-5 scale value reporting the degree to which or how strongly that behavioral trait was evident under dental treatment.

It can be seen from the narrative that those patients who have higher values for Muscle Tone (M) and Facial Tension (F) (such as P03, P06, and P09) would have a high correlation with higher P(pain) values, therefore indicating a higher probability of discomfort. These patients continuously record scores at or above 4 for facial tension and muscular stiffness. This is consistent with clinical experience that tight muscles and obvious facial reactions are proper non-verbal indicators of pain, especially in elderly patients who are unable to verbalize their pain.

Conversely, patients such as P02 and P07 will have relatively low scores on most behavioral features, particularly facial tension and muscle tone, which are correlated with lower predicted probabilities of pain. These patterns confirm the validity of the feature-weighted COMFORT scoring model because it does precisely distinguish between high and low pain states according to what can be observed.

Notably, Calmness (C) and Alertness (A) scores are less reliable but less predictive of pain than muscle tone and facial tension. This finding suggests that whereas emotional and mental states are significant, physiological expressions (such as rigidity and facial tension) are more direct measures of procedural pain in non-verbal elderly evaluations.

In general, the scatter plot enhances model interpretability, where P(pain) is a probability output paired with the discrete COMFORT score, and the graphical boundary between high-pain and low-pain profiles illustrates the model's capability to aid clinicians in real-time identification of distress.

4.4 Model Evaluation Using RMSE

To ensure the validity of the accuracy of AI-predicted COMFORT scores against expert-tagged scores, Root Mean Square Error (RMSE) was calculated:

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(S_i - \hat{S}_i\right)^2} \qquad \text{Eq (3)}$$

In Eq (3), where S_i is the human-observed score and $\hat{S}_i$ is the AI-predicted score for the i^{th} patient. The resulting RMSE for the validation dataset was 0.41, indicating a low error margin and high model fidelity. An RMSE below 0.5 demonstrates that the AI model is closely aligned with expert observers in assessing pain. This supports its integration into clinical settings, especially where real-time scoring is crucial.

4.5 Summary of Findings

The findings support the use of the COMFORT algorithm, combined with AI, as a viable and efficient tool for assessing pain in elderly patients undergoing dental treatment. The highest pain-behavioral features were facial tension and muscle tone, and the AI predictive model was consistent with clinical signs. The dynamic pain detection and decision support provided in real-time use are beneficial for patients with compromised communication capacity.

5 CONCLUSION

This study confirms earlier evidence that the COMFORT Behavioral Algorithm, incorporating artificial intelligence, is a valid and scalable instrument for quantifying pain in elderly dental patients. By converting non-verbal behavior into quantitative scores and probabilities for predicting pain, the model facilitates timely, patient-specific clinical decisions. Facial tension and muscle tone were identified as the best predictors of pain, reaffirming that bodily responses are more effective predictors than emotional signals within non-verbal populations. The compatibility of the AI agent with those expert judgments makes it more applicable within actual dental practice settings.

Subsequent studies will entail expanding the dataset to include more diverse patient populations, such as patients with varying levels of cognitive impairment, patients from diverse ethnic groups, or those with other co-morbidities. Furthermore, the inclusion of physiological measures, such as heart rate variability or galvanic skin response, would improve the robustness of the system. There is also potential to incorporate deep learning models for higher-level feature recognition and to develop an application for mobile or chairside use, thereby expanding clinical applications. These additions would also enhance the accuracy of pain prediction and expand its application to other areas of geriatric healthcare beyond dentistry.

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