RESEARCH ARTICLE

Effects of occupational risk factors on dental diseases in industrial workers: a machine learning approach

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ARTICLE INFO

ABSTRACT

Objective: Dental disease is a longstanding global health problem, yet the role of occupational exposures in its development is underexplored. Using a large occupational health dataset of 66,449 industrial workers, this study investigates the relationship between occupational risk factors and dental diseases. This study investigates the relationship between occupational risk factors and dental diseases in a large industrial workforce.

Methods: A cross-sectional study was conducted on a dataset comprising 66,449 industrial workers to examine associations between occupational risk factors and the prevalence of dental diseases, including residual roots, missing teeth, dental caries, periodontal disease, deposits on dental hard tissues, and other dental diseases. Machine learning was employed to evaluate the relationship between occupational exposures and dental disease outcomes.

Results: Noise exposure (alone and in combination with dust) was associated with a higher predicted likelihood of periodontal disease in machine learning analyses, although these estimates should be interpreted cautiously given the low prevalence of periodontal disease in this screening dataset. Age and sex were associated with selected oral disease outcomes. Oral disease patterns also varied by industry sector, with exploratory associations between dental caries and employment in the power supply and metal structure manufacturing sectors. Enterprise size was associated with several oral health outcomes.

Conclusion: This study identifies associations between demographic and occupational exposures and screening-detected oral disease outcomes in an industrial workforce. Future research should validate these findings in prospective studies and evaluate workplace-based prevention strategies that address potentially modifiable exposures and barriers to oral healthcare.

1. Introduction

Dental diseases are among the most widespread non-communicable conditions globally, affecting an estimated 3.5 billion people, with dental caries being the most common condition across all age groups worldwide.[1] Severe periodontal disease impacts around 10% of the global population and is associated with systemic inflammation, increasing the risk for cardiovascular diseases, diabetes, and adverse pregnancy outcomes.[2]

Despite significant advances in dental prevention and treatment, oral health inequalities persist, particularly among low-income groups and workers exposed to occupational hazards.[1,3] Preventive strategies at both the individual and community level, such as oral hygiene education, regular dental visits, and water fluoridation are often underuti-

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┌─────────────────────────────────────────────────────────────┐
│ Collect the occupational health examination records of the    │
│ occupational disease prevention and control hospitals in       │
│ Jiangmen City from 2023 to 2024                                │
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                    │
                    │──────────┌──────────────────────────────────┐
                               │ 95,379 participants were collected│
                               └──────────────────────────────────┘
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Data aggregation: Identify the necessary variables to be included and synthesized, combine the collected information into a single dataset	Data cleaning: Check the value range of each data item and record the data that exceeds the expected range. Merge the data items with the same meaning but different expressions	Data transformation: Convert certain numerical variables of the individual check data into corresponding categorical or ordinal variables, while keeping the names and formats of these variables consistent

