AI-Driven Patient Profiling for Clinical Decision Support in Dental Treatment under General Anesthesia

Anita Petreska, Julijana Nikolovska, Efka Zabokova Bilbilova, Blagoj Ristevski, *IEEE Senior Member*, and Nikola Rendevski

***Abstract* — Planning dental treatment under general anesthesia represents a significant clinical challenge due to the heterogeneity of patients in terms of medical, neurodevelopmental, behavioral, and treatment-related characteristics. This study proposes an AI-based framework for patient profiling to support dental treatment planning under general anesthesia. Using selected demographic, behavioral, clinical, medical, and neurodevelopmental variables, together with indicators of treatment burden, a two-stage methodology was applied. In the first stage, unsupervised clustering analysis was performed to identify clinically meaningful patient profiles. Based on quantitative criteria and clinical interpretability, four clinically interpretable patient profiles were identified, reflecting different patterns of medical complexity, neurodevelopmental burden, preventive behavior, and treatment needs. In the second stage, the derived profile labels served as the target variable in a multiclass classification task to assess whether profile membership could be predicted from the available patient-level data. Among the tested models, Logistic Regression achieved the best performance. However, because the target labels were obtained from the clustering procedure, classification performance was interpreted as evidence of profile assignability rather than as independent validation of clinical outcome relevance. Overall, the findings suggest that AI-driven patient profiling can serve as a clinically useful decision-support approach, enabling more personalized treatment planning and more data-driven dental care for patients with complex needs undergoing treatment under general anesthesia.**

I. Introduction

Planning dental treatment under general anesthesia represents a significant clinical and organizational challenge, particularly in patients with special needs, limited cooperation, dental fear, complex oral conditions, or coexisting medical and neurodevelopmental disorders [1], [2], [16]. These patients form a heterogeneous population with diverse clinical, behavioral, and functional characteristics that directly influence treatment choice, extent, urgency, and resource planning. In such settings, traditional assessment based solely on individual clinical judgment may be insufficient, especially when timely identification of patient groups requiring different treatment strategies is needed [3], [12].

AI-based approaches can support the analysis of multidimensional clinical data and enable the identification of meaningful patient subgroups based on age, medical history, behavioral characteristics, neurodevelopmental status, oral health risks, and required interventions [4], [5], [15]. In dental treatment under general anesthesia, patient profiling may therefore contribute to a better understanding of population heterogeneity and support more precise, personalized, and efficient treatment planning. Combining unsupervised and supervised learning allows latent patient patterns to be discovered and then used to predict the profile membership of new patients, providing a basis for AI-supported clinical decision-making [7], [17], [23].

Existing studies have mainly focused on predicting risk, complications, treatment complexity, indications, and treatment needs [4], [6]. However, AI-based patient profiling for stratification and planning support in dental general-anesthesia populations remains underexplored. Unlike approaches focused on predefined outcomes, this study integrates unsupervised profile discovery, statistical profile characterization, and supervised profile assignment within a *single* interpretable decision-support framework. The contribution is therefore primarily clinical and translational rather than algorithmic. This study proposes a two-phase AI-based framework for patients undergoing dental treatment under general anesthesia. First, unsupervised learning is applied to identify clinically meaningful profiles using demographic, behavioral, clinical, medical, and neurodevelopmental variables. Then, the resulting cluster labels are used as target classes in supervised multiclass classification models to predict profile membership [11], [13], [14]. Interpretable modeling and feature-importance analysis are used to identify the predictors that contribute most strongly to profile discrimination.

The main contribution of this study is the development of an interpretable AI-based patient-profiling framework that supports clinical decision-making, personalized treatment planning, and efficient resource allocation in a heterogeneous special-care dental population. The remainder of the paper is structured as follows: Section II presents the data and methodology, Section III describes the identified patient profiles, Section IV reports the predictive modeling results and their interpretation, Section V concludes the paper, and Section VI outlines future research directions.

