



Graph representation of the oral cavity as a method for screening the general condition of the patient

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Abstract

AIM. To analyze the ability of the oral cavity, represented as a patient–tooth graph and processed by a graph neural network, to reflect systemic health, using the detection of concomitant cardiovascular disease as an example.

MATERIALS AND METHODS. On a large population-based cohort, each patient was represented as a heterogeneous patient–tooth graph encoding periodontal status and dentition configuration, and a Heterogeneous Graph Transformer with attention was trained. The capacity of the structure to carry a systemic signal was probed two ways: ablation of the graph structure while keeping the aggregate DMFT index and the graph contribution in a dental-chair scenario (“age, sex + tooth graph” vs “age and sex only”). The cardiovascular example comprised atherosclerotic cardiovascular disease (ASCVD) and chronic heart failure (CHF); discrimination was assessed by AUC with the DeLong test and applicability by an operating point.

RESULTS. The cardiovascular signal resided in the graph structure: removing the tooth structure while keeping the DMFT index significantly reduced AUC for both cardiovascular outcomes – CHF (-0.024 ; $p = 0.026$) and ASCVD (-0.011 ; $p = 0.032$). In the dental-chair scenario the graph yielded an AUC gain of $+0.083$ for CHF ($p = 2 \times 10^{-4}$) and $+0.030$ for ASCVD ($p = 1.5 \times 10^{-5}$); at ~ 0.80 sensitivity the model reached 0.70 – 0.74 specificity and 0.97 – 0.99 negative predictive value.

CONCLUSION. This is the first confirmation that a graph representation of the oral cavity can be “read” as a map of systemic health: the cardiovascular signal lies in the structure of the dentition and is irreducible to aggregate indices. Periodontal examination is applicable as a screening point for concomitant cardiovascular disease with referral to a physician.

Keywords: periodontitis, neural networks, computer, mouth, cardiovascular diseases, heart failure, mass screening, machine learning

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Графовое представление полости рта как способ скрининга общего состояния пациента

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Резюме

ЦЕЛЬ. Анализ способности полости рта, представленной графом «пациент – зуб» и обработанной графовой нейронной сетью, отражать системное здоровье на примере выявления сопутствующей сердечно-сосудистой патологии.

МАТЕРИАЛЫ И МЕТОДЫ. На крупной популяционной выборке каждый пациент представлен гетерогенным графом «пациент – зуб», отражающим пародонтальный статус и конфигурацию зубного ряда; обучен гетерогенный графовый трансформер с механизмом внимания. Способность структуры нести системный сигнал проверена двумя способами: удалением графовой структуры при сохранении суммарного индекса КПУ и оценкой вклада графа в сценарии стоматологического кресла (модель «возраст, пол + граф» против «только возраст и пол»). В качестве примера выбраны атеросклеротические сердечно-сосудистые заболевания (АССЗ) и хроническая сердечная недостаточность (ХСН); дискриминацию оценивали по АУС с тестом Делонга, применимость – рабочей точкой.

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РЕЗУЛЬТАТЫ. Сигнал сердечно-сосудистой патологии содержится именно в графовой структуре: удаление структуры зубов при сохранении индекса КПУ значимо снижало AUC для обоих сердечно-сосудистых исходов – ХСН ($-0,024$; $p = 0,026$) и АССЗ ($-0,011$; $p = 0,032$). В сценарии стоматологического кресла граф давал прирост AUC $+0,083$ для ХСН ($p = 2 \times 10^{-4}$) и $+0,030$ для АССЗ ($p = 1,5 \times 10^{-5}$); при чувствительности около 0,80 модель обеспечивала специфичность 0,70–0,74 и отрицательную прогностическую ценность 0,97–0,99.

ВЫВОДЫ. Получено первое подтверждение гипотезы о том, что графовое представление полости рта может «читаться» как карта системного здоровья: сердечно-сосудистый сигнал заключен в структуре зубного ряда и не сводится к суммарным индексам. Пародонтологический осмотр применим как точка скрининга сопутствующей сердечно-сосудистой патологии с направлением к врачу.