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                    ┌──────────────────────────────────────────────┐
                    │ Excluded participants without data on dental   │
                    │ disease examination and the risk factors       │
                    │ (n = 28,930)                                   │
                    └──────────────────────────────────────────────┘
                    │
┌─────────────────────────────────────────────────────────────┐
│ Bootstrap forest model analysis for participants in the dental │
│ disease examination. Optimize the modeling results by using    │
│ alternative classification algorithms (n = 66,449)            │
└─────────────────────────────────────────────────────────────┘
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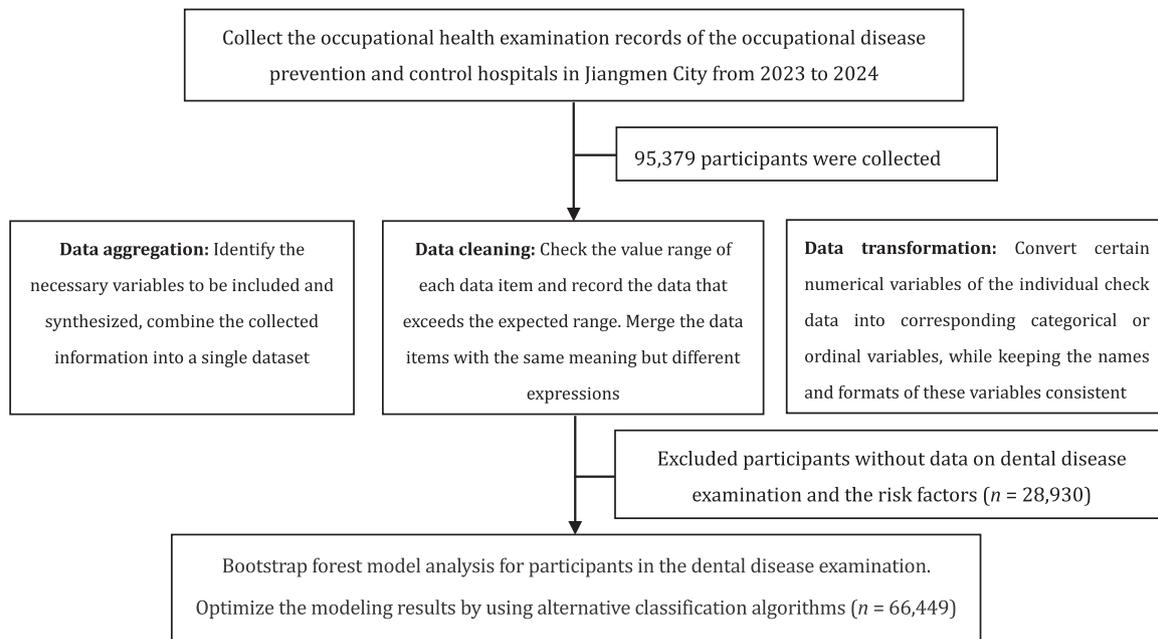
Fig. 1. Flow chart of the steps of analysis performed in the study.

lized in occupational populations.[4] Worldwide, the burden of dental disease is substantial, affecting productivity, well-being, quality of life, and healthcare expenditure.[5]

Occupational exposure refers to contact with physical, chemical, biological or psychosocial hazards arising from work-related activities. Its impact on general health has been increasingly studied. In occupational settings, particularly among industrial, mining, construction, agricultural, and healthcare, workers are frequently exposed to chemical agents such as acids, solvents, metals, and dusts,[6-9] physical agents including radiation,[10] heat, dehydration, and noise,[11] as well as biological hazards such as pathogenic microorganisms. These exposures may contribute to dental diseases directly or indirectly.

While the association between occupational exposures and systemic health conditions is well documented,[12] and oral health recognized as an integral component of general health, it has received comparatively limited attention in occupational health research. In particular, the impact of occupational exposures on oral health has not been explored explicitly in large occupational population-based studies. For example, previous research has primarily focused on highlighting musculoskeletal disorders,[13] percutaneous injuries,[14] and stress-related conditions,[15] and few studies have assessed the broader working population and occupational risk factors with oral health outcomes.[16,17]

To address these research gaps, this study aimed to explore the relationship between occupational risk factors and dental diseases in a large industrial population, while controlling for confounding factors. Traditional regression models often struggle with data that is high-dimensional, nonlinear, and multi-level, making it difficult to capture complex variable relationships. As a result, these traditional models may have limited generalization ability and may not meet the needs of multi-level prevention and control. In contrast, ensemble machine learning models like AdaBoost, Bootstrap Forest, Decision Tree, Neural Boosted, and Naive Bayes, and XGBoost are more adaptable. They can more effectively uncover patterns in high-dimensional data, handle nonlinear relationships and interactions, and improve predictive accuracy in scenarios with multiple risk factors. Accordingly, this study adopts an exploratory analytic framework, incorporating multiple demographic and occupational variables to evaluate associations, rather than to infer causality. For the present study, we used predictive machine learning models to identify key predictors, evaluate classification performance, and generate actionable insights to inform targeted occupational oral health prevention and interventions.

2. Methods

2.1. Study population

This study employed a cross-sectional design and analyzed occupational health examination data collected in Jiangmen, Guangdong Province, between January 2023 and December 2024. The dataset included health records of 95,379 individuals who underwent occupational health assessments during the study period. After excluding 28,930 records with missing data on oral disease, age, gender, industry type, economic type, enterprise size, and job type, the final sample comprised 66,449 records. Each participant was comprehensively assessed on 386 health examination items, including demographic information, occupational classifications, clinical measurements, and laboratory indicators (Fig. 1). All data were de-identified before analysis to protect participant identity and confidentiality.