Anita Petreska is with the Faculty of Information and Communication Technologies, University “St. Kliment Ohridski” - Bitola, Macedonia, e-mail: petreska.anita@uklo.edu.mk

Julijana Nikolovska is with the Faculty of Dentistry, University Ss. Cyril and Methodius, Skopje, Macedonia
e-mail: jnikolovska@stomfak.ukim.edu.mk

Efka Zabokova Bilbilova is with the Faculty of Dentistry, University Ss. Cyril and Methodius, Skopje, Macedonia
e-mail: ezabokova@stomfak.ukim.edu.mk

Blagoj Ristevski is with the Faculty of Information and Communication Technologies, University “St. Kliment Ohridski” - Bitola, Macedonia
e-mail: blagoj.ristevski@uklo.edu.mk

Nikola Rendevski is with the Faculty of Information and Communication Technologies, University “St. Kliment Ohridski” - Bitola, Macedonia
e-mail: nikola.rendevski@uklo.edu.mk

II. Data and Methodology

In this study, an AI-based approach was applied to profile patients undergoing dental treatment under general anesthesia. The methodological framework was organized as a two-phase process combining unsupervised and supervised machine learning techniques. In the first phase, clustering analysis was used to identify clinically meaningful patient profiles [24]. In the second phase, the resulting profile membership labels served as the target variable in multiclass classification models to predict the corresponding clinical profile [25].

The analysis included selected demographic, behavioral, clinical, medical, neurodevelopmental, and treatment-burden indicators [27]. Before modeling, preprocessing included missing-value imputation, categorical data transformation, binary indicator recoding, and standardization of continuous variables [6]. The final clustering feature set consisted of 28 variables selected from the initial 41 available variables based on clinical relevance, data completeness, and relevance to treatment planning under general anesthesia. These variables included demographic characteristics, oral health behaviors, preventive attendance, medical and neurodevelopmental indicators, previous exposure to general anesthesia, and treatment-burden measures.

To examine the robustness of the clustering solution, K-means clustering was repeated across multiple random initializations, and the consistency of cluster assignments and clinically interpretable profile characteristics was assessed. K-means was applied to the standardized feature matrix using candidate values of $k = 2, 3, 4$, and 5. The final solution was selected using a combined criterion that considered silhouette score, profile interpretability, and clinical usefulness for treatment planning.

For the supervised classification stage, the derived cluster label was used as the target variable. The dataset was divided into training and testing subsets using an 80/20 split, resulting in 64 test cases. Classification models were evaluated using accuracy, macro F1-score, weighted F1-score, precision, recall, and confusion matrix analysis. To improve interpretability, the predictors with the strongest influence on profile membership were also analyzed. Through this approach, the study aims to describe the heterogeneity of patients treated under general anesthesia and provide a foundation for a practically applicable clinical decision-support framework for dental treatment planning..

A. Dataset Description and Initial Data Characteristics

The initial analytical dataset consisted of 320 patients treated under general anesthesia and included 41 input variables. Each row represented one patient, while each column corresponded to a demographic, behavioral, clinical, medical, or neurodevelopmental characteristic relevant to dental treatment planning. The dataset was dominated by male patients (70.31%), while female patients accounted for 28.12%, with a small proportion of missing records. Most patients were from urban areas (71.88%), whereas 26.56% were from rural settings. Socioeconomically, the largest groups were patients from families with both parents employed (38.44%) or one employed parent (37.81%), and most families had an average financial status (62.50%). The mean age at treatment was 17.00 ± 9.11 years, and the average number of previous general anesthesia procedures was 1.66 ± 1.97. The dataset reflected marked oral health vulnerability: tooth brushing once daily was the most common pattern (40.62%), whereas 32.19% of patients rarely or never brushed their teeth. Most patients attended dental care only when a problem occurred (69.69%), while regular preventive attendance was reported in only 10.00% of cases. From a medical and neurodevelopmental perspective, systemic disease was present in 27.24% of patients with available data, and previous exposure to general anesthesia was recorded in 66.88%. Autism spectrum disorder was present in 42.22% of patients, intellectual disability in 25.08%, cerebral palsy in 21.59%, epilepsy in 13.65%, developmental delay in 6.98%, and attention-deficit/hyperactivity disorder in 4.44%. Treatment-related indicators further confirmed the clinical complexity of the population. The mean number of planned teeth was 11.70 ± 5.25, the mean total number of procedures was 11.68 ± 5.38, the mean number of restorations was 6.63 ± 4.54, and the mean number of extractions was 5.02 ± 4.87. Most cases were elective (82.50%), while 15.94% were urgent. Because missing values were present across several variables, preprocessing included imputation, categorical transformation, and standardization of continuous features.