Ключевые слова: пародонтит, графовые нейронные сети, полость рта, сердечно-сосудистые заболевания, сердечная недостаточность, стоматологический скрининг, машинное обучение

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INTRODUCTION

The association between chronic periodontal inflammation and cardiovascular diseases has been recognized for many years, and its evidence base continues to strengthen. Severe periodontitis is independently associated with atherosclerotic cardiovascular diseases, with systemic inflammation, endothelial dysfunction, and bacteremia considered to be the main mechanisms underlying this association [1]. Periodontal treatment has been shown to improve endothelial function [2], while clinical and population-based studies have demonstrated associations between periodontitis and chronic heart failure [3], as well as with cardiovascular pathology in general in a bidirectional manner [4].

However, this relationship remains largely confined to population-level epidemiological observations and is rarely applied to individual assessment of systemic risk. One of the reasons is methodological: conventional approaches to summarizing dental status – cumulative indices (primarily the decayed, missing, and filled teeth index, DMFT) or individual clinical parameters – discard the spatial organization and interrelationships of the dentition, namely, information about which specific teeth are affected and how these conditions are distributed within the dental arch. Meanwhile, dentists observe this complex structure as a whole, often earlier than a cardiovascular diagnosis is formally established. Moreover, even conventional statistical approaches applied to detailed dental formula characteristics fail to capture these structural relationships [5].

The development of artificial intelligence methods in dentistry is actively progressing, including in Russian research [6; 7]; however, graph-based representation of the dentition for assessment of systemic health has not previously been investigated. A tooth and its surrounding periodontal tissues – gingiva, periodontal ligament, cementum, and alveolar bone – form a single tooth – periodontal complex [8], while adjacent and antagonistic complexes are interconnected within the dentition. This provides a natural anatomical basis for representing the oral cavity as a graph. We hypothesize

that the oral cavity, represented not as a set of isolated indices but as a graph of “patient – tooth” relationships, can serve as a map of systemic health.

Graph neural networks enable the analysis of structural patterns within such representations. A heterogeneous graph transformer can weight the contribution of individual teeth and their relationships through an attention mechanism [9], allowing the model to determine which teeth and connections are most relevant for prediction, unlike simpler graph neural networks that treat all nodes and edges with equal importance [10]. The present study provides the first evidence supporting this hypothesis by demonstrating the potential of graph-based oral representations for detecting concomitant cardiovascular pathology. This research is part of a broader program; results concerning other systemic conditions and external validation will be presented separately.

AIM

To evaluate the ability of a graph-based representation of the oral cavity processed by a graph neural network to reflect systemic health, using the detection of concomitant cardiovascular pathology (atherosclerotic cardiovascular diseases and chronic heart failure) as an example.

MATERIALS AND METHODS

The data source was a large open population-based cohort with a standardized examination protocol, including dental assessment and periodontal measurements (10,175 participants). The cohort was divided at the patient level into training, validation, and test subsets using stratification; all values reported below were calculated on the test subset. The reporting of this study follows the TRIPOD guidelines for prediction model studies [11]. The investigated outcomes were atherosclerotic cardiovascular diseases and chronic heart failure; their prevalence rates and sample sizes are presented in Table 1.

Each patient was represented as an individual heterogeneous graph, i.e., a graph containing different types of nodes (Fig. 1). The graph included two types

of nodes: one “patient” node and one “tooth” node for each existing tooth (numbered according to the FDI system). Four types of edges were defined: belongs_to and has_tooth (tooth ↔ patient), adjacent (anatomically neighboring teeth), and antagonist (occlusal contacts between teeth of opposing jaws).

Each “tooth” node was assigned a feature vector consisting of 25 parameters, including tooth presence, carious lesions, mean periodontal pocket depth, maximum clinical attachment loss, mean gingival recession, and localization-related characteristics. Thus, each node represented not an isolated crown, but a tooth–periodontal complex – a tooth together with its supporting tissues (gingiva, periodontal ligament, cementum, and alveolar bone), which anatomically and functionally form an integrated unit [8]. Therefore, the node vector combined characteristics of the tooth itself with periodontal parameters. Adjacency and antagonist edges interconnected these complexes, transforming a set of teeth into a unified relational structure – a map in which the model could identify not only “how many” teeth were affected, but also “how” pathological changes were distributed throughout the dentition.

To prevent the model from indirectly accessing the target diagnosis through variables that are part of its own definition (a phenomenon known in machine learning as label leakage), the feature vector of the “patient” node in the primary experiments was limited exclusively to sociodemographic and anthropometric characteristics. Laboratory parameters included in the diagnostic criteria of the studied conditions were excluded from this vector.

