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Derivation and Validation of the Periodontal and Tooth Profile Classification System for Patient Stratification

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Abstract

Background—Our goal was to develop data analytical tools that enable the identification and definition of distinct periodontal profile and tooth profile classes (PPC/TPC) of individuals using detailed clinical measures at the tooth-level, including both periodontal measurements and tooth loss.

Materials and Methods—Full-mouth clinical periodontal measurements (7 indices) from 6,793 subjects from the Dental Atherosclerosis Risk in Communities Study (DARIC) were used to identify PPC. A custom Latent Class Analysis (LCA) procedure was developed to identify seven distinct PPC/TPC. Each PPC/TPC was associated with different clinical phenotypes. The NHANES (2009-2010/2011-2012) and the Piedmont study populations were used for validation with total of 7,785 subjects.

Results—LCA method identified members of seven distinct periodontal profile classes (PPC A-G) and seven distinct tooth profile classes (TPC A-G) ranging from health to severe periodontal disease status. The method enabled the identification of classes with common clinical manifestations that are hidden under the current periodontal classification schemas. Class

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assignment was robust with small misclassification error in the presence of missing data. PPC algorithm was applied and confirmed in three distinct cohorts.

Conclusions—These findings suggest that periodontal and tooth profile classes using LCA can provide robust periodontal clinical definitions that reflect disease patterns in the population at a subject and tooth level. These classifications potentially can be used for patient stratification and thus provide tools for integrating multiple datasets to assess risk for periodontitis progression and tooth loss in dental patients.

Abstract

Summary: Latent class analysis defined seven periodontal classes with distinct phenotypes.

INTRODUCTION

Precise stratification is an important and highly desirable goal, from both clinical and public health standpoints. In the oral health domain, accurate stratification has the promise of optimizing diagnoses, treatment decisions and overall care. For example, estimating tooth loss propensities at the individual and tooth levels can be highly informative for planning personalized, risk-based care.

Clustering methods based upon principal component analyses have been widely employed to identify microbial community structures and a combination of clinical signs that describe characteristics of the population.[1–3] However, most traditional clustering techniques neither categorize individuals to enable person-specific predictions, nor are they sensitive to change in status over time. Most existing models use person-level summary variables of clinical parameters, such as mean or extent scores for various signs of disease including plaque scores, gingival indices, probing depths, and clinical attachment levels, that reflect person-level disease and are not always linked to tooth type or tooth loss patterns. Other classifications are minimalist in nature seeking the fewest number of sites or probing measures to place individuals into mutually exclusive categories of disease status.[4, 5]

Latent class analysis (LCA) is a statistical method used to identify a set of discrete, mutually exclusive latent classes of individuals based on their responses to a set of observed categorical variables.[6] It is a data-driven, person-centered approach that considers heterogeneity among individuals that can be grouped into relatively homogeneous subclasses with similar clinical patterns or trait endorsements.[7, 8] LCA can also be used to explore the association between a set of observed categorical variables through assumed unobserved, latent classes. Researchers in numerous areas have been increasingly using LCA to discover hidden (latent) classes of individuals including the behavioral sciences[9, 10], autism[11], HIV infection[12], and asthma[13]. To our knowledge, LCA has not been used before to derive periodontal or tooth profile classes.

In this study we developed analytical procedures for implementing person-level LCA to identify discrete classes of individuals that are discriminated by tooth-level clinical parameters. We also applied tooth-level LCA to discriminate different classes of teeth using tooth/site level clinical parameters. Finally, we applied the resulting estimates as model parameters to systematically examine other large randomly sampled populations to ascertain

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whether tooth-based clinical parameters could effectively segregate different clinical periodontal classes, even in the presence of incomplete data. This study reports the derivation and validation of the LCA classes. The clinical application of this new stratification system will be presented in future reports.

MATERIALS & METHODS

Analytical Approach for Classification of Subjects into Subgroups

The analytical approach implemented person-level LCA to identify discrete classes of individuals was based upon 7 tooth-level clinical parameters, including: ≥1 site with interproximal attachment level (IAL) ≥3mm, ≥1 site with probing depth (PD) ≥4mm, extent of bleeding on probing (BOP, dichotomized at 50% or ≥3 sites per tooth), gingival inflammation index[14] (GI, dichotomized as GI=0 vs. GI≥1), plaque index[15] (PI, dichotomized as PI=0 vs. Pl≥1), the presence/absence of full prosthetic crowns for each tooth, and tooth status presence (present vs. absent). We used the Dental Atherosclerosis Risk in Community Study (DARIC) cohort (n=6793)[16] and applied the resulting estimates as model parameters to systematically examine other large-sample populations to ascertain whether tooth-based clinical parameters associated with baseline status could effectively discriminate between different clinical periodontal classes, even in the presence of incomplete data.

Individuals were classified into mutually exclusive latent classes based on their responses to a set of observed categorical variables. Criteria used to determine the optimal number of classes included the Akaike Information Criterion (AIC) and the Bayesian Information Criterion (BIC), while ensuring that clinically relevant categories were maintained. We used Milligan and Cooper's[23] recommendation for the maximum number (n) of classes, suggesting to stop when the newly-added class (n+1) is not clinically distinct from the previous number (n) of identified classes. Additionally, we verified that mean posterior probabilities of correct class assignment were >0.7, which according to Nagin[24] indicates adequate class separation and membership precision. In the first step of LCA, the person-level LCA was used to classify individuals into seven latent classes based on 224 dichotomous variables (derived from 7 tooth-level variables, using the clinical parameters referred to above for each of 32 teeth). The class membership probabilities represent the overall, unconditional proportions of individuals in each of seven latent classes. The model parameters from the first step were then used to compute the posterior probabilities (the probability of event A occurring given that event B has occurred) of each individual's membership into each class conditional upon the values of the 224 items, or as many of them as were observed for that individual.

