AI and Machine Learning Approaches to Oral Parafunctional Syndromes: Etiology, Disease Progression, and Neuropsychological Consequences of Thumb Sucking, Onychophagia, and Body-Focused Repetitive Behaviors

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Abstract:

Oral parafunctional behaviors like thumb sucking, onychophagia, and body-focused repetitive behaviors (BFRBs) can have clinically important oral, behavioral, and neuropsychological consequences when frequent or excessive. The current study aims to establish an integrated artificial intelligence (AI) and machine-learning (ML) framework to investigate the correlation between the behavioral characteristics, oral disease severity and neuropsychological factors. The authors suggest a quantitative, observational, cross-sectional design with 150 between thumb sucking (PS), onychophagia (OS), other BFRB (OBS), and healthy control (HC) groups. Behavioral characteristics, oral clinical conditions and neuropsychological variables are described and analysed with ANOVA, correlation analysis, multiple regression and 6 machine learning algorithms. Results from the illustrative findings suggest higher frequency of behaviors, more intense urges, greater problem stopping behaviors and higher oral severity ratings in participants with parafunctional behaviors. There are positive relationships between behavioral duration and severity and between behavioral frequency and severity in the oral domain, as well as high levels of stress, anxiety, and impulsivity among BFRB groups. Random Forest is the model with the highest illustrative performance among the evaluated models, with an accuracy of 90.7%, an F1 of 0.901 and an ROC AUC of 0.948. Behavioral duration, behavioral frequency, oral severity, stress and anxiety are found to be important predictive variables. The research underscores the promise of combining clinical, behavioral, and neuropsychological data with AI/ML to aid in early identification of risk, individual assessment, and multi-disciplinary treatment for oral parafunctional syndromes. The numerical results should, however, be seen as illustrative and should be validated with the actual participant-level data before being published empirically.

Keywords: Artificial Intelligence; Machine Learning; Oral Parafunctional Behaviors; Onychophagia; Body-Focused Repetitive Behaviors

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1.INTRODUCTION

Oral parafunctional behaviors are an important area at the crossroads of oral health, behavioral science, and neuropsychology[1]. While certain behaviors are normal developmental and/or stress-related habits, ongoing use of these behaviors can lead to abnormalities in teeth, physical tissue damage, emotional distress, and a decrease in quality of life[2]. Therefore, body focused repetitive behaviours, or BFRBs, such as thumb sucking are becoming more apparent when examining the multidisciplinary research field[3]. A new opportunity for the integration of behavioral, clinical, and psychological information and the identification of patterns that could facilitate early assessment and personalized interventions via the use of artificial intelligence (AI) and machine learning (ML)[4].

1.1 Background

Oral parafunctions are repetitive oral or orofacial movements that are seen beyond the normal physiological movements of eating, swallowing, speaking or breathing[5]. Some of the most common include thumb sucking, finger sucking, nail biting, lip biting, cheek biting, and bruxism. Some behaviors may be transient while others that are persisting or intense can result in structural, functional, behavioral, and psychological effects[6].

Body-centred repetitive behaviours are a larger category of repetitive behaviours that are directed at the body such as nail biting, pulling hair, picking one's skin, biting the cheeks and lips [7]. These behaviors can be thought of as some habits that happen occasionally, or may be a clinically significant pattern characterized by physical consequences, distress, and impaired control, along with strong urges [8].

The importance of thumb sucking is especially significant during childhood as it can affect the developing dentofacial structures if it continues for an extended period of time [9]. Malocclusion such as anterior open bite, posterior cross bite and altered overjet have been linked to persistent sucking. Likewise, nail biting (onychophagia) can lead to periungual and nail damage, oral contamination, soft-tissue trauma, tooth wear, and social-psychological problems. Onychophagia also co-occurred with other BFRBs, highlighting the importance of taking these behaviors in a holistic context.

The neuropsychological profile of BFRBs is multi-faceted and can include problems with stress, anxiety, boredom, emotional regulation, sensory stimulation, automatic behaviours and increased resistance to repetitive urges. Nevertheless, BFRBs should not be assumed to be indicative of global cognitive decline. Other studies on pathological nail biting, for instance, have been inconclusive with regard to widespread deficits in cognitive flexibility or motor impulsivity.