The core architecture used in this study was a heterogeneous graph transformer [9]. Unlike conventional approaches that treat all teeth and connections equally, this model learns the relative contribution of each individual tooth and each type of inter-tooth relationship to the prediction outcome.

The contribution of periodontal information was isolated using two paired comparisons with identical remaining input compositions: M5 (complete questionnaire + tooth graph) versus M1 (questionnaire only), and the dental-chair scenario M7 (age, sex + tooth graph) versus M_demo (age and sex only). To verify that the predictive signal was derived specifically from graph structure, an ablation analysis was performed. In machine learning, ablation refers to the intentional removal of a model component to assess its contribution; in this experiment, the tooth graph structure was removed from the configuration containing explicit DMFT indices.

The primary performance metric was the model’s ability to distinguish patients with the target condition from those without it (known as discrimination). This was quantified using the area under the receiver operating characteristic curve (AUC). AUC has a straightforward interpretation: it represents the probability that, for a randomly selected patient with the condition, the model will assign a higher predicted risk than for a randomly selected patient without the condition. An AUC value of 0.5 corresponds to random classification, whereas 1.0 indicates perfect discrimination.

We deliberately selected AUC as the main performance metric rather than accuracy or a single sensitivity–specificity pair. Accuracy can be misleading in the presence of rare conditions: for example, if chronic heart failure occurs in approximately 2.5% of patients, a model that classifies all individuals as “healthy” would achieve 97% accuracy while being clinically useless. Moreover, both accuracy and individual sensitivity–specificity pairs depend on the selected threshold separating “at risk” from “not at risk”, whereas AUC evaluates discrimination across all possible thresholds and is independent of this choice. The clinical threshold (operating point) was defined separately, targeting a sensitivity of approximately 0.80 (Table 2), thereby translating overall discriminative ability into a practical rule for identifying positive cases.

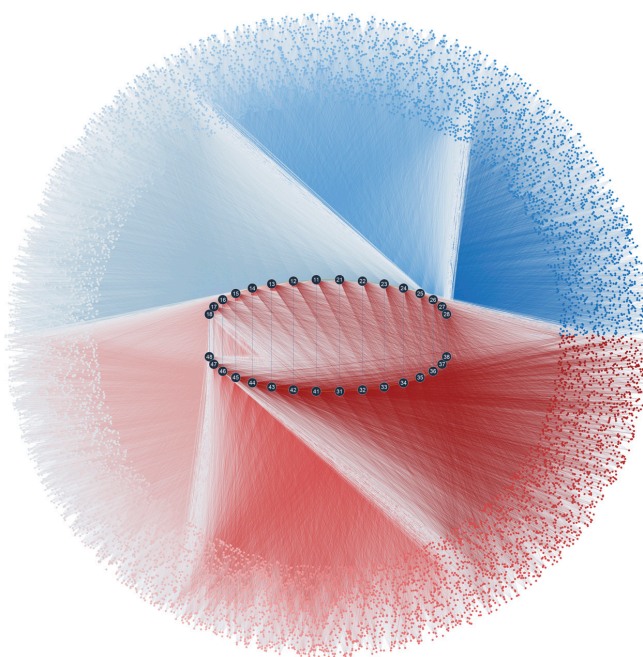


Fig. 1. Heterogeneous patient-tooth graph (10,175 patients): Color codes the patient’s HGT prediction – the probability of having a cardiovascular disease, based on the cohort rank (percentile), not the absolute value: blue – patients considered healthy by the model (low predicted cardiovascular risk, lower ranks); red – patients with a high predicted cardiovascular risk (upper ranks); gray – the middle of the scale: patients with an average risk rank, whom the model confidently classifies as neither healthy nor at risk

Рис. 1. Гетерогенный граф «пациент – зуб» (10175 пациентов): цвет кодирует предсказание HGT по пациенту – вероятность наличия сердечно-сосудистой патологии, причем по рангу внутри когорты (перцентиль), а не абсолютное значение: синий – пациент, которого модель считает здоровым (низкий предсказанный сердечно-сосудистый риск, нижние ранги), красный – пациент с высоким предсказанным сердечно-сосудистым риском (верхние ранги), серый – середина шкалы: пациенты со средним рангом риска, модель не относит их уверенно ни к здоровым, ни к рискованным

To compare AUC values between two models, the DeLong test was applied [12], a statistical method specifically designed for this purpose. The comparison was performed among patients with available predictions for both evaluated configurations. This approach explains why the reported Δ AUC values in the text may slightly differ from the simple difference between AUC values presented in tables, where each configuration was calculated using all available observations.