To ensure the quality and integrity of the dataset, a structured four-phase preprocessing procedure was implemented. In the first phase, data aggregation was conducted to consolidate multiple or repeated records from the same individual. The second phase involved individual data cleaning, which included identifying and handling missing values, detecting and resolving outliers, and correcting inconsistencies across key variables. In the third phase, data transformation, all variable formats were standardized, and categorical data were encoded for statistical analysis. Finally, the fourth phase, data reorganization, ensured the dataset was appropriately structured for downstream statistical modeling and machine learning analysis

2.2. Ethical approval and consent to participate

The study was reviewed and approved by the Griffith University Human Research Ethics Committee (GU Ref No: 2023/325). Written informed consents were obtained from participants included in the study.

2.3. Data aggregation

The collected information included personal details of the participants (e.g. examination ID, name, gender, ID number, age), work-related information (e.g. industry, economic type, enterprise size, exposure to hazardous factors, years of exposure, and job type), examination information (e.g. examination package, examination category, examination conclusion, handling suggestions), and examination indicators (various examination results). Subsequently, the above-mentioned examination information from 24 months (2023–2024) were merged into a single dataset. Age was converted into four age groups (< 20, 20–< 40, 40–< 60, and ≥ 60) for descriptive analysis. Finally, categorical character variables of the examination information were converted into corresponding numerical coded variables based on a pre-designed coding menu.

2.4. Individual data cleaning phase and data transformation

Based on the coding menu, the value range of each data item was checked, and data falling outside the expected range was recoded. For cases where the same meaning was expressed differently (e.g., "X-ray" and "x-ray" in hazardous factors), the values were merged. Data were checked for outliers, and incorrect characters or numerical variables (e.g., entry errors) were directly deleted. Examination items with excessively high missing rates were removed.

Based on the coding menu, all variable formats were standardized. During statistical dataset processing, the name and format of this variable were kept consistent.

2.5. Data reorganization for dental diseases and risk factors

2.5.1. Risk factors of dental diseases identification

Oral conditions were identified during routine occupational health examinations conducted by trained dental professionals according to standardized protocols. Residual roots were defined as retained tooth roots in which the coronal enamel structures were absent, often due to advanced dental caries or tooth fracture. Missing teeth refer to the complete absence of a tooth, commonly due to caries, periodontal disease, or tooth extraction. The category residual roots and missing teeth indicated the presence of both conditions. Dental caries was diagnosed based on the clinical detection of cavitated carious lesions and recorded as present or absent, detailed measures of caries severity were not available. Periodontal disease was recorded as present or absent during assessment, and detailed periodontal parameters such as probing depth, clinical attachment loss, or bleeding on probing were not available. Deposits on hard dental tissues indicated the presence of visible dental deposits, including calculus. The category other dental diseases included oral conditions not classified elsewhere, such as non-carious tooth loss (including erosion, attrition, abrasion, and abfraction), periapical disease, and other significant oral abnormalities.

The present study aimed to assess the prevalence of dental diseases and related risk factors in the selected population. After excluding participants with incomplete data on dental diseases, gender, age, years of exposure, hazardous factors, job type, industry sector, enterprise size, and business type, 66,449 participants were included in the subsequent analysis (Fig. 1). Based on the examination results, participants' oral conditions were categorized into the following eight groups: no abnormality, residual roots, missing teeth, residual roots and missing teeth, dental caries, periodontal disease, deposits on dental hard tissue, and other dental diseases. Outcome categories were coded as mutually exclusive based on the recorded diagnostic category in the occupational health record.