Recognizing that individuals with periodontal disease have teeth with diagnoses ranging from health to severe disease, we carried out a tooth-level LCA analysis to capture the distribution of these tooth-specific classes within each person-level subgroup. This tooth-level analysis enabled us to refine the individual tooth status at a person-level within each Periodontal Profile Class (PPC) for risk assessment modeling. The tooth-level LCA classified teeth into 7 latent Tooth Profile Classes (TPC), based on 14 categorical clinical parameters similar to those referenced above. These 14 clinical parameters included IAL

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(<3mm=0, ≥1 site with 3 or 4mm=1, and ≥5mm=2), direct attachment level [DAL, measured at direct buccal and lingual (<3mm=0, ≥1 site with 3 or 4mm=1, and ≥5mm=2)], interproximal PD (<4mm=0, ≥1 site with 4 or 5mm=1, and ≥6mm=2), direct PD (<4mm=0, ≥1 site with 4 or 5mm=1, and ≥6mm=2), interproximal gingival recession (IGR, dichotomized as IGR≤1 vs. IGR>1), direct GR (measured at direct buccal and lingual, dichotomized as DGR≤1 vs. DGR>1), BOP (dichotomized at <3 vs. ≥3 sites per tooth), GI[14] (dichotomized as GI=0 vs. GI≥1), PI[15] (dichotomized as PI=0 vs. PI≥1), decayed coronal surface (DCS, dichotomized as DCS=0 vs. DCS≥1), filled coronal surface (FCS, dichotomized as FCS=0 vs. FCS≥1), decayed root surface (DRS, dichotomized as DRS=0 vs. DRS≥1), filled root surface (FRS, dichotomized FRS=0 vs. FRS≥1), and the presence/absence of full prosthetic crowns. These steps were carried out using the SAS PROC LCA procedure#.[6]

The LCA model parameter estimates obtained from DARIC were used to estimate the posterior class membership probabilities of three additional populations. This process involved the creation of a novel scoring algorithm that directly computed the likelihood of each class membership (using the posterior probabilities). The scoring code creates what we are referring to as the University of North Carolina (UNC) Periodontal and Tooth Profile Classes (PPC/TPC). The underlying statistical model and handling of missing data are presented in some detail in the supplemental methods. In brief, for all examined populations, an individual was classified into the latent class for which he/she had the corresponding largest posterior membership probability. As a measure of the quality of the classification assignments, the percentage of individuals with the largest class membership probability exceeding a certain threshold was determined for each study population.

Study Populations

All participants provided written informed consent to a protocol that was reviewed and approved by the Institutional Review Board on research involving human subjects at the University of North Carolina and/or at each study performance site.

DARIC participants were recruited from the ARIC population study and included dentate participants who did not have contraindications for periodontal probing.[16] The DARIC sample consisted of 6,793 individuals living in four United States communities. These subjects had full-mouth periodontal examinations at six sites per tooth, including third molars, as measured by trained and calibrated examiners.

Two additional datasets from the National Health and Nutrition Examination Survey (NHANES; 2009-2010 and 2011-2012) were used as the second study population. The technical details of the surveys, including sampling design, periodontal data collection protocols, and data availability, have been described elsewhere.[17, 18] Briefly, periodontal measurements were collected for 3,750 individuals (NHANES 2009-2010) and for 3,338 individuals (NHANES 2011-2012). The third study population was from the Piedmont 65+ Dental Study (PDS), which was based on a stratified random clustered sample of all people aged 65 and over in the five adjacent counties in the Piedmont area of North Carolina.[19] The

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PDS began in 1988 with a random subsample of 697 dentate individuals with periodontal data available. Although PDS is a longitudinal study, in this report these analysis were conducted using the baseline data. Additional population characteristics are described in detail in previous publications.[20, 21]

Statistical Analyses for Comparison of Latent Class Subgroups within Populations

The seven latent classes were compared with respect to participants' demographic characteristics in the DARIC population, which facilitated their labeling with monikers that briefly summarize the clinical impression of each class. Pearson chi-square tests were used to test for overall differences in the seven classes with respect to these characteristics and one-way ANOVA F-tests were used to test for differences with respect to periodontal variables. A conventional $p<0.05$ statistical significance criterion was used for all analyses.

Additional analyses compared periodontal status across the seven classes for each of the three validation datasets with class membership derived from the LCA model developed from the DARIC data. Sensitivity analyses with the DARIC dataset were conducted to assess the utility and performance of the LCA model for assigning members into the seven PPCs when a periodontal measure was entirely missing (e.g., data not collected). Using DARIC as the gold standard when all seven periodontal indices were available for analysis, the average posterior probabilities were calculated for each of the seven person-level and tooth-level LCA classes. The average posterior probabilities were calculated within each of the seven indices omitted singly from the DARIC dataset.