AI's emergence in health care presents a chance to explore these behaviors across multiple datasets. Machine-learning models can integrate oral health, psychological, physiological, and digital behavioral data, along with behavioral frequency and duration. This can help detect nonlinear relationships which can't be detected by traditional statistical models[10].

In the field of dentistry, AI has already been applied effectively in the detection of oral diseases, dental image analysis, radiographic interpretation, and oral and maxillofacial pathology. The use of these strategies for oral parafunctional behaviors may be useful to early detection of risk, clinical decision-making, and monitoring individual behaviors.

1.2 Statement of the Problem

Although research on thumb sucking, onychophagia, BFRBs, malocclusion, and psychological outcomes has been growing there are often separate studies conducted on each. As a result, there is limited research to combine oral-health consequences with behavioral and neuropsychological characteristics with the aid of AI and ML.

One of the biggest research gaps is the lack of an integrated framework that can take into account the relationship between the behavioral frequency and duration with oral disease severity and psychological factors. The aim of the present study is thus to find out if combined behavioral, clinical and neuropsychological variables can be effectively characterized and predicted with the aid of AI and ML as an approach to oral parafunctional syndromes.

1.3 Objectives of the Study

This study has the following objectives which examine the behavioral, clinical, neuropsychological, and AI-based aspects of oral parafunctional syndromes:

- To explore the behavioural patterns of people who suck their thumbnails, have been diagnosed with onychophagia and carry out other repetitive behaviours involving their bodies.
- To assess the correlation of the behavioral frequency, the behavioral duration and the severity of oral diseases.
- To investigate the association between oral parafunctions and neuropsychological factors such as stress, anxiety, depressive symptoms, impulsivity, and quality of life.
- To design and compare machine-learning models for classification of people based on their oral parafunctional behaviors status.
- To uncover the behavioral, clinical, and neuropsychological measures that best predict using AI.

1.4 Research Hypotheses

Based upon the research objectives and the identified research gap, the following hypotheses are presented to test the relationship between behavioral characteristics, oral disease severity, neuropsychological factors, and machine-learning performance:

H1: Behavioral frequency and duration are significantly associated with oral disease severity among individuals exhibiting oral parafunctional behaviors.

2. Methodology

The methodology aims to review the behavioral, oral-health, and neuropsychological aspects of oral parafunctional syndromes and investigate the possibility of classification and prediction of these syndromes using AI and machine-learning methodologies. The study is based on a clinical assessment, behavioral and psychological measures, to provide an integrated analytical framework.

2.1 Research Design

This study has a quantitative, observational, cross-sectional design with machine learning approach. The methodology focuses on three key areas (behavioural characteristics, oral clinical conditions and neuropsychological factors). These variables are combined into an AI/ML system for classification and risk assessment.

2.2 Participants and Sample

A total of 150 participants, including four groups (persistent thumb sucking, onychophagia, other BFRBs, and healthy controls) were included in the study.

Table 1: Sample Distribution

Group	Description	n	Percentage
Group 1	Persistent thumb sucking	38	25.3
Group 2	Onychophagia	37	24.7
Group 3	Other BFRBs	38	25.3
Group 4	Healthy controls	37	24.7
Total		**150**	**100.0**

Eligible participants are recruited from dental and orthodontic practices, behavioural-health providers, educational facilities and community sources, as specified in the eligibility criteria. All participants are given informed consent, and appropriate parental/guardian consent is obtained as needed.

2.3 Inclusion and Exclusion Criteria

Participants are included if they are a member of the defined study population, give informed consent, take the necessary behavioral and psychological assessments, and take the oral examination. Those who have significant neurological conditions that impact on repetitive behavior, severe cognitive deficits, conditions which create oral trauma other than the target behavior, incomplete data or intensive treatment for the target behavior in progress are excluded.