B. Statistical Characterization of the Identified Profiles

To examine differences among the identified patient profiles, a bivariate analysis was conducted. For numerical variables, ANOVA and Kruskal–Wallis tests were applied, while χ^2 tests were used for categorical variables, with a statistical significance threshold of $p < 0.05$.The results indicated that the most pronounced differences between the profiles were related to neurodevelopmental burden, medical complexity, previous exposure to general anesthesia, and treatment burden. The strongest associations (all $p<0.001$) were observed for attention-deficit/hyperactivity disorder, autism spectrum disorder, epilepsy, cerebral palsy, age at treatment, previous general anesthesia, the number of previous anesthesia procedures, systemic disease, and treatment-related indicators, including the number of planned teeth, total procedures, restorations, and extractions. Additionally, statistically significant differences were observed for intellectual disability ($p=0.0029$), sensory characteristics ($p=0.0043$), developmental delay ($p=0.0053$), assistance with oral hygiene ($p=0.0104$), and missed or canceled appointments ($p=0.0265$). In contrast, tooth brushing frequency ($p=0.4423$), preventive dental visits ($p=0.1934$), treatment urgency ($p = 0.8004$), cooperation level ($p=0.7910$), and nighttime consumption of sugary drinks ($p=0.9229$) did not show statistically significant differences between profiles. Meanwhile, consumption of sugary snacks ($p=0.0865$) and fluoride use ($p=0.0645$) showed a trend toward differences but did not reach statistical significance. These findings suggest that the patient profiles primarily reflect clinical complexity, neurodevelopmental characteristics, and treatment burden.

III. Identification of Patient Profiles

Unsupervised clustering analysis was applied to 28 selected variables to identify clinically meaningful patient profiles [9], [24]. Solutions with 2, 3, 4, and 5 clusters were tested, yielding silhouette scores of 0.0798, 0.0763, 0.0822, and 0.0691, respectively. The four-cluster solution yielded the highest silhouette value among the tested alternatives; however, the absolute value remained low, indicating weak geometric separation and partial overlap among the patient profiles. Therefore, the four-cluster solution was not selected solely on the basis of the silhouette score, but rather as the best compromise among quantitative evaluation, clinical interpretability, and usefulness for treatment-planning support. The resulting profiles should be interpreted as clinically meaningful phenotypic patterns rather than as strictly discrete or fully separated patient classes. Mean age ranged from 12.02 to 21.07 years; the mean number of previous general anesthesia procedures ranged from 0.70 to 2.79; the total number of procedures ranged from 6.64 to 15.18; and the number of extractions ranged from 2.53 to 8.04.