RESULTS

Periodontal and Tooth Profile Classes Derived from Tooth Level Clinical Parameters

The person-level LCA procedure enabled us to select 7 PPCs (A-G), in the DARIC population with distinct clinical phenotypes. The demographic characteristics for the 7 PPCs labeled A-G with class clinical monikers are shown in Table 1. There were significant group differences with regard to race, sex, age, diabetes, smoking (history and pack/year), obesity, access to dental care, socio-economic status, and educational level. In general, the demographics followed expected patterns with regards to the clinical phenotypes. The clinical periodontal phenotype as defined by the 7 PPCs compared to the 4-level Center for Disease Control/American Academy of Periodontology (CDC/AAP) definition[5] is shown in Table 1 and illustrates the differences in clinical presentation comparing the two classifications. For example, 45% of the CDC/AAP healthy individuals fall under the PPC-A (Healthy) class. While 29% of these CDC/AAP healthy individuals are assigned to the PPC-F (Severe Tooth Loss) class. For the CDC/AAP severe classification 32% and 26% are in PPC-E (Posterior Disease) and PPC-G (Severe), respectively.

The underlying differences in the PPC classifications based upon the seven clinical measures for all 32 teeth are illustrated in Figure 1. The posterior probabilities (1=present; 0=absence) for tooth presence vs. absence, crown presence vs. absence, IAL≥3mm, PD≥4mm, GI≥1, PI≥1, and higher BOP are shown for each tooth type (1-32) representing both arches graphically in a heatmap for each clinical parameter (Figure 1). In this figure, both the upper

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and lower arch are represented for each PPC for each tooth with green indicating high probability of tooth presence and healthy clinical signs with shifts to yellow and red indicating more disease-associated signs or tooth loss. For example, one can see that most teeth are present (except 3rd molars) with healthy clinical signs in PPC-A (Health), whereas, only mandibular anterior teeth remain with disease in PPC-F (Severe Tooth Loss). Interestingly, the person-level LCA identified a high gingivitis/inflammation group; PPC-C. PPC-E (15% of individuals) displayed posterior disease reflected in probing depths and attachment loss with the most severe disease patterns in PPC-G (7% of individuals). It is readily apparent in this figure that there is marked symmetry in disease patterns, with significant differences between arches. Importantly, these clinical patterns of disease and tooth loss represent typical patterns of disease that clinicians observe and are entirely data-derived.

The description of clinical parameters for each PPC appears in Table 2. As expected, there were significant differences among all seven PPCs, and these values were provided for descriptive and comparative purposes. PPC-A (Health) had the lowest mean extent of BOP, GI≥1, and PI≥1. The mean extent of IAL≥3mm of 8% and a mean extent of PD≥4mm of 2% were the lowest among all 7 periodontal profile classes. PPC-B (Mild Disease) was mainly characterized by a slight increase in IAL≥3mm and PD≥4mm mean extent scores, and significant higher BOP (3-fold) and GI (9-fold) when compared to PPC-A. PPC-C (High GI) was notably marked by the highest mean extent GI score among all periodontal profile classes and was seen in 10% of the population. PPC-D (Tooth Loss) was characterized by fewer teeth. PPC-E (Posterior Disease) was marked by a moderate mean extent of IAL≥3mm of 33% mainly located at the posterior dentition. PPC-F (Severe Tooth Loss) was characterized by the lowest mean number of teeth (8 teeth), where the remaining teeth were mainly mandibular anterior teeth with an edentulous maxilla and reflected 13% of the population. Finally, PPC-G (Severe Disease) was characterized by the highest mean extent of IAL≥3 mm of 54% and PD≥4 mm of 25%. Higher BOP, GI, and PI extent scores were also found in this generalized severe disease profile and was a more severe disease group than the CDC/AAP severe group (data not shown).

The tooth-level LCA procedure enabled us to identify 7 TPCs (A-G), in the DARIC population. The description of the 14 clinical parameters for each TPC is described in the Supplementary Table 1. As expected, there were significant differences among all seven TPCs, and these values are provided for descriptive and comparative purposes. For example, TPC-A included teeth with the least attachment loss, PD, BOP, recession, GI, PI, caries, and number of crowns. On the other hand, TPC-G included teeth with signs of periodontitis represented by substantial attachment loss, deep PD, high GI and PI. Supplementary Figure 1 shows the distribution of TPCs by tooth and arch for all PPCs. The percentage distribution is shown for each tooth type (1-32) representing both arches graphically in a heatmap for each PPC.

Joint Distribution of Periodontal and Tooth Profile Classes

Figure 2 shows the distribution of the seven TPCs for each of the seven PPCs. PPC-A (Health) is composed by 59% of teeth classified as TPC-A (Health), 11% as TPC-B

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(Recession), 17% as TPC-C (Crown), 2% as TPC-D (GI), 8% as TPC-E (Interproximal Disease), 3% as TPC-F (Reduced Periodontium), and less than 1% as TPC-G (Severe). Moreover, PPC-C (High GI) is mostly comprised of TPC-D (GI) teeth (53%). As expected, PPC-G (Severe Disease) is mainly composed of teeth under the TPC-G (Severe) (28%), with the other major classes being TPC-D (GI; 28%) and TPC-E (Interproximal Disease; 23%).

Periodontal Profile Class Replication/Validation Among Different Populations

Table 3 presents the results of the person-level LCA DARIC-derived model as applied to or "scored" in the three external population-based cohorts including a total of 7,785 individuals; the NHANES 2009-2010, the NHANES 2011-2012, which are both nationally-representative samples and the PDS. There were remarkable similarities in frequency distributions between the 2 NHANES datasets; the prevalence of each PPC category was either identical or within 2 percentage points. As expected, the older, more diseased and edentate PDS individuals display more disease and higher PPC class assignments.