Sociodemographic and occupational variables were categorized according to standardized occupational health records. Age was grouped into four categories (< 20, 20–< 40, 40–< 60, and ≥ 60) for descriptive analyses, while sex was recorded as male or female. Job type (occupation) was classified based on the primary workplace and task recorded at the time of examination and included categories such as operator, electrician, nuclear power plant maintenance worker, and other occupations. Industry sector was classified according to the primary workplace and included power supply, paint manufacturing, metal structure manufacturing, electronic circuit, nuclear power generation, and general hospital. Enterprise (economic) type was classified according to ownership structure as state-owned enterprise, private limited liability company, foreign-invested enterprise, other limited liability company, or joint-stock company. Enterprise size was classified as micro, small, medium, or large. Occupational hazard exposures were categorized based on workplace exposures, such as noise, noise and dust, noise and other exposures, electrical work at height, electrical work at height combined with other hazards, X-ray radiation, X-ray combined with other hazards, organic solvents, organic solvents combined with other hazards, dust combined with other hazards, and high temperature.

2.5.2. Data reorganization and model input variables

For analytical purposes, these occupational hazard variables were further reorganized into consolidated exposure categories used in subsequent machine learning analyses.

Gender, age, job type, industry type, enterprise size, economic type, and occupational hazard factors were included as input variables in the machine learning models.

2.6. Statistical analysis

All analyses were performed using JMP software (version 18.2) and SPSS (version 30.0). Descriptive statistics were first used to summarize the demographic, occupational, and clinical characteristics of the study population. Continuous variables were expressed as means with standard deviations (SD), and categorical variables were presented as frequencies and percentages. Differences between groups were evaluated using appropriate statistical tests: the chi-square test for categorical variables and the independent t-test or ANOVA for continuous variables, depending on distributional assumptions. Machine learning predictive models were used to estimate the likelihood of dental disease outcomes based on occupational and demographic factors. To evaluate the predictive relationship between occupational and clinical variables and the presence of dental diseases, supervised machine learning algorithms were implemented. The dataset was divided into 60% training and 40% validation subsets with internal cross-validation applied within the training dataset for machine learning analysis including Bootstrap Forest, Decision Tree, Neural Boosted, and Naive Bayes to optimize the modeled results.

The machine learning model provides model-derived estimates with associated uncertainty, reported here as estimates and standard errors to facilitate interpretation of variable-outcome associations.

The model was evaluated for overfitting by comparing performance metrics such as entropy R^2 and root average squared error (RASE) in both training and validation sets. Feature importance was assessed to identify the most influential predictors within the model.

Particular attention was paid to potential class imbalance, which was examined using confusion matrices and misclassification rates. These models were selected to provide comparative insights across varying model complexities and assumptions. The synthetic minority oversampling technique with edited nearest neighbor (SMOTE-ENN) method was used to address class imbalance in the training dataset prior to model fitting. The model performance was evaluated after resampling. Performance evaluation metrics included validation area under the receiver operating characteristic (ROC) curve (group-based), RASE, and classification accuracy. Hyperparameter tuning was conducted using grid search and cross-validation where applicable to ensure independent model assessment. Prior to model training, all data were preprocessed, including normalization of continuous features and encoding of categorical variables. The target outcome was classified into multiple categories based on diagnostic status.

Machine learning analysis was performed to evaluate associations between occupational risk factors and oral disease outcomes, incorporating multiple demographic and occupational variables, including age, sex, industry sector, enterprise size, economic type, and occupational hazard category. Age was converted into four age groups (< 20, 20–< 40, 40–< 60, and ≥ 60) for descriptive analyses and included as a continuous variable in the machine learning model.

P-values are reported to provide an indication of uncertainty around the machine-learning-derived estimates and were interpreted cautiously with this exploratory analysis.

3. Results

3.1. Demographic characteristics

The study population of 66,449 individuals was predominantly male (79.10%), with a mean age of (38.76 ± 10.03) years. The largest age group was 20–< 40 years old, comprising 52.1% of participants. Most participants (43.2%) were employed in medium-sized enterprises, with the most prevalent job type being operator (18.2%). Hazard factors showed significant variability, with noise or noise together combined with other risk factors being the most common exposure (55.06%) (Table 1).