Profile 1: Medically Complex Repeated-GA Risk: This profile was characterized by the highest mean age (21.07), the highest prevalence of previous general anesthesia (0.89), and the highest mean number of previous interventions (2.79). In addition, greater medical complexity was observed, including systemic disease (0.55) and epilepsy (0.45), as well as the highest restorative burden (9.36). From a behavioral perspective, 44% of patients rarely or never brushed their teeth, 81% attended dental visits only when problems occurred, and in 50% of cases, brushing was provided by a parent or caregiver

Profile 2: Neurodevelopmental High-Treatment-Burden Profile: This profile showed the highest treatment burden and a pronounced neurodevelopmental component. The mean age was 12.02, and the prevalence of autism spectrum disorder was 0.62. Regarding treatment indicators, this profile had the highest number of planned teeth (15.13), total procedures (15.18), and extractions (8.04). Behaviorally, 29% of patients rarely or never brushed their teeth, 67% had problem-based preventive attendance, 28% consumed sugary snacks two to three times daily, and 13% more than three times daily. The prevalence of previous general anesthesia was 0.42, and the mean number of previous interventions was 0.70.

Profile 3: Neurobehavioral Preventive-Neglect Profile: The most pronounced neurobehavioral structure characterized this profile. The prevalence of attention-deficit/hyperactivity disorder was 1.00, while the prevalence of autism spectrum disorder was 0.57. Previous exposure to general anesthesia was 0.86, and the mean number of previous interventions was 1.79. In terms of treatment burden, the profile had 11.21 planned teeth, 11.21 total procedures, and 4.43 extractions. Its most distinctive feature was preventive neglect: 86% of patients attended dental care only when problems occurred; no patient had regular preventive visits at least twice a year; 50% consumed sugary snacks once daily; and 57% received brushing support from both the child and the parent.

Profile 4: Lower-Burden Mixed Clinical Profile: he lowest treatment burden distinguished this profile. The mean age was 20.24, the number of planned teeth was 6.69, the total number of procedures was 6.64, and the number of extractions was 2.53. Unlike the other profiles, this group showed the only higher value for pulp procedures (0.12). Medical and neurodevelopmental characteristics were moderately expressed, with systemic disease (0.20), previous general anesthesia (0.79), and mean number of previous interventions (1.97), autism spectrum disorder (0.46), Down syndrome (0.11), and developmental delay (0.12). Behaviorally, 30% of patients rarely or never brushed their teeth; 43% brushed once daily; 24% twice daily; 68% had problem-based visits; 20% attended approximately once a year; 12% attended at least twice a year; and the proportion of urgent cases was 0.19.

IV. PREDICTIVE MODELING OF PROFILE MEMBERSHIP

After identifying the four patient profiles, the profile membership labels were used as the target variable in a supervised multiclass classification task. Since these labels were derived from the preceding clustering procedure, the supervised models were not intended to validate an independent clinical outcome, but to evaluate whether the identified profiles could be consistently assigned using the available patient-level variables. Therefore, classification performance was interpreted as a measure of operational reproducibility and profile assignability rather than external clinical validation. For this purpose, two machine learning algorithms, Logistic Regression (LR) and Random Forest (RF), were applied and evaluated using accuracy, macro F1-score, and weighted F1-score [20]. Among the tested models, LR achieved the best performance, with an accuracy of 0.9219, a macro F1-score of 0.9294, and a weighted F1-score of 0.9196. In comparison, RF achieved an accuracy of 0.8281, a macro F1-score of 0.6378, and a weighted F1-score of 0.8093. These results indicate that the derived profile labels can be assigned from the available variables with high test-set performance; however, they should be interpreted as evidence of profile assignability rather than independent clinical validation [9], [25].

Further analysis showed that medical complexity and repeated exposure to general anesthesia predominantly defined the medically complex profile. High treatment burden and autism spectrum conditions characterized the neurodevelopmental high-treatment-burden profile, while attention-deficit/hyperactivity disorder contributed most strongly to the neurobehavioral profile. Finally, lower treatment burden combined with mixed developmental characteristics defined the lower clinical-burden profile. To contextualize model performance, a majority-class baseline was also included, assigning all test cases to the most frequent profile as a lower-bound comparison for the supervised models.