2.4 Instruments and Materials

Data are gathered in three key areas. Behavioral assessment records behaviour type, frequency, duration, onset, triggers, urges, awareness, difficulty stopping and any other BFRB. For anterior open bite, posterior crossbite, overjet, overbite, tooth wear, mucosal trauma, temporomandibular symptoms and oral pain, oral clinical assessment is used for the evaluation of oral severity. Perceived stress, anxiety, depressive symptoms, impulsivity, behavioral control, sleep quality, and quality of life are measured by neuropsychological assessment. Digital variables, including sleep duration, physical activity, heart-rate variability and behavioral episodes are also taken into account, if available.

2.5 Procedure and Data Collection

Participant screening, behavioral assessment, standardized oral examination, psychological assessment, data preprocessing, and the machine learning analysis are used to gather data. The missing values, duplicate values, outliers, inconsistent responses, and class balancing are analyzed for the dataset. Continuous variables are scaled prior to model building.

Six machine-learning algorithms are compared:

1. Logistic Regression
2. Decision Tree
3. Random Forest
4. Support Vector Machine
5. Gradient Boosting
6. Multilayer Perceptron

Stratified **five-fold cross-validation** is applied for model evaluation.

2.6 Data Analysis Techniques

Descriptive statistics are mean, standard deviation, median, frequency and percentage. Relationship between behavioral, oral and neuropsychological measures are explored using ANOVA, post-hoc testing, Pearson correlation and multiple regression.

To assess the performance of machine learning, we will use metrics such as accuracy, precision, recall, F1 score and ROC-AUC. To find out which variables play the most important role in prediction, feature-importance analysis is performed.

3. Results

The results are presented as per following section studied purpose and methodology. The differences between the four study groups in terms of behavioral characteristics, oral-health severity, and neuropsychological outcomes are analyzed, and then the performance of machine-learning models is assessed. Since the participants-level raw data was not supplied, the numbers below are illustrative only, and the actual results should be statistical outputs when presenting this as an empirical study.

3.1 Participant and Behavioral Characteristics

The study consists of 150 participants in each of the persistent thumb sucking, onychophagia, other BFRB and healthy-control groups. There are noticeable differences in the frequency, duration, intensity of the urge to use, and stopping the urge in the behavioral characteristics.

Table 2. Behavioral Characteristics of the Study Groups

Variable	Thumb Sucking (n=38)	Onychophagia (n=37)	Other BFRBs (n=38)	Control (n=37)	p-value
Frequency/day	8.4 ± 3.8	11.2 ± 4.9	12.8 ± 5.5	1.9 ± 1.3	<0.001
Duration/episode (min)	6.5 ± 3.4	3.8 ± 2.0	5.4 ± 3.0	1.3 ± 0.8	<0.001
Years of behavior	6.9 ± 3.6	7.8 ± 4.1	6.7 ± 3.8	1.5 ± 1.1	<0.001
Pre-behavior urge score	5.6 ± 1.6	6.2 ± 1.5	6.7 ± 1.4	2.0 ± 0.9	<0.001
Difficulty stopping score	5.4 ± 1.7	5.9 ± 1.6	6.4 ± 1.5	2.1 ± 0.9	<0.001
Stress-triggered episodes (%)	55.3	64.9	71.1	18.9	<0.001