Uncertainty estimates (95% confidence intervals) were obtained using bootstrap resampling, involving repeated calculations on randomly sampled subsets of the original dataset. Differences were considered statistically significant when $p < 0.05$ and the confidence interval did not include zero.

The practical clinical utility of the models was additionally assessed using decision curve analysis [13], which evaluates whether clinical decision-making based on the model provides greater benefit compared with the strategies of examining all patients or examining none. Finally, predicted probabilities were calibrated by adjusting model outputs so that the predicted probability corresponded to the observed prevalence of the condition. All analyses can be reproduced using the stored patient-level predictions.

RESULTS

The explicit addition of patients' DMFT indices to the graph-based model did not result in a significant improvement in predictive performance – the model was already able to extract this information through graph structure and attention mechanisms.

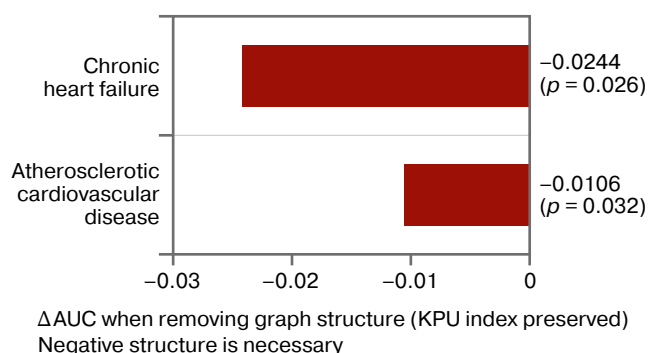


Fig. 2. Ablation of the tooth-graph structure (DMFT index retained): change in AUC for the two cardiovascular outcomes – atherosclerotic cardiovascular disease and chronic heart failure (a negative value indicates that the prognosis worsens without the graph structure, i.e., it is necessary; the change is statistically significant for both)

Рис. 2. Абляция графовой структуры зубов (индекс КПУ сохранен): изменение AUC для двух сердечно-сосудистых исходов – атеросклеротические сердечно-сосудистые заболевания и хроническая сердечная недостаточность (отрицательное значение означает, что без графовой структуры прогноз ухудшается, т.е. она необходима; для обоих исходов изменение статистически значимо)

The opposite experiment was decisive: removal of the tooth graph structure while retaining DMFT indices resulted in a statistically significant decrease in AUC for both cardiovascular outcomes: chronic heart failure (-0.024 ; $p = 0.026$) and atherosclerotic cardiovascular diseases (-0.011 ; $p = 0.032$) (Fig. 2).

Thus, the cardiovascular signal is embedded specifically in the configuration of the dentition and cannot be reduced solely to “how many” teeth are affected.

The contribution of graph structure to the detection of cardiovascular pathology is presented in Fig. 3 and Tables 1 and 2. When a complete questionnaire was available (M5 vs M1), the addition of the graph significantly improved discrimination for cardiovascular diseases (Δ AUC = $+0.014$; $p = 0.032$) and heart failure (Δ AUC = $+0.042$; $p = 0.029$).

In the dental-chair scenario (M7 vs M_demo), which included only age, sex, and dental examination data, the contribution of the graph was more pronounced: Δ AUC = $+0.030$ for cardiovascular diseases ($p = 1.5 \times 10^{-5}$) and $+0.083$ for heart failure ($p = 2 \times 10^{-4}$). The absolute AUC values of the dental-chair model were 0.834 and 0.823, respectively (Table 1).

The paired Δ AUC improvements reported in the text were calculated using the DeLong test on the subset of patients with valid predictions for both configurations and therefore may not correspond exactly to the difference between the AUC values presented here.

At the operating point with a sensitivity of approximately 0.80 (Table 2, Fig. 3, B), the dental-chair model demonstrated a high negative predictive value (0.97–0.99), corresponding to the profile of a reliable risk-exclusion tool: patients with a negative result are highly unlikely to have the target pathology, whereas patients with a positive result can be referred for further evaluation by an internal medicine specialist.

In the decision curve analysis, configurations incorporating the graph structure provided greater net clinical benefit than the reference strategies of “treating all” and “treating none” for both cardiovascular outcomes.