TABLE I. PERFORMANCE METRICS OF THE TESTED CLASSIFICATION MODELS

Model	Performance metrics of the tested classification models		
	Accuracy	***Macro F1-score***	***Weighted F1-score***
LR	0.9219	0.9294	0.9196
RF	0.8281	0.6378	0.8093

Both machine learning models outperformed the majority-class baseline, indicating that the available variables contained discriminative information for assigning the derived profiles. Nevertheless, because the labels were obtained from clustering, these results should not be interpreted as independent validation of clinical outcomes. The results showed that LR achieved better performance, with accuracy = 0.9219, macro F1-score = 0.9294, and weighted F1-score = 0.9196, whereas RF achieved accuracy = 0.8281, macro F1-score = 0.6378, and weighted F1-score = 0.8093. At the class level, LR achieved an F1-score of 0.81 for the first profile, 0.93 for the second, 1.00 for the third, and 0.97 for the fourth profile, indicating high discriminative ability. In contrast, RF showed lower stability, particularly for the smallest class, where the F1-score was 0.00, suggesting greater sensitivity to the profiles' imbalanced distribution.

A. Confusion Matrix Analysis

The confusion matrix analysis further confirmed that LR has a very good ability to distinguish the four identified profiles. Out of 64 test cases, the model correctly classified 59 and misclassified 5, yielding an accuracy of 92.19%. For the first profile, out of 15 actual cases, 11 were correctly classified, and 4 were incorrectly predicted as the second profile, yielding a recall of 73.3%. For the second profile, all 26 cases were correctly classified, yielding a recall of 100%. For the third profile, all 3 cases were correctly classified, with a recall of 100%, though caution is warranted given the small number of examples. For the fourth profile, 19 of 20 cases were correctly classified, with 1 case incorrectly classified as the first profile, yielding a recall of 95.0%. Figure 1 presents the confusion matrix for the best-performing model, namely LR.

The greatest overlap was observed between the first and second profiles, suggesting partial similarity between medically complex patients with repeated general anesthesia and patients with high neurodevelopmental and treatment burden. Overall, the results indicate that profile membership can be successfully modeled, supporting the potential application of the proposed approach to dental treatment planning under general anesthesia [8].

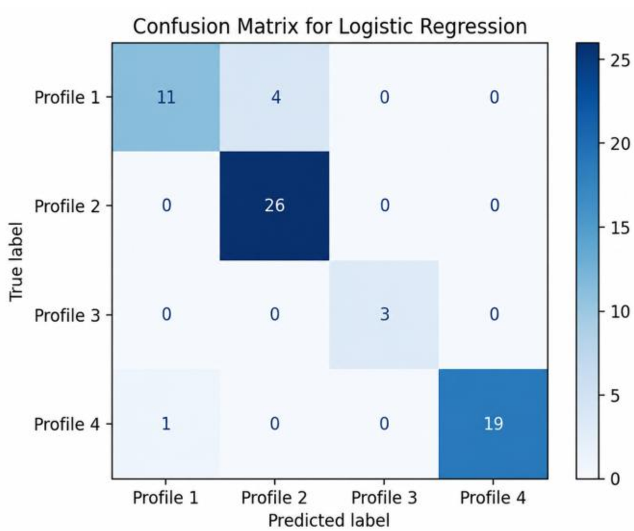

Figure 1. Confusion Matrix for Logistic Regression.

B. Visualization and Interpretation of the Profiles

To further assess the structure of the identified profiles, a principal component analysis (PCA) with 2 components was performed. Figure 2 presents the two-dimensional PCA projection of the patient profile.