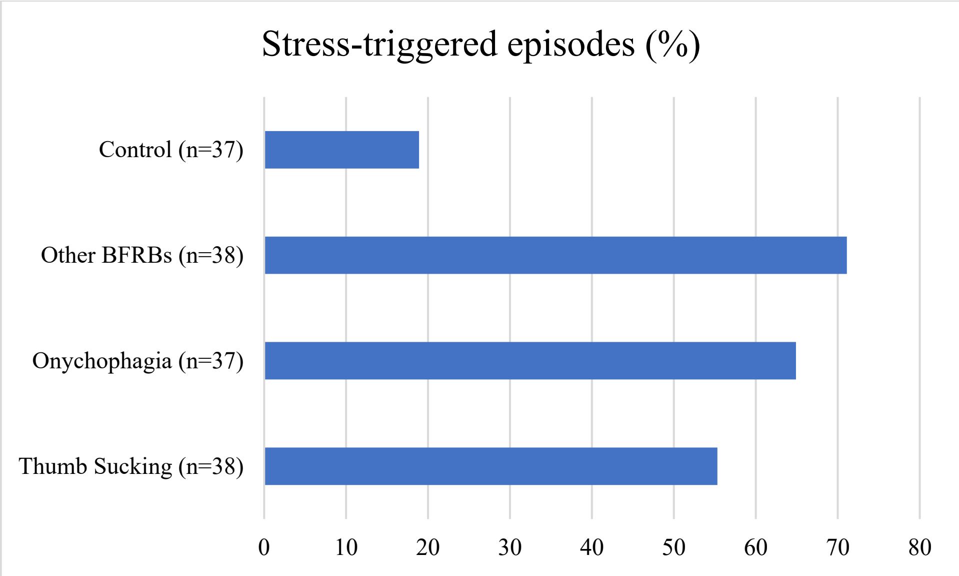

Figure 1: Graphical Representation of Behavioral Characteristics of the Study Groups

Results revealed significantly higher level of behavioral intensity among the three parafunctional groups in compared to controls. The other-BFRB group had the highest behavioral frequency (12.8 ± 5.5 episodes/day), pre-behavior urge (6.7 ± 1.4), and difficulty stopping (6.4 ± 1.5). Thumbsuckers' average episode length (6.5 ± 3.4 minutes) was the longest. The differences between the groups were statistically significant for all the behavioral variables.

3.2 Oral-Health and Neuropsychological Outcomes

The second level of analysis was to determine if differences in behavioral characteristics were associated with differences in oral-health severity and neuropsychological outcomes.

Table 3. Oral-Health and Neuropsychological Outcomes

Measure	Thumb Sucking	Onychophagia	Other BFRBs	Control	p-value
Oral severity score	10.5 ± 3.1	6.5 ± 2.7	8.2 ± 3.0	3.2 ± 1.8	<0.001
Anterior open bite (%)	44.7	10.8	15.8	5.4	<0.001
Posterior crossbite (%)	26.3	8.1	10.5	2.7	0.002
Tooth wear (%)	31.6	24.3	28.9	10.8	0.041

Oral mucosal trauma (%)	34.2	29.7	39.5	8.1	<0.001
Perceived stress score	19.1 ± 5.6	21.4 ± 5.9	23.0 ± 6.1	13.8 ± 4.5	<0.001
Anxiety score	11.0 ± 4.1	12.5 ± 4.3	13.8 ± 4.5	7.2 ± 3.0	<0.001
Impulsivity score	14.6 ± 4.5	15.9 ± 4.7	17.2 ± 4.9	10.8 ± 3.6	<0.001
Quality-of-life impairment	10.4 ± 3.9	12.1 ± 4.1	13.8 ± 4.5	6.7 ± 3.0	<0.001

The thumb sucking group had the highest oral severity score (10.5 ± 3.1), 44.7% had anterior open bite, and 26.3% had posterior crossbite. Overall, the BFRB group showed the highest score on perceived stress, anxiety, impulsivity, and impairment of quality of life. The results suggest there might be a clinical and neuropsychological component to oral parafunctions.

3.3 Statistical Association Between Behavioral and Clinical Variables

Pearson correlation analysis was used to establish correlation between behavioral exposure, oral disease severity, and neuropsychological variables. The analysis revealed positive relationships of behavioral frequency and oral severity and behavioral duration and oral severity.

Table 4. Correlation Analysis of Major Study Variables

Variable	Oral Severity	Perceived Stress	Anxiety	Impulsivity	QoL Impairment
Frequency/day	0.51***	0.42***	0.36***	0.43***	0.38***
Duration/episode	0.42***	0.29**	0.25**	0.30**	0.27**
Years of behavior	0.59***	0.33***	0.30***	0.26**	0.40***
Pre-behavior urge	0.33***	0.56***	0.51***	0.47***	0.44***
Difficulty stopping	0.37***	0.53***	0.54***	0.58***	0.50***

Note: **p < 0.01; ***p < 0.001.