Table 1. Cardiovascular outcomes: prevalence and area under the ROC curve (AUC) for the four configurations in the test subset

Таблица 1. Сердечно-сосудистые исходы: распространенность и площадь под ROC-кривой (AUC) четырех конфигураций на тестовой подвыборке

Outcome	n (n+)	M_demo	M1	M5	M7
ASCVD	2571 (247)	0.805	0.820	0.836	0.834
Heart failure	2574 (65)	0.739	0.774	0.824	0.823

Note. n+ represents the number of positive cases; M_demo – age and sex; M1 – questionnaire data; M5 – questionnaire data + tooth graph; M7 – age, sex + tooth graph (“dental-chair” scenario).

Примечание. n+ – количество положительных случаев; M_demo – возраст и пол; M1 – данные анкеты; M5 – данные анкеты + график зубов; M7 – возраст, пол + график зубов (сценарий «стоматологическое кресло»).

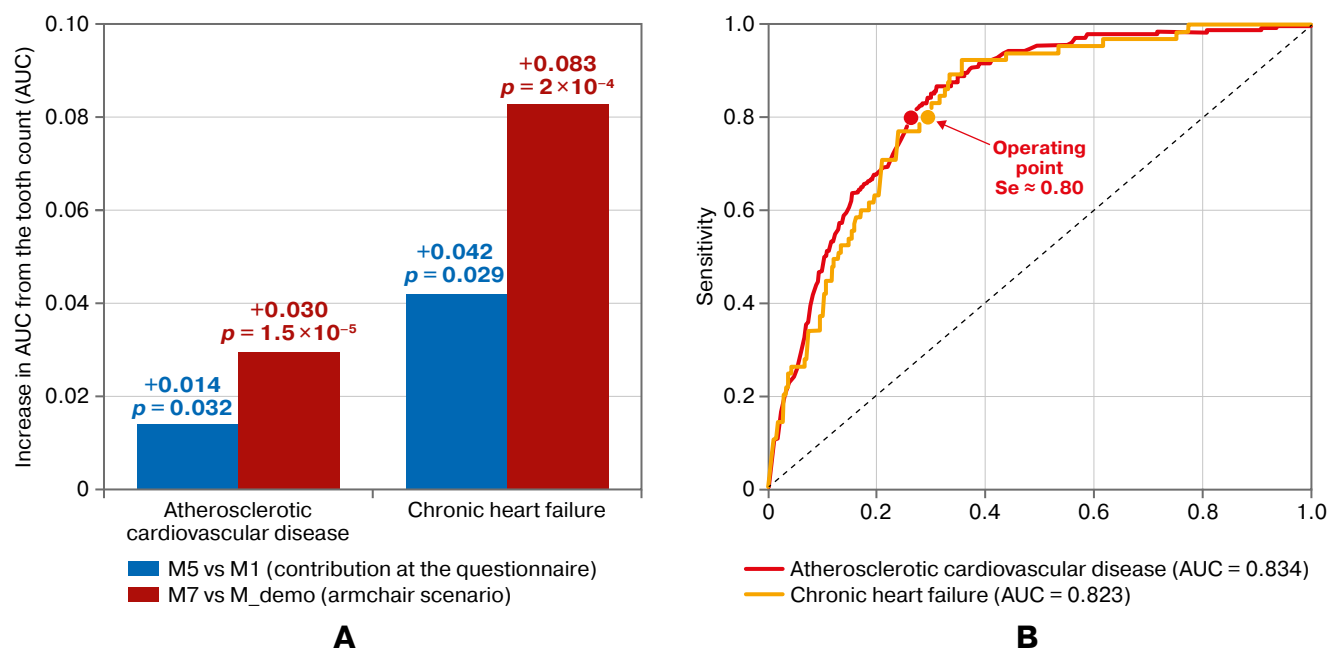


Fig. 3. Cardiovascular example: (A) AUC gain from the tooth graph for atherosclerotic cardiovascular disease and chronic heart failure in two scenarios (M5 vs M1; M7 vs M_demo); (B) ROC curves of the dental-chair model (M7)

Рис. 3. Сердечно-сосудистый пример: (A) прирост AUC от графа зубов для атеросклеротических сердечно-сосудистых заболеваний и хронической сердечной недостаточности в двух сценариях (M5 против M1; M7 против M_demo); (B) ROC-кривые модели кресла (M7)

Table 2. Operating characteristics of the dental-chair model (M7) for cardiovascular outcomes at ~ 0.80 sensitivity

Таблица 2. Рабочие характеристики модели стоматологического кресла (M7) для сердечно-сосудистых исходов при чувствительности около 0,80

Outcome	Se	Sp	PPV	NPV	Referral fraction, %
ASCVD	0.80	0.74	0.24	0.97	32
Heart failure	0.80	0.70	0.07	0.99	31

Note. Se – sensitivity, Sp – specificity; PPV – positive predictive value; NPV – negative predictive value.