3.2. Machine learning model based on the results

Among all machine learning models, the Bootstrap Forest model was selected as the optimal model based on the R^2, RASE and classification rate (Table 2). The Bootstrap Forest model explained 17.60% and 14.94% of the total R^2 in the training and validation datasets, respectively, and achieved RASE values of 0.559 and 0.561 that were lower than those of other machine learning models, including Decision Tree, Neural Boosted, and Naïve Bayes. The misclassification rate for the Bootstrap Forest model was 0.305.

3.3. Machine learning model performance

In this study, the SMOTE-ENN was applied to the training dataset to address class imbalance prior to model fitting; performance was evaluated on the hold-out validation dataset. Model performance was evaluated in the validation dataset. The evaluation of the model performance metrics is shown in Table 2, and the ROC curves for each model are shown in Fig. 2. Among all the evaluated models, the Bootstrap Forest model demonstrated the best performance, with an area under the curve (AUC) value of 0.720, an accuracy of 69.5%, indicating acceptable discriminatory ability for predicting dental disease outcomes. The ROC values for the seven dental diseases (residual roots, missing teeth, residual roots and missing teeth, dental caries, periodontal disease, deposits on dental hard tissue, other dental diseases) were: 0.683, 0.688, 0.722, 0.781, 0.805, 0.765, 0.632, respectively.

3.4. Association between occupational hazard risk factors and dental diseases

Machine learning models identified key predictors of dental diseases (Table 3), and evaluated associations between demographic and occupational risk factors and dental disease outcomes (Table 4), using age, sex, industry sector, enterprise size, economic type, and occupational hazard category as model inputs.

For periodontal disease, machine learning analysis suggested a higher predicted likelihood among workers exposed to noise (Estimate = 0.514, SE = 0.168, P = 0.002) and combined noise and dust (Estimate = 0.463, SE = 0.165, P = 0.005), and organic solvents (Estimate = 0.385, SE = 0.195, P = 0.048); however, given the low prevalence of periodontal disease in this screening dataset, these estimates

Table 1
Characteristics of the population in Jiangmen occupational prevention and control hospital from 2023-2024 [n (%)].

Characteristics	Data
Gender	
Male	52,564 (79.1)
Female	13,885 (20.9)
Age group	
< 20 years	614 (0.9)
20–< 40 years	34,631 (52.1)
40–< 60 years	30,789 (46.3)
≥ 60 years	415 (0.6)
Hazard factors	
None	578 (0.9)
Noise	13,274 (20.0)
Noise and dust	16,057 (24.2)
Noise and other exposure	7254 (10.9)
Electrical work at heights	2825 (4.3)
Electrical work at heights and other exposure	4350 (6.5)
X-ray radiation	3421 (5.1)
X-ray and other exposure	130 (0.2)
Organic solvents	6769 (10.2)
Organic solvents and other exposure	3815 (5.7)
Dust and other exposure	2629 (4.0)
High temperature	427 (0.6)
Others	4920 (7.4)
Industry	
Power supply	5144 (7.7)
Paint manufacturing	3234 (4.9)
Metal structure manufacturing	1988 (3.0)
Electronic circuit manufacturing	2057 (3.1)
Nuclear power generation	1709 (2.6)
General hospital	1902 (2.9)
Others	50,415 (75.8)
Economic type	
State-owned enterprise	3855 (5.8)
Private limited liability company	7592 (11.4)
Foreign-invested enterprise	2912 (4.4)
Other limited liability company	29,277 (44.1)
Joint-stock limited company	5064 (7.6)
Other enterprises	17,749 (26.7)
Size of enterprise	
Large	11,744 (17.7)
Medium	28,700 (43.2)
Small	23,035 (34.7)
Micro	2870 (4.3)
Others	100 (0.2)
Job type / Occupation	
Operator	12,083 (18.2)
Electrician	3848 (5.8)
Nuclear power plant maintenance worker	1630 (2.5)
Press operator / Stamping worker	898 (1.4)
Welder	3516 (5.3)
Production worker	1912 (2.9)
Grinding worker	1842 (2.8)
Maintenance worker	618 (0.9)
Others	40,102 (60.4)
Dental illness	
No abnormality	46,143 (69.4)
Residual roots	2208 (3.3)
Missing teeth	8069 (12.1)
Residual roots and missing teeth	1375 (2.1)
Dental caries	520 (0.8)
Periodontal disease	788 (1.2)
Deposits on dental hard tissues	2881 (4.3)
Other dental diseases	4465 (6.7)