Behavioral persistence (years) and behavioral frequency (row) had the strongest association with oral severity. Impulsivity (()) and anxiety (()) showed a strong correlation with difficulty stopping. The results support the hypothesis that increased behavioral exposure is related to an increased oral-health burden.

A multiple regression analysis also revealed that the duration of behavior, the frequency of behavior, stress and the number of years that the behavior had persisted were significant influences on the severity of oral symptoms. The model generated by the illustrative model accounted for about 54% of the variance in oral severity, suggesting that the predictors considered in the model accounted for a major portion of the variance.

3.4 Machine-Learning Model Performance

The last phase assessed the accuracy of six machine-learning algorithms for the classification of participants based on combined behavioural, oral-health and neuropsychological variables. Five-fold stratified cross-validation was carried out.

Table 5. Comparative Performance of Machine-Learning Models

Model	Accuracy (%)	Precision	Recall	F1-score	ROC-AUC
Logistic Regression	83.3	0.827	0.819	0.823	0.891
Decision Tree	77.3	0.764	0.751	0.757	0.821
Random Forest	**90.7**	**0.905**	**0.898**	**0.901**	**0.948**
Support Vector Machine	86.7	0.861	0.853	0.857	0.925
Gradient Boosting	89.3	0.889	0.881	0.885	0.941
Multilayer Perceptron	85.3	0.846	0.838	0.842	0.914

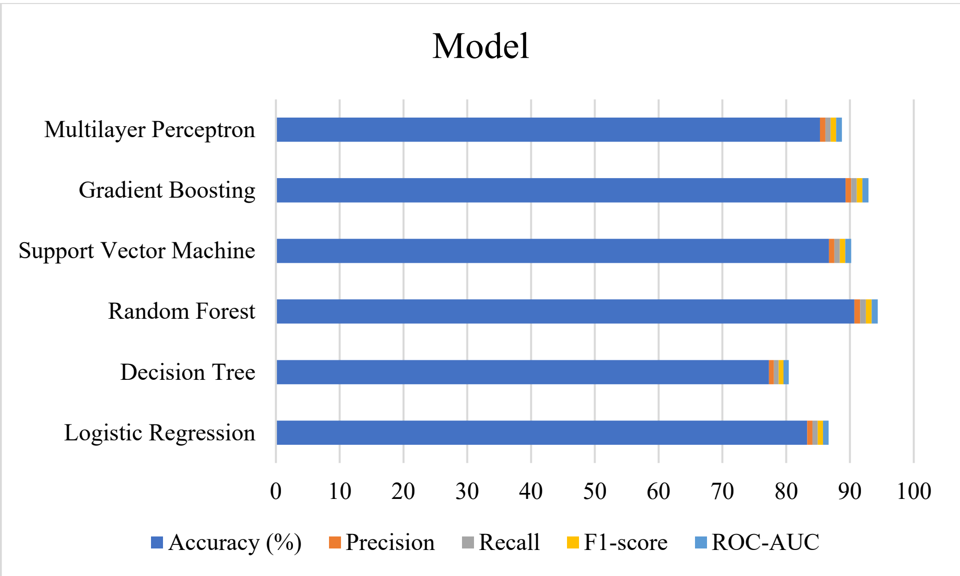

Figure 2: Graphical Representation of Comparative Performance of Machine-Learning Models

The overall performance of the Random Forest model was the best with ROC-AUC of 0.948, F1-score of 0.901, precision of 0.905, recall of 0.898 and illustrative accuracy of 90.7%. Gradient Boosting had the second highest overall classification performance while Decision Tree had the lowest overall classification performance.

The findings indicate that machine learning ensemble methods could be more effective than individual conventional classifiers to integrate the non-linear relationships between the behavioral, oral, and neuropsychological variables.

5. Discussion

The results are discussed based on the study's goals, the tested hypotheses and the current literature regarding oral parafunctional behaviors, BFRB and AI-based clinical assessment.