In contrast to the DARIC population, the PDS and NHANES population datasets did not include GI, PI, BOP, or number of prosthetic crowns. Despite a substantial amount of incomplete data relative to the full-mouth periodontal assessment, the person-level LCA model produced PPCs for each validation dataset with qualitatively similar profiles as in DARIC in terms of CDC/AAP and PPC classifications, extent IAL, extent PD and number of teeth. When indices were omitted singly from the DARIC dataset, the person-level LCA model was able to allocate members into the 7 distinct PPCs with minimal misclassification error, as shown in the Supplementary Table 2. For example, the lowest posterior probability of individual assignment when BOP is missing from the dataset was 0.96 (PPC-B). When GI was excluded from the dataset the lowest posterior probability of individual assignment was 0.95 (PPC-B and PPC-D). The average posterior probability for all classes considering up to four parameters missing is shown in Supplementary Table 3. It can be observed that even with the lack of 4 clinical parameters, the lowest average posterior probability for correct class assignment was 0.90.

Mean Posterior Probabilities for Periodontal Profile and Tooth Profile Classes

Table 4 presents the mean posterior probabilities of assignment to each PPC or TPC. For example, the mean posterior probability for a person to be assigned into the PPC-A is 0.978 with a chance of 0.022 to be assigned in any other PPC. For all other PPCs the mean posterior probabilities for each person to be assigned in each PPC was extremely high, with PPC-B (Mild Disease) showing the lowest mean posterior probability of 0.96. For TPCs, the lowest mean posterior probability for each tooth to be assigned to a specific TPC was 0.823 (TPC-D). The highest mean posterior probability was 0.953 for TPC-B.

DISCUSSION

In this manuscript we describe the development and validation of a novel patient stratification system based upon the definition of periodontal and tooth profile classes. There are several strategic advantages of the proposed 7-class person-level LCA model that we are designating the University of North Carolina Periodontal Profile Class (UNC-PPC)

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classification. It includes tooth-level data on 7 clinical parameters (PD, IAL, BOP, GI, PI, missing teeth and crown restorations) with 7 PPCs that reflect typical tooth loss patterns and disease patterns that mirror what is seen by clinicians. The method does not use any *a priori* assumptions of disease patterns or characteristics to define disease states and is an agnostic approach to disease definition. For example, it does not require a certain number of teeth or sites with some predefined level of disease for class assignment. Furthermore, the algorithm can be applied robustly to other datasets or individuals for class assignment, even in the presence of partial exams (number of teeth and/or number of indices). In contrast to principal component analyses which define traits within a population[22], the LCA method defines distinct categories of members (people or teeth) with previously "hidden" combinations of characteristics, to create mutually exclusive latent classes.

It is significant that this model was developed using the DARIC cohort of 6,793 individuals, but was validated using two cross-sectional NHANES populations and the PDS longitudinal study representing a total of 14,578 individuals. Surprisingly, the effects of partial mouth examinations or missing clinical parameters did not result in significant misclassification error. In contrast to the DARIC population, clinical examinations conducted in the NHANES and PDS studies did not collect data on PI, GI, BOP, number of prosthetic crowns, and third molars. However, additional analyses (Supplementary Table 2 and 3) demonstrated the proportion of individuals misclassified when one or more of the clinical parameters were missing was minimal. Thus, the method appears rather robust as it demonstrates a relative consistency on correctly assigning individuals into classes even with some clinical parameters is completely missing. This suggests that the mapping of existing datasets to these categories to create "harmonized" data could enable a robust disease classification for bioinformatics analytics that can correctly assign individuals into classes even with incomplete clinical data (Suppl Table 2).

Although we selected seven distinct PPCs for this classification, the LCA method enabled us to choose the number of classes in the final model. We selected seven distinct classes that enabled us to create clinically relevant categories, based on the recommendation of Milligan and Cooper[23], in that an additional eighth class was not clinically distinct from the an class among the existing seven-class model. In addition, the mean posterior probabilities achieved with both person- and tooth-level LCA provided extremely high probability of correct class assignment. The lowest mean posterior probability was 0.823 (TPC-D). According to Nagin, a mean posterior probability >0.7 indicates adequate separation and classification precision.[24]

As shown in Figure 1, PPC-A was mainly associated with a healthy periodontal phenotype. PPC-B associated with a mild periodontal disease profile. PPC-C had predominantly individuals with mild pocketing and attachment loss but with much higher GI and plaque scores and higher (53%) of the gingivitis TPC-D teeth (Figure 2). PPC-D predominantly comprised individuals with moderate periodontal disease associated with more missing teeth. PPC-E was characterized by severe molar disease primarily located on posterior teeth. PPC-F was marked by the presence of mainly anterior mandibular teeth to include scattered premolars and an edentulous maxilla. Classifying individuals into distinct classes that include tooth loss and disease patterns is novel to this classification schema. PPC-G was

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predominantly composed of individuals with generalized severe periodontal disease. Interestingly, the LCA model differentiated individuals into separate clinical phenotypes that would be collapsed under the CDC/AAP classification (Table 1) as well as other common clinical classifications. For example, the CDC/AAP moderate disease group is the largest disease group with approximately 42% of individuals. Table 1 shows that individuals with moderate disease (CDC/AAP) are distributed across all PPCs with approximately 20% following into health (PPC-A) and 6% into severe (PPC-G), suggesting that these individuals with moderate disease have other important hidden or latent characteristics beyond the clinical measures used to define the CDC/AAP moderate disease category (PD, clinical attachment level, and BOP). This means that the LCA-derived definition of periodontal profile classes enables a more detailed and precise stratification than the CDC/AAP classification.