Примечание. Se – чувствительность, Sp – специфичность, PPV – положительная, NPV – отрицательная прогностическая ценность, referral fraction – доля направленных к врачу.

DISCUSSION

The main finding of this study is conceptual in nature. Three independent lines of evidence converge toward a single conclusion: the systemic (cardiovascular) signal of the oral cavity is embedded in the structure of interrelationships within the dentition.

First, our previously published study conducted on an independent clinical cohort ($n = 127$) demonstrated that this signal cannot be detected by conventional statistical methods, even when comprehensively applied to detailed dental formula characteristics [5]. Second, this signal cannot be reduced to the cumulative DMFT

index: removal of the graph structure while preserving the index significantly impaired prediction of cardiovascular outcomes (Fig. 2). Third, the graph-based model was able to extract this signal and transform it into a clinically applicable prediction tool (Fig. 3). Collectively, these findings provide the first evidence supporting the hypothesis that the “patient–tooth” graph can be interpreted as a map of systemic health.

The cardiovascular example was selected deliberately: the association between periodontitis, atherosclerotic cardiovascular diseases, and heart failure is supported by reproducible pathophysiological mechanisms. Chronic periodontal inflammation contributes to sustained systemic inflammatory burden, including increased levels of C-reactive protein, interleukin-6, and tumor necrosis factor- α , thereby promoting endothelial dysfunction and atherogenesis [1; 2]. The damaged epithelium of periodontal pockets serves as a gateway for recurrent bacteremia and the entry of bacterial lipopolysaccharides into the bloodstream, enhancing vascular inflammation and destabilization of atherosclerotic plaques [1]. The same systemic inflammatory and neurohumoral activation pathways contribute to myocardial remodeling and progression of heart failure [3].

Finally, the configuration of the dentition – which specific teeth are affected or lost and in what combinations – reflects the cumulative inflammatory and metabolic history of an individual. Therefore, the predictive signal is carried by the structure of interconnected tooth–periodontal complexes rather than by the total number of affected teeth.

The practical implication is that periodontal examination may serve as a screening point for concomitant cardiovascular pathology directly in the dental chair. At a sensitivity of approximately 0.80, the model based only on age, sex, and dental examination data achieved a negative predictive value of up to 0.99, representing a profile suitable for early risk exclusion and referral of potentially high-risk patients to a physician.

This improvement is unlikely to represent a random finding. The effect was demonstrated not through extensive feature selection, but through a predefined comparison performed on the same patients: only the graph structure was removed from the model while all other information remained unchanged. The decrease in AUC was confirmed by the DeLong test, with confidence intervals not crossing zero. The effect was consistently reproduced in two independent scenarios – with a full questionnaire and in the dental-chair setting – and across both cardiovascular outcomes.

Moreover, the direction of the observed effect corresponds to biological expectations: the association between periodontal disease, atherosclerosis, and heart failure is supported by established pathogenic mechanisms, making improved prediction of these

outcomes biologically plausible. When a stable predictive effect aligns so closely with a predefined biological hypothesis, the likelihood that it represents a chance observation becomes substantially less probable.

CONCLUSION

The oral cavity represented as a “patient–tooth” graph and processed by a graph neural network can contain an interpretable signal of systemic health. This study provides the first confirmation of this hypothesis using concomitant cardiovascular pathology as an example.

The signal is embedded specifically in the graph structure of the dentition and cannot be reduced to the cumulative DMFT index: removal of the graph structure significantly worsens the predictive performance for chronic heart failure (CHF) and atherosclerotic cardiovascular diseases (ASCVD).

In the dental-chair scenario (age, sex, and clinical examination), the model identifies concomitant cardiovascular pathology with a negative predictive value of 0.97–0.99, supporting its potential role as a screening tool and a method for referring patients for further medical evaluation.

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