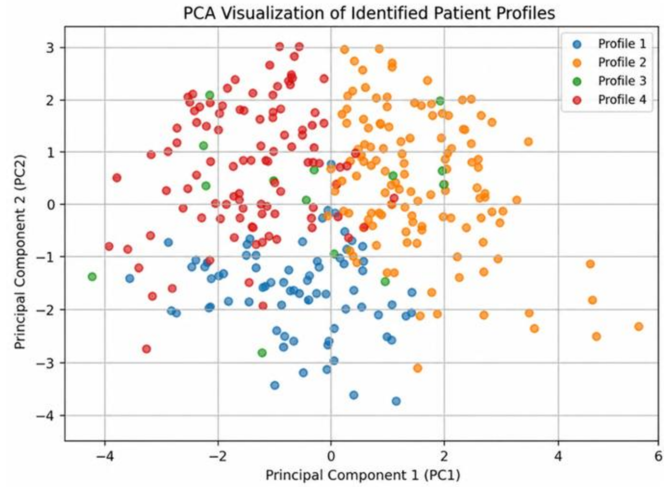

Figure 2. PCA Visualization of Patient Profiles

The PCA visualization showed that the patient profiles were partially separated, but not fully isolated. The most pronounced spatial separation was observed between one profile positioned predominantly on the right side of the space and another profile more grouped in the left and upper parts of the plot. The remaining profiles showed partial overlap, which is expected in real clinical data with multidimensional heterogeneity. The first principal component explained 11.65% of the total variance, while the second explained 9.23%, corresponding to a total of 20.88%. Although these two components do not capture the entire data structure, they provide a useful two-dimensional visualization of the relative distribution and overlap among the profiles. This finding is consistent with moderate silhouette scores and further indicates that the profiles possess a recognizable, though not completely discrete, structure.

C. Model Interpretation and Clinical Implications

To interpret the best-performing model, the coefficient matrix of LR, with dimensions (4, 28), was analyzed. Since LR achieved the best results, its coefficients were used to identify the predictors contributing most to each profile's membership. For the Medically Complex Repeated-GA Risk Profile, the strongest positive predictors were epilepsy (1.2948), cerebral palsy (1.0800), and systemic disease (0.9867), indicating marked medical and neurological complexity. For the Neurodevelopmental High-Treatment-Burden Profile, the strongest positive predictors were the number of planned teeth (1.3301), the total number of procedures (1.0604), the number of extractions (0.7669), and autism spectrum disorder (0.6278), confirming the dominant treatment and neurodevelopmental burden. For the Neurobehavioral Preventive-Neglect Profile, the most pronounced positive predictor was attention-deficit/hyperactivity disorder (1.7495), followed by developmental delay (0.2761) and autism spectrum disorder (0.2373), indicating a clearly expressed neurobehavioral structure. For the Lower-Burden Mixed Clinical Profile, positive predictors included Down syndrome (0.6629), age (0.4117), and treatment urgency (0.3946), whereas the strongest negative predictors were the number of planned teeth (-1.6232) and the total number of procedures (-1.3861), confirming its lower interventional burden. These findings show that patients undergoing dental treatment under general anesthesia do not represent a homogeneous clinical group, but a population with clearly expressed heterogeneity [26]. The identified profiles indicate that patient complexity cannot be reduced to a single factor, such as medical diagnosis or treatment extent, but arises from the interaction of medical, neurodevelopmental, behavioral, and treatment-related characteristics. This supports the potential value of patient stratification for more robust and personalized dental treatment planning under general anesthesia. A particularly important finding is that profile membership could be assigned with high test-set performance, with LR achieving an accuracy of 0.9219 and a macro F1-score of 0.9294. This suggests that the derived profiles can be operationally approximated from the available patient-level variables. However, because the labels were generated by clustering, these results should be interpreted as evidence of reproducible profile assignment rather than proof of externally validated clinical outcome categories.

From a clinical decision-support perspective, the profiles may help organize patients according to dominant patterns of medical complexity, neurodevelopmental burden, preventive behavior, and treatment need. Such stratification may help clinicians anticipate cases requiring more extensive planning, repeated general anesthesia, additional caregiver support, or intensive preventive follow-up. These implications remain hypothesis-generating and require validation against independent clinical outcomes before routine implementation. In addition, LR's better performance than RF suggests that the relationships between the selected predictors and profile membership are relatively clear and interpretable. Clinically, this may support earlier identification of cases with repeated need for general anesthesia, high treatment burden, or pronounced neurobehavioral complexity, as well as better resource organization and more precise treatment planning [28]. However, the results should be interpreted in light of several limitations. The silhouette scores were moderate, indicating partial overlap among profiles, and some profiles included fewer cases, which may affect model stability. In addition, the analysis was based on a single dataset; therefore, the generalizability of the findings requires caution and further external validation. Nevertheless, the findings suggest that AI-driven patient profiling is a promising approach for developing intelligent clinical decision-support systems for dental treatment planning under general anesthesia.