should be interpreted cautiously. Employees in the electrical work at height and other duties were predicted to have a higher likelihood of residual roots (Estimate = 0.436, SE = 0.114, P < 0.001) and missing teeth (Estimate = 0.483, SE = 0.180, P = 0.007). The combination of residual roots and missing teeth outcome was more prevalent in the electrical work at height and other (Estimate = 0.619, SE = 0.127, P < 0.001) and employees engaged solely in electrical work at height (Estimate = 0.490, SE = 0.107, P < 0.001) sectors. Additionally, workers

Table 2
Machine learning screening procedure.

Method	Number (n)	Entropy R^2	Misclassification rate	AUC	RASE	Generalized R^2
Training subset						
Bootstrap forest	39,869	0.077	0.305	0.720	0.559	0.176
Decision tree	39,869	0.061	0.305	0.674	0.561	0.142
Neural boosted	39,869	0.055	0.305	0.667	0.563	0.130
Naive bayes	39,869	0.045	0.305	0.650	0.564	0.106
Validation subset						
Bootstrap forest	26,580	0.064	0.306	0.681	0.561	0.149
Decision tree	26,580	0.057	0.306	0.664	0.562	0.132
Neural boosted	26,580	0.055	0.306	0.665	0.563	0.130
Naive bayes	26,580	0.044	0.306	0.648	0.565	0.106

RASE: root average squared error; AUC: area under the curve.

Table 3
Contribution to each factor using Bootstrap Forest model.

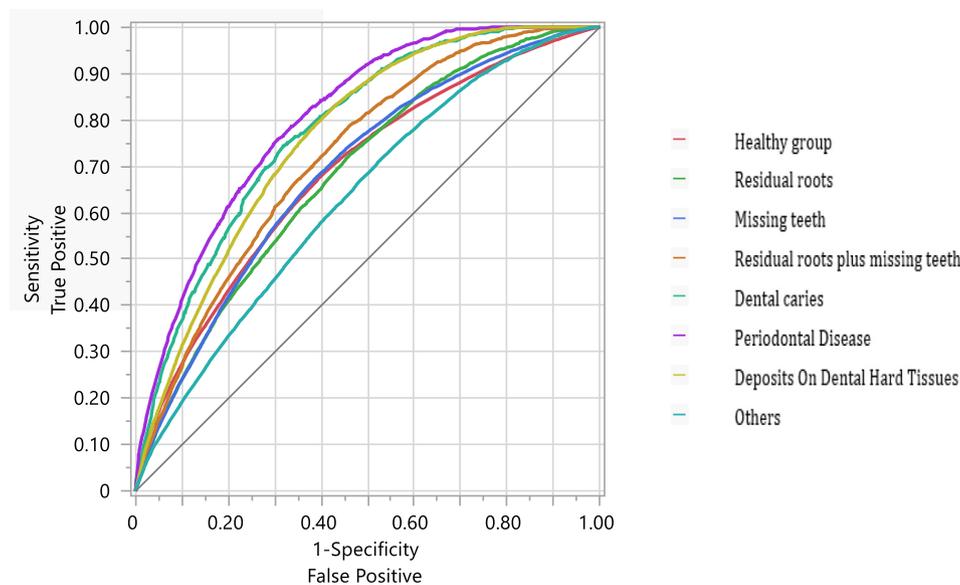| Term	Number of splits (n)	G^2	Matrix	Portion
Age	373	1785.99502		0.399
Occupational hazard category	5743	673.565768		0.150
Sex	292	601.936536		0.135
Economic Type	4119	600.689616		0.134
Enterprise size	2699	414.526508		0.093
Industry	1950	394.940426		0.088

Fig. 2. Receiver operating characteristic curves on validation data.

exposed to X-rays were predicted to have a higher likelihood of residual roots (Estimate = 0.359, SE = 0.118, P = 0.002). Workers in electrical work at height (Estimate = 0.419, SE = 0.146, P = 0.004) and those exposed to the combined electrical work at height and other hazards (Estimate = 0.678, SE = 0.164, P < 0.001) were predicted to have a higher likelihood of other dental diseases.