The AAP classification is based upon the presence of attachment/bone loss which reflects history of disease[4], as is the American Dental Association (ADA/AAP) classification[25] – both of which are relatively insensitive to changes in individual status, tooth loss or disease activity, but are widely used in healthcare settings. LCA is an increasingly popular statistical modeling technique used to uncover heterogeneity in response patterns or clinical characteristics within a population. LCA usage is common in the social and behavioral sciences and unlike factor analysis, which groups correlated response items, it is a person-centered approach.[26] Recently, LCA has been used to analyze data related to HIV[12], mental disorders[27], and cancer.[28] Finite mixture models, such as LCA, present an opportunity to approach subgroup analysis from a different perspective. These statistical models are appropriate when one posits that a population is comprised of two or more underlying, latent subgroups defined by the intersection of numerous individual characteristics.[29] In other words, LCA is a useful tool for identifying a set of underlying subgroups of individuals based on the intersection of multiple observed clinical characteristics. Thus, in this application the LCA successfully classified subjects into 7 periodontal classes with distinct clinical manifestations versus the 3–4 categories associated with other classifications. Admittedly, the rationale underlying nosological strategies fall under two broad philosophies “lumpers vs. splitters”” and this method provides a data-derived splitting classification. It is our contention that this reduction in heterogeneity within each PPC will ultimately enable us to better assess risk, treatment outcomes and design better precision periodontal medicine therapies.

The strengths of our study include a new stratification model developed on a large population-based sample and validated in three additional large population-based cohorts. Patient stratification based on person-level risk factors has recently been used to evaluate the outcomes of preventive care in dentistry.[30] Patient stratification aiming towards the development of personalized dentistry might be an important approach for improving preventive care. Although beyond the scope of this manuscript, the PPC/TPC classifications can offer improvements for 1) combining or “harmonizing” clinical datasets from different studies, 2) developing risk models for attachment and tooth loss and 3) providing sensitive tools for measuring the effects of therapy among differing PPC, and perhaps at a TPC level.. Potential limitations in our study include the mean age of the DARIC and the PDS populations were 62 and 73 years, respectively, thus the model was developed among older

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adults. Nevertheless, it appears to perform well among younger populations, as in the two NHANES samples (NHANES 2009-2010: mean age 51 years [range 30-80 years]; NHANES 2011-2012: mean age 52 years [range 30-80 years]). A second limitation of the LCA method lies in its “analytical sophistication”, in that it requires the application of a statistical algorithm for class assignment, rather than simple rules associated with specific periodontal measures. To overcome this shortcoming, the algorithm could be easily and efficiently made available via a web-based application, and then widely available for analyses and patient class assignment.

This study demonstrates how multiple clinical characteristics can be used to identify clinically distinct periodontal and tooth profile classes. Overall, the UNC-PPC/TPC classification represents a novel application of the LCA methodology that is promising for patient stratification and tailoring of treatment, targeting health promotion efforts and optimizing individualized treatment decisions for dental rehabilitation.

Supplementary Material

Refer to Web version on PubMed Central for supplementary material.

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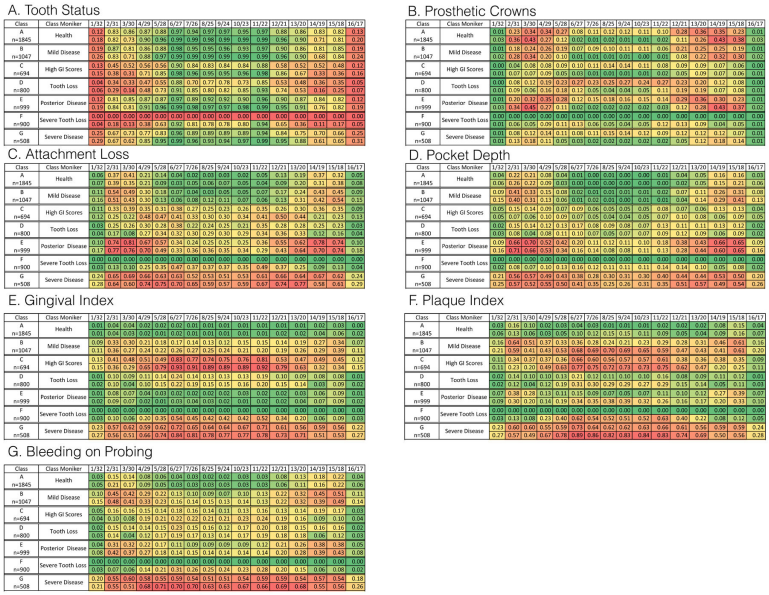

Figure 1.

Item response probabilities conditional on class membership for **A.** Tooth Status (presence or absence), **B.** Prosthetic Crowns (presence or absence), **C.** Interproximal Attachment Loss ≥3mm, **D.** Pocket Depth ≥4mm, **E.** Gingival Index (GI, dichotomized as ≥1 sites with GI≥1 vs none), **F.** Plaque Index (PI, dichotomized at ≥1 sites with PI≥1), **G.** Bleeding on Probing (BOP, dichotomized at 50% or ≥3 sites per tooth). Probabilities are illustrated for each tooth type (1-32) representing both arches graphically in a heatmap for each clinical parameter in the DARIC sample. The upper and lower arch are represented for each Periodontal Profile Class (PPC) for each tooth, with green indicating high probability of tooth presence, crown absence, and healthy clinical signs shifting to yellow and red indicating more disease-associated signs.