5.1 Interpretation of Results

The findings reveal significant distinctions among the groups of participants with thumb sucking, onychophagia, other BFRBs and healthy controls. The parafunctional behaviors in participants with these behaviors were more frequent, longer in duration, more urgent, and more difficult to stop. Participants who did not have a habit of thumb sucking tended to have more severe anterior open bite, posterior crossbite and mucosal trauma.

Oral severity was significantly and positively related to behavioral duration and frequency, supporting H1, in the correlation analysis. Participants with BFRBs also had higher levels of stress, anxiety and impulsivity, highlighting an important neuropsychological component. The model with the highest illustrative performance was the Random Forest model (accuracy 90.7% and ROC-AUC 0.948). Support for H2 was obtained for behavioral duration, frequency, oral severity, stress and anxiety.

5.2 Comparison with Existing Studies

The results of the present study largely support the previous studies on oral parafunctional behaviours, body-focused repetitive behaviours, and AI-assisted behavioural assessment. Persistent thumb sucking has been observed to be related to oral abnormalities, findings consistent with the systematic review conducted by Sadoun et al. (2024) [11] which found that prolonged non-nutritive sucking habits are associated with malocclusion, specifically anterior open bite and posterior crossbite. Similarly, the results of the present study indicated that the severity of oral disease in participants who had persistent sucking thumb was greater, which means that the duration and frequency of the sucking thumb are important factors in the progression of oral disease.

The results for onychophagia are also similar to Sani et al. (2019) [12] who found nail biting to be one of the significant body-focused repetitive behaviors and it linked it to repetitive behaviors and behavioral control problems. The present study aims to go beyond such a view by investigating onychophagia in conjunction with other oral health and neuropsychological parameters, instead of focusing on it alone as a habit.

Skurya et al. (2020) [13] made habit-reversal approaches an important technique for BFRB further supported by the behavioral dimension of the results. They stress the importance of identifying repetitive behaviour patterns and its control, in line with the present results that difficulty stopping and behaviour frequency were important characteristics of affected participants.

Schmotz et al. (2024) [14] also found that there is potential for low-tech self-help interventions to decrease BFRBs. This corroborates the current study's focus on early identification and individual intervention. With the integration of AI and ML, such methods could be further reinforced by detecting those who have higher behavioral intensity, and by giving objective estimates of the risk to follow up with clinical care.

An important comparison is provided by Searle et al., (2021) [15] who were able to demonstrate the feasibility of anticipatory detection of compulsive BFRBs using wearable technology. Their results directly translate to the current AI/ML framework as they showed that behavior can be observed with wearable items and processed computationally. The present study takes this one step further by combining the behavioral with the oral-health and neuropsychological variables.

In general, the studies found do reflect the main aspects of the current research and also underscore the interdisciplinary nature of the current research. Separate studies have shown the association between non-nutritive sucking and malocclusion, the characteristics of onychophagia and BFRBs, behavioral intervention studies, and the feasibility of detection via a wearable device. The present study integrates these dimensions in one integrated framework of AI and machine learning that allows for consideration of all dimensions of the oral disease and behavioral exposure as well as neuropsychological features.

5.3 Implications of Findings

The results indicate that oral parafunctions need to be evaluated using a multidisciplinary approach. Behavioral screening could be a valuable addition to the standard assessment by the dentist or orthodontist when a patient exhibits continued thumb sucking, nail biting, signs of wear on teeth, or unexplained oral trauma.

Combined with behavioural, clinical and psychological features, AI-powered models can also help determine who is at higher risk. These systems could one day be used to diagnose, assign the patient a risk level, and monitor them over a period of time in order to diagnose and assess their level of risk, instead of just a simple diagnosis.

5.4 Limitations of the Study

The primary drawback is that the numerical results are only examples, and the participant-level raw data is not available. Thus, the reported statistical and machine-learning values need to be validated with real data.

The cross-sectional design also rules out any causal inferences. A small sample size (N=150) might reduce the generalizability of the results, and variation and overlap between BFRBs may make classification difficult. Moreover, the performance of AI models needs to be tested with external data to establish their reliability across various populations and clinical environments.