Machine learning analysis indicated that oral disease categories varied by industry sector. For instance, employees in the power supply sector showed higher predicted likelihoods for several outcomes, including periodontal disease (Estimate = 0.764, SE = 0.386, P = 0.048) and other dental diseases (Estimate = 0.471, SE = 0.148, P = 0.002), and an exploratory association with dental caries (Estimate = 0.444, SE = 0.210, P = 0.035). Workers in paint manufacturing had a higher predicted likelihood of missing teeth (Estimate = 0.291, SE = 0.138, P = 0.035), residual roots and missing teeth (Estimate = 0.218, SE = 0.094, P = 0.021). Staff in metal structure manufacturing had a higher predicted likelihood of missing teeth (Estimate = 0.977, SE = 0.138, P < 0.001), dental de-

posits (Estimate = 0.799, SE = 0.206, P < 0.001) and other dental diseases (Estimate = 0.380, SE = 0.148, P = 0.010), and an exploratory association with dental caries (Estimate = 0.880, SE = 0.177, P < 0.001). Electronic circuit manufacturing workers had higher predicted likelihoods of periodontal disease (Estimate = 0.751, SE = 0.257, P = 0.004). Employment in the general hospital industry demonstrated a higher predicted likelihood of residual roots (Estimate = 0.655, SE = 0.171, P < 0.001), residual roots and missing teeth (Estimate = 0.568, SE = 0.200, P = 0.005), and other dental diseases (Estimate = 0.722, SE = 0.273, P = 0.008). Workers in the nuclear power generation sector showed lower predicted likelihoods across multiple oral disease categories. Specifically, they were less likely to be predicted to have residual roots (Estimate = -0.304, SE = 0.094, P = 0.001), missing teeth (Estimate = -1.360, SE = 0.248, P < 0.001), combined residual roots and missing teeth (Estimate = -1.053, SE = 0.148, P < 0.001), dental caries (Estimate = -1.470, SE = 0.457, P = 0.001), periodontal disease (Estimate = -2.474, SE = 0.886, P = 0.005), dental deposits (Estimate = -0.698, SE = 0.338,

Table 4

Machine learning-derived estimates of associations between occupational risk factors and dental diseases [Estimate (SE)][a].