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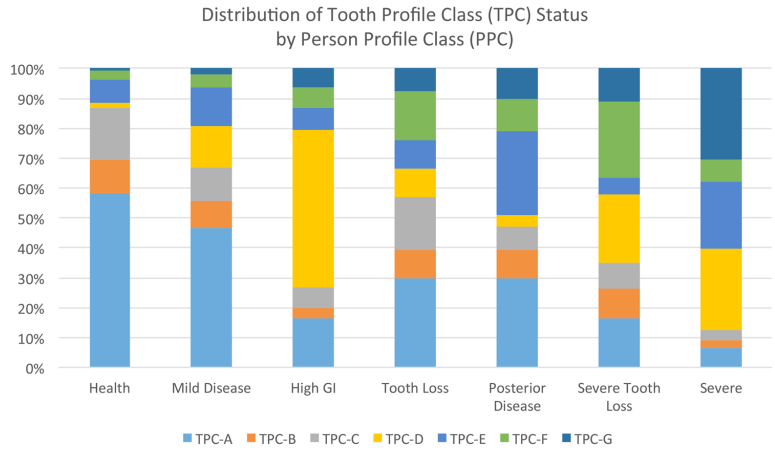

Figure 2.

Distribution of the seven Tooth Profile Classes (TPC) for each of the seven Periodontal Profile Classes (PPC). TPC-A (Health), TPC-B (Recession), TPC-C (Crown), TPC-D (GI), TPC-E (Interproximal Disease), TPC-F (Reduced Periodontium), and TPC-G (Severe Disease).

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Table 1

Demographics, risk factors, and clinical characteristics of the DARIC sample (N=6,768) stratified by Periodontal Profile Class (PPC).

LCA Classes	PPC-A	PPC-B	PPC-C	PPC-D	PPC-E	PPC-F	PPC-G	
Class Monikers	**Health n=1,845 (27%)**	**Mild Disease n=1,047 (15%)**	**High GI n=694 (10%)**	**Tooth Loss n=800 (11%)**	**Posterior Disease n=999 (15%)**	**Severe Tooth Loss n=900 (13%)**	**Severe Disease n=508 (7%)**	**p-value**
CDC/AAP Health	351 (19.0%)	93 (8.9%)	31 (4.5%)	75 (9.4%)	0 (0.0%)	225 (25.0%)	0 (0.0%)	
Mild	867 (47.0%)	402 (38.4%)	286 (41.2%)	204 (25.5%)	50 (5.0%)	207 (23.0%)	19 (3.7%)	
Moderate	582 (31.5%)	486 (46.4%)	284 (40.9%)	370 (46.3%)	573 (57.4%)	328 (36.4%)	176 (34.7%)	
Severe	45 (2.4%)	66 (6.3%)	93 (13.4%)	151 (18.9%)	376 (37.6%)	140 (15.6%)	313 (61.6%)	<0.0001
African American	62 (3.4%)	33 (3.2%)	502 (72.3%)	147 (18.5%)	17 (1.7%)	308 (34.3%)	231 (45.9%)	
Caucasian	1,777 (96.6%)	1,010 (96.8%)	192 (27.7%)	647 (81.5%)	979 (98.3%)	591 (65.7%)	272 (54.1%)	<0.0001
Female	1,227 (66.5%)	489 (46.7%)	385 (55.5%)	436 (54.4%)	445 (44.5%)	512 (56.9%)	192 (37.8%)	
Male	618 (33.5%)	558 (53.3%)	309 (44.5%)	364 (45.5%)	554 (55.5%)	388 (43.1%)	316 (62.2%)	<0.0001
Age, mean (standard error)	61.8 (0.13)	62.4 (0.17)	61.6 (0.21)	63.7 (0.20)	62.9 (0.19)	63.1 (0.19)	61.8 (0.25)	<0.0001
Diabetic	154 (8.4%)	126 (12.1%)	147 (21.7%)	125 (15.7%)	108 (10.8%)	167 (18.9%)	111 (22.2%)	
Non-Diabetic	1,688 (91.6%)	920 (88.0%)	531 (78.3%)	672 (84.3%)	888 (89.2%)	719 (81.2%)	388 (77.8%)	<0.0001
Current Heavy Smoker	86 (4.8%)	51 (5.0%)	43 (6.7%)	105 (13.7%)	136 (14.0%)	141 (16.7%)	55 (11.4%)	
Current Light Smoker	35 (1.9%)	8 (0.8%)	32 (5.0%)	17 (2.2%)	21 (2.2%)	34 (4.0%)	19 (3.9%)	
Former Heavy Smoker	245 (13.6%)	136 (13.3%)	67 (10.5%)	181 (23.7%)	223 (23.0%)	188 (22.3%)	69 (14.3%)	
Former Light Smoker	424 (24.0%)	251 (24.6%)	151 (23.6%)	133 (17.4%)	227 (23.4%)	162 (19.2%)	106 (22.0%)	
Never Smoker	1008 (55.8%)	574 (56.3%)	348 (54.3%)	329 (43.0%)	363 (37.4%)	320 (37.9%)	234 (48.5%)	<0.0001
Pack-Years, mean (standard error)	9.1 (0.47)	9.5 (0.62)	10.3 (0.80)	18.2 (0.72)	18.7 (0.64)	20.3 (0.69)	14.0 (0.91)	<0.0001
Obese	438 (23.8%)	318 (30.5%)	309 (44.7%)	285 (35.7%)	314 (31.4%)	349 (38.8%)	208 (41.0%)	
Non-Obese	1404 (76.2%)	726 (69.5%)	382 (55.3%)	513 (64.3%)	685 (68.6%)	550 (61.2%)	299 (59.0%)	<0.0001
Episodic DDS User	139 (7.6%)	165 (15.8%)	358 (52.0%)	224 (28.1%)	124 (12.4%)	524 (58.7%)	280 (55.3%)	
Regular DDS User	1,696 (92.4%)	878 (84.2%)	331 (48.0%)	573 (71.9%)	873 (87.6%)	368 (41.3%)	226 (44.7%)	<0.0001
Seen DDS > 1 Year	152 (8.3%)	166 (15.9%)	267 (38.8%)	156 (19.6%)	123 (12.3%)	405 (45.4%)	231 (46.0%)	
< 1 year	1683 (91.7%)	876 (84.1%)	422 (61.3%)	639 (80.4%)	874 (87.7%)	487 (54.6%)	271 (54.0%)	<0.0001
Income (<$25K/Year)	261 (14.6%)	178 (17.6%)	280 (43.2%)	209 (27.2%)	146 (14.9%)	386 (44.5%)	183 (38.5%)	
$25k–$50k	622 (34.9%)	379 (37.5%)	216 (33.3%)	334 (43.4%)	373 (38.2%)	329 (37.9%)	157 (33.0%)	
$50k+	901 (50.5%)	455 (45.0%)	152 (23.5%)	226 (29.4%)	458 (46.9%)	153 (17.6%)	136 (28.6%)	<0.0001
Years of Education, <12 years	100 (5.4%)	84 (8.0%)	165 (23.9%)	131 (16.4%)	59 (5.9%)	259 (28.8%)	120 (23.6%)	
12–16 years	770 (41.8%)	472 (45.2%)	223 (32.3%)	388 (48.5%)	445 (44.6%)	425 (47.2%)	197 (38.8%)	