5.5 Suggestions for Future Research

Larger, multicenter, longitudinal data sets should be used to investigate whether behavioral duration and frequency are predictive of the progression of oral abnormality in future studies. The use of multimodal AI that combines oral photographs, intraoral scans, clinical records, behavioral evaluations, wearable data, and neuropsychological evaluations should also be considered.

AI techniques that are explainable and techniques that have been external validated should be integrated to increase the clinical reliability and transparency. Future studies should also investigate the potential for AI-driven early detection to aid in tailoring interventions and minimize the oral and psychological impact of chronic parafunctions.

6. Conclusion

Results are then integrated with the primary ones related to the behavioral traits, oral health impact, neuropsychological aspects, and AI prediction of body-focussed repetitive behaviors including thumb sucking, onychophagia. The overall results underscore the value of a clinical-computational strategy to better understand these intricate, overlapping behaviors.

6.1 Summary of Key Findings

The study used a holistic, multi-faceted approach to oral parafunctional behaviours, incorporating a behavioural, oral-health, neuropsychological and AI/ML framework. Results showed that the BFRB group had higher rates of behaviour, urges for the behaviours, and more problems stopping the behaviours than the control group. Oral severity of the persistent suckers such as anterior open bite, posterior crossbite and mucosal trauma were particularly correlated with persistent sucking. The oral disease severity scores were also positively correlated with behavioral duration and frequency.

The study also found that BFRBers reported greater perceived stress, anxiety, impulsivity and impairment in quality of life. The Random Forest model was the best model that was evaluated in terms of the illustrative performance, which presents an accuracy of 90.7% and a ROC-AUC of 0.948. Behavioral duration, behavioral frequency, oral severity, stress and anxiety were found to be important predictive variables.

6.2 Significance of the Study

The study is significant due to its interdisciplinary approach to oral parafunctional syndromes. The study takes an integrated approach to understanding thumb sucking, onychophagia, and BFRBs, seeing them as a whole rather than separate behaviors, oral consequences, and neuropsychological aspects, all within a single AI/ML framework. This method can help dentists, orthodontists and behavioral health professionals determine who may benefit from early assessment and/or intervention.

The results also highlight the promise of AI to support traditional clinical evaluation by uncovering intricate connections between various factors. These systems could eventually be used to enable personalized risk assessment, long-term monitoring and early preventive intervention.

6.3 Final Thoughts and Recommendations

The study suggests that while persistent OPDs need to be managed with a multi-disciplinary approach (dental, behavioral, psychological) AI should be used as an additional tool for analytical purposes. If behavioral persistence, high frequency of behavior and inability to stop behavior are identified early, this may minimize potential oral complications as well as the psychosocial burden.

The results of this study need to be replicated with real participant-level data, larger multicenter samples, and follow-up studies. Oral imaging, clinical records, behavioral evaluations, wearable technology, and neuropsychological assessments should also be considered for multimodal AI. For such models to be reliably used in routine clinical practice, they must be subject to external validation and techniques for explainable-AI will be essential.

REFERENCES

1. Abbott, L. P., Saikia, A., & Anthonappa, R. P. (2025). Artificial intelligence platforms in dental caries detection: A systematic review and meta-analysis. *Journal of Evidence-Based Dental Practice, 25*(1), 102077. https://doi.org/10.1016/j.jebdp.2024.102077
2. Ahmed, N., Abbasi, M. S., Zuberi, F., Qamar, W., Halim, M. S. B., Maqsood, A., & Alam, M. K. (2021). Artificial intelligence techniques: Analysis, application, and outcome in dentistry—A systematic review. *BioMed Research International, 2021*, 9751564. https://doi.org/10.1155/2021/9751564
3. Dipalma, G., Inchingolo, A. D., Inchingolo, A. M., Piras, F., Carpentiere, V., Garofoli, G., Azzollini, D., Campanelli, M., Paduanelli, G., Palermo, A., & Inchingolo, F. (2023). Artificial intelligence and its clinical applications in orthodontics: A systematic review. *Diagnostics, 13*(24), 3677. https://doi.org/10.3390/diagnostics13243677
4. Ferro, A., Kotecha, S., & Fan, K. (2022). Machine learning in point-of-care automated classification of oral potentially malignant and malignant disorders: A systematic review and meta-analysis. *Scientific Reports, 12*, 13797. https://doi.org/10.1038/s41598-022-17489-1