V. CONCLUSION

This study presents an AI-based approach to patient profiling to support dental treatment planning under general anesthesia. A two-phase framework combining unsupervised clustering and supervised multiclass classification was developed using demographic, behavioral, clinical, medical, and neurodevelopmental characteristics. Rather than predicting a single isolated clinical outcome, the approach enabled the identification of clinically meaningful patient profiles and their automated prediction. The results showed that patients treated under general anesthesia do not constitute a homogeneous population, but can be stratified into four distinct profiles with varying medical, neurodevelopmental, behavioral, and treatment-related complexities. The resulting cluster structure was clinically interpretable, and further analysis showed that the profiles differed most strongly with respect to neurodevelopmental indicators, medical complexity, previous exposure to general anesthesia, and overall treatment burden.

In the predictive modeling phase, LR achieved the best performance among the evaluated models, with an accuracy of 0.9219, a macro F1-score of 0.9294, and a weighted F1-score of 0.9196. These results indicate that the derived profile labels can be assigned from the available input data with high test-set performance. However, because the target labels were generated through clustering, this finding should be interpreted as evidence of operational profile assignability rather than as independent validation of clinical outcome relevance. Model interpretation showed that each profile was associated with a different pattern of predictors, supporting the clinical interpretability of the proposed framework.

Overall, the findings suggest that AI-driven patient profiling represents a promising approach for supporting clinical decision-making in dental treatment planning under general anesthesia [18], [21]. The proposed framework enables a better understanding of patient heterogeneity, more precise stratification according to clinical complexity, and potentially more efficient organization of treatment and resources [19].

Despite the encouraging results, future studies should validate the proposed profiles in larger, multicenter datasets and examine their association with independent clinical outcomes, such as postoperative complications, treatment duration, repeated need for general anesthesia, and long-term oral health outcomes. Such validation is necessary before the framework can be considered for routine clinical deployment. Nevertheless, the present study provides an initial interpretable profiling approach that may support more structured dental treatment planning for patients with complex needs under general anesthesia [22]..

VI. FUTURE RESEARCH DIRECTIONS

Despite the encouraging results, this study has several limitations. First, although the clustering analysis yielded clinically interpretable profiles, the low silhouette scores indicate weak geometric separation and partial overlap among profiles. This overlap is expected in real-world clinical data characterized by multidimensional heterogeneity; however, the profiles should be interpreted as overlapping phenotypic patterns rather than strictly discrete patient classes. Second, the supervised classification task used cluster-derived labels as the target variable. Therefore, high classification performance does not by itself demonstrate external clinical validity or prediction of independent outcomes, but rather indicates that the derived profiles can be operationally approximated from available patient-level variables. Future work should validate whether these profiles are associated with independent clinical outcomes not used during clustering, such as postoperative complications, treatment duration, failed or canceled appointments, repeated need for general anesthesia, or long-term oral-health outcomes. Third, the analysis was based on a single dataset from a specific patient population treated under general anesthesia, so generalizability to other institutions, healthcare systems, or patient populations remains uncertain. In addition, one profile included a relatively small number of cases, which may affect the stability of model estimates and class-level performance metrics.

Future research should focus on multicenter and external validation, larger datasets, and additional outcome-based evaluation. Methodological extensions may include comparison with alternative clustering techniques, cluster stability analysis, and evaluation of additional interpretable classifiers. These steps are necessary to further assess the robustness, clinical usefulness, and deployment potential of the proposed decision-support framework.

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