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LCA Classes	PPC-A	PPC-B	PPC-C	PPC-D	PPC-E	PPC-F	PPC-G	
Class Monikers	**Health n=1,845 (27%)**	**Mild Disease n=1,047 (15%)**	**High GI n=694 (10%)**	**Tooth Loss n=800 (11%)**	**Posterior Disease n=999 (15%)**	**Severe Tooth Loss n=900 (13%)**	**Severe Disease n=508 (7%)**	**p-value**
17+ years	972 (57.2%)	489 (46.8%)	303 (43.9%)	281 (35.1%)	494 (49.5%)	216 (24.0%)	191 (37.6%)	<0.0001

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Table 2

Clinical parameters of the 7 Periodontal Profile Classes (PPC) in the DARIC sample.

Periodontal Profiles Classes	PPC-A	PPC-B	PPC-C	PPC-D	PPC-E	PPC-F	PPC-G	
Class Monikers	Health	Mild Disease	High GI	Tooth Loss	Posterior Disease	Severe Tooth Loss	Severe Disease	p-value
Extent IAL ≥3mm *	7.84 (0.46)	12.0 (0.61)	26.1 (0.74)	28.0 (0.69)	33.4 (0.62)	37.0 (0.65)	54.5 (0.87)	<0.0001
Extent PD ≥4mm *	2.07 (0.23)	4.27 (0.31)	4.52 (0.38)	6.61 (0.35)	14.2 (0.31)	7.41 (0.33)	24.6 (0.44)	<0.0001
Extent BOP *	11.7 (0.47)	27.7 (0.62)	24.2 (0.77)	26.4 (0.71)	24.3 (0.64)	31.7 (0.67)	61.5 (0.90)	<0.0001
Extent GI ≥1 *	2.67 (0.58)	27.6 (0.75)	92.8 (0.90)	30.1 (0.90)	5.53 (0.82)	61.5 (0.81)	82.9 (1.07)	<0.0001
Extent PQ ≥1 *	9.08 (0.67)	53.2 (0.86)	75.9 (1.06)	32.9 (1.03)	28.2 (0.93)	69.8 (0.94)	81.7 (1.24)	<0.0001
Mean Number of Teeth	26.0 (0.08)	26.1 (0.10)	20.1 (0.13)	16.8 (0.12)	25.8 (0.11)	7.74 (0.11)	24.5 (0.15)	<0.0001
Mean Number of Crowns	5.54 (0.09)	4.28 (0.13)	1.93 (0.15)	4.28 (0.14)	5.77 (0.13)	1.09 (0.14)	2.70 (0.18)	<0.0001

IAL, interproximal attachment loss; PD, probing depth; BOP, bleeding on probing; GI, gingival index; PQ, plaque;

* Extent Scores are represented as Mean (standard error), total N=6,793

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Table 3

Distribution of periodontal status by Periodontal Profile Class (PPC) for the three validation/replication datasets.