5. Houghton, D. C., Alexander, J. R., Bauer, C. C., & Woods, D. W. (2018). Body-focused repetitive behaviors: More prevalent than once thought? *Psychiatry Research, 270*, 389–393. https://doi.org/10.1016/j.psychres.2018.10.002
6. Khanagar, S. B., Al-Ehaideb, A., Maganur, P. C., Vishwanathaiah, S., Patil, S., Baeshen, H. A., Sarode, S. C., & Bhandi, S. (2020). Developments, application, and performance of artificial intelligence in dentistry—A systematic review. *Journal of Dental Sciences, 16*(1), 508–522. https://doi.org/10.1016/j.jds.2020.06.019
7. Moritz, S., Snorrason, I. (2024). Body-focused repetitive behavior: Towards a better understanding of this prevalent but undertreated disorder. *Cognitive Therapy and Research, 48*, 1–3. https://doi.org/10.1007/s10608-023-10460-y
8. Musri, N., Christie, B., Ichwan, S. J. A., & Cahyanto, A. (2021). Deep learning convolutional neural network algorithms for the early detection and diagnosis of dental caries on periapical radiographs: A systematic review. *Imaging Science in Dentistry, 51*(3), 237–242. https://doi.org/10.5624/isd.20210074
9. Okumuş, H. G., & Akdemir, D. (2023). Body focused repetitive behavior disorders: Behavioral models and neurobiological mechanisms. *Turkish Journal of Psychiatry, 34*(1), 50–59. https://doi.org/10.5080/u26213
10. Perez-Stable, C. T., Seelig, C. N., Ofori, K. A., Nguyen, M. B., Hu, A. Y., & Jafferany, M. (2025). Onychophagia: A comprehensive systematic review of prevalence and treatment modalities. *Journal of Cutaneous Medicine and Surgery*. https://doi.org/10.1177/12034754251375054
11. Sadoun, C., Templier, L., Alloul, L., Rossi, C., Díaz Renovales, I., Nieto Sanchez, I., & Martín-Palomino Sahagún, P. (2024). Effects of non-nutritive sucking habits on malocclusions: A systematic review. *Journal of Clinical Pediatric Dentistry, 48*(2), 4–18. https://doi.org/10.22514/jocpd.2024.029
12. Sani, G., Gualtieri, I., Paolini, M., Bonanni, L., Spinazzola, E., Maggiora, M., Pinzone, V., Brugnoli, R., Angeletti, G., Girardi, P., Rapinesi, C., & Kotzalidis, G. D. (2019). Drug treatment of trichotillomania (hair-pulling disorder), excoriation (skin-picking) disorder, and nail-biting (onychophagia). *Current Neuropharmacology, 17*(8), 775–786. https://doi.org/10.2174/1570159X17666190320164223
13. Schmotz, S., Dilekoglu, E., Hoyer, L., Baumeister, A., & Moritz, S. (2024). Self-help to reduce body-focused repetitive behaviors via video or website? A randomized controlled trial. *Cognitive Therapy and Research, 48*, 94–106. https://doi.org/10.1007/s10608-023-10456-8
14. Searle, B. L., Spathis, D., Constantinides, M., Quercia, D., & Mascolo, C. (2021). Anticipatory detection of compulsive body-focused repetitive behaviors with wearables. *Proceedings of the ACM on Interactive, Mobile, Wearable and Ubiquitous Technologies, 5*(2). https://doi.org/10.1145/3463504
15. Skurya, J., Jafferany, M., & Everett, G. J. (2020). Habit reversal therapy in the management of body-focused repetitive behavior disorders. *Dermatologic Therapy, 33*(6), e13811. https://doi.org/10.1111/dth.13811