Periodontal Profile Class	PPC-A	PPC-B	PPC-C	PPC-D	PPC-E	PPC-F	PPC-G	
Class Monikers	**Health**	**Mild Disease**	**High GI**	**Tooth Loss**	**Posterior Disease**	**Severe Tooth Loss**	**Severe Disease**	**p-value**
NHANES 2009–2010 population								
N	2,015 (53%)	264 (7%)	277 (7%)	439 (12%)	188 (5%)	242 (6%)	325 (8%)	p-value
CDC/AAP Health	1,069 (53.1%)	0 (0.0%)	2 (0.72%)	51 (11.6%)	0 (0.0%)	55 (22.7%)	0 (0.0%)	
Mild	595 (29.5%)	81 (30.7%)	34 (12.3%)	75 (17.1%)	13 (6.91%)	27 (11.2%)	4 (1.23%)	
Moderate	345 (17.1%)	169 (64.0%)	204 (73.7%)	226 (51.5%)	121 (64.4%)	134 (10.3%)	106 (32.6%)	
Severe	6 (0.30%)	14 (5.3%)	37 (13.4%)	87 (19.8%)	54 (28.7%)	26 (10.7%)	215 (66.2%)	<0.0001
Extent IAL ≥3mm *	3.57 (0.38)	17.2 (1.06)	33.5 (1.04)	34.4 (0.82)	35.9 (1.26)	47.4 (1.11)	64.7 (0.96)	<0.0001
Extent PD ≥4mm *	0.46 (0.18)	5.90 (0.49)	2.38 (0.47)	7.87 (0.38)	13.6 (0.58)	5.08 (0.51)	30.3 (0.44)	<0.0001
Number of Teeth	27.1 (0.07)	28.4 (0.19)	22.2 (0.19)	15.4 (0.14)	27.9 (0.23)	7.22 (0.20)	25.3 (0.17)	<0.0001
NHANES 2011–2012 population								
N	1,772 (53%)	221 (6%)	322 (9%)	392 (12%)	180 (5%)	214 (6%)	237 (7%)	p-value
CDC/AAP Health	563 (31.8%)	0 (0.0%)	2 (0.62%)	22 (5.61%)	0 (0.0%)	36 (16.8%)	0 (0.0%)	
Mild	849 (47.9%)	16 (7.24%)	43 (13.4%)	76 (19.4%)	2 (1.11%)	33 (15.4%)	0 (0.0%)	
Moderate	352 (19.9%)	175 (79.2%)	246 (19.6%)	191 (48.7%)	99 (55.0%)	117 (54.7%)	73 (30.8%)	
Severe	8 (0.45%)	30 (13.6%)	31 (9.63%)	103 (26.3%)	79 (43.9%)	28 (13.1%)	164 (69.2%)	<0.0001
Extent IAL ≥3mm *	6.72 (0.43)	25.9 (1.21)	42.2 (1.00)	43.1 (0.91)	51.3 (1.34)	59.0 (1.23)	75.8 (1.17)	<0.0001
Extent PD ≥4mm *	0.44 (0.19)	4.32 (0.53)	1.92 (0.44)	6.52 (0.39)	10.8 (0.58)	7.01 (0.53)	23.3 (0.51)	<0.0001
Number of Teeth	27.2 (0.07)	28.2 (0.21)	22.7 (0.17)	14.8 (0.16)	28.4 (0.21)	6.91 (0.21)	25.1 (0.20)	<0.0001
Piedmont 65+ Dental Study (PDS)								
N	135 (19%)	31 (4%)	187 (27%)	159 (23%)	6 (1%)	131 (19%)	48 (7%)	p-value
CDC/AAP Health	49 (36.3%)	0 (0.0%)	8 (4.3%)	21 (13.2%)	0 (0.0%)	38 (29.0%)	0 (0.0%)	
Mild	56 (41.5%)	9 (29.0%)	31 (16.6%)	24 (15.1%)	0 (0.0%)	17 (13.0%)	0 (0.0%)	
Moderate	30 (22.2%)	16 (51.6%)	110 (58.8%)	75 (47.2%)	6 (100%)	57 (43.5%)	14 (29.2%)	
Severe	0 (0.0%)	6 (19.4%)	38 (20.3%)	39 (24.5%)	9 (0.0%)	19 (14.5%)	34 (70.8%)	<0.0001
Extent IAL ≥3mm *	10.0 (2.38)	28.2 (4.96)	47.5 (2.02)	53.2 (2.19)	50.1 (11.3)	64.4 (2.41)	81.4 (3.98)	<0.0001
Extent PD ≥4mm *	0.81 (1.05)	7.61 (2.20)	6.47 (0.90)	9.54 (0.97)	10.6 (5.00)	10.9 (1.07)	27.7 (1.77)	<0.0001
Number of Teeth	25.1 (0.97)	27.8 (0.89)	19.7 (0.55)	12.4 (0.77)	26.8 (1.37)	6.0 (0.69)	26.6 (0.70)	<0.0001

IAL, interproximal attachment loss; PD, probing depth,

* Extent Scores are represented as mean (standard error)

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Table 4

Mean posterior probabilities of class assignment for each of the periodontal and tooth profile classes (PPC/TPC).

	Post-Prob-A	Post-Prob-B	Post-Prob-C	Post-Prob-D	Post-Prob-E	Post-Prob-F	Post-Prob-G
PPC-A	**0.978**	0.007	0.000	0.006	0.010	0.000	0.000
PPC-B	0.011	**0.967**	0.003	0.004	0.012	0.000	0.002
PPC-C	0.000	0.004	**0.985**	0.006	0.000	0.000	0.004
PPC-D	0.016	0.004	0.006	**0.968**	0.006	0.000	0.001
PPC-E	0.015	0.011	0.000	0.004	**0.968**	0.000	0.002
PPC-F	0.000	0.000	0.000	0.000	0.000	**1.000**	0.000
PPC-G	0.000	0.007	0.009	0.002	0.002	0.000	**0.981**
TPC-A	**0.865**	0.000	0.055	0.078	0.001	0.000	0.000
TPC-B	0.000	**0.953**	0.000	0.001	0.012	0.032	0.001
TPC-C	0.013	0.004	**0.934**	0.011	0.037	0.000	0.000
TPC-D	0.094	0.008	0.036	**0.823**	0.031	0.007	0.001
TPC-E	0.000	0.005	0.012	0.020	**0.927**	0.018	0.018
TPC-F	0.000	0.010	0.000	0.002	0.014	**0.928**	0.046
TPC-G	0.000	0.000	0.000	0.000	0.035	0.037	**0.927**

Post-Prob, mean posterior probability of individuals or teeth to be assigned to the correct periodontal or tooth profile class.