Characteristics	Residual roots	Missing teeth	Residual roots and missing teeth	Dental caries	Periodontal disease	Deposits on dental hard tissues	Other
Male	-0.370 (0.024) ***	-0.262 (0.035) ***	-0.276 (0.027) ***	-0.326 (0.040) ***	-0.454 (0.056) ***	0.301 (0.068) ***	1.225 (0.087) ***
Age	-0.044 (0.002) ***	-0.003 (0.003)	0.035 (0.002) ***	0.024 (0.003) ***	-0.047 (0.005) ***	0.067 (0.005) ***	0.035 (0.003) ***
Power supply	0.063 (0.107)	-0.044 (0.177)	0.201 (0.120)	0.444 (0.210) *	0.764 (0.386) *	-0.069 (0.285)	0.471 (0.148) **
Paint manufacturing	0.036 (0.077)	0.291 (0.138) *	0.218 (0.094) *	0.314 (0.182)	0.237 (0.281)	-0.108 (0.215)	0.241 (0.128)
Metal structure manufacturing	-0.288 (0.091) **	0.977 (0.138) ***	-0.010 (0.109)	0.880 (0.177) ***	-0.615 (0.362)	0.799 (0.206) ***	0.380 (0.148) *
Electronic circuit	-0.132 (0.086)	-0.454 (0.193) *	-0.129 (0.117)	-0.288 (0.262)	0.751 (0.257) **	-0.068 (0.296)	-0.494 (0.190) **
Nuclear power generation	-0.304 (0.094) **	-1.360 (0.248) ***	-1.053 (0.148) ***	-1.470 (0.457) **	-2.474 (0.886) **	-0.698 (0.338) *	-1.596 (0.286) ***
General hospital	0.655 (0.171) ***	0.240 (0.300)	0.568 (0.200) **	-0.336 (0.433)	0.941 (0.520)	0.232 (0.668)	0.722 (0.273) **
State-owned enterprise	0.355 (0.076) ***	-0.011 (0.133)	0.060 (0.089)	-0.343 (0.176)	0.121 (0.227)	-0.664 (0.277) *	0.242 (0.105) *
Private limited liability company	-0.019 (0.048)	0.081 (0.078)	0.015 (0.057)	0.196 (0.092) *	0.040 (0.137)	0.263 (0.119) *	0.048 (0.072)
Foreign-invested enterprise	-0.074 (0.064)	-0.393 (0.120) **	0.029 (0.075)	-0.378 (0.148) *	0.337 (0.163) *	-0.484 (0.202) *	-0.316 (0.107) **
Other limited liability company	-0.122 (0.032) ***	0.034 (0.054)	-0.111 (0.038) **	0.133 (0.065) *	-0.200 (0.094) *	0.072 (0.091)	-0.012 (0.048)
Joint-stock company	-0.100 (0.053)	0.102 (0.088)	-0.114 (0.065)	0.238 (0.106) *	-0.403 (0.169) *	0.322 (0.140) *	0.058 (0.082)
Size of enterprise	0.049 (0.024) *	0.141 (0.039) ***	0.042 (0.028)	0.195 (0.047) ***	-0.089 (0.068)	0.199 (0.060) ***	0.144 (0.036) ***
Noise	-0.004 (0.051)	-0.046 (0.087)	-0.006 (0.061)	1.167 (152.425)	0.514 (0.168) **	0.190 (0.137)	0.033 (0.107)
Noise and dust	-0.121 (0.048) *	-0.100 (0.083)	-0.200 (0.059) ***	1.116 (152.425)	0.463 (0.165) **	0.204 (0.131)	0.054 (0.102)
Noise and others	-0.093 (0.061)	0.041 (0.103)	-0.239 (0.076) **	0.948 (152.425)	-0.279 (0.228)	-0.076 (0.176)	-0.063 (0.122)
Electrical work at height	0.175 (0.095)	0.272 (0.152)	0.490 (0.107) ***	1.656 (152.425)	0.159 (0.331)	0.249 (0.233)	0.419 (0.146) **
Electrical work at height and others	0.436 (0.114) ***	0.483 (0.180) **	0.619 (0.127) ***	1.535 (152.425)	-0.243 (0.414)	-0.173 (0.299)	0.678 (0.164) ***
X-ray radiation	0.359 (0.118) **	-0.087 (0.200)	-0.103 (0.143)	1.382 (152.425)	-0.281 (0.397)	-0.979 (0.474) *	-0.164 (0.210)
X-ray and others	-0.063 (0.313)	-0.044 (0.614)	0.051 (0.395)	-14.429 (1829.095)	0.237 (0.984)	-0.009 (0.980)	-1.294 (0.974)
Organic solvents	-0.022 (0.063)	-0.145 (0.108)	-0.128 (0.076)	1.033 (152.425)	0.385 (0.195) *	0.052 (0.171)	-0.011 (0.124)
Organic solvents and others	-0.040 (0.073)	-0.115 (0.124)	-0.056 (0.088)	1.323 (152.425)	0.289 (0.231)	0.162 (0.187)	0.132 (0.132)
Dust and others	-0.172 (0.078) *	-0.233 (0.136)	-0.239 (0.094) *	1.089 (152.425)	-0.161 (0.279)	-0.120 (0.205)	0.082 (0.138)
High temperature	-0.248 (0.169)	0.013 (0.280)	-0.077 (0.201)	1.427 (152.425)	-0.033 (0.571)	0.263 (0.379)	-0.004 (0.267)

[a] Estimates are derived from machine learning models and represent model-based associations reflecting changes in predicted likelihoods rather than causal effects. Estimates for low-prevalence outcomes should be interpreted cautiously due to sparse data and potential model instability, reflected by large standard errors in some categories. *$P < 0.05$, **$P < 0.01$, ***$P < 0.001$.

$P = 0.039$), and other dental diseases (Estimate = -1.596, SE = 0.286, $P < 0.001$).

Our findings also show that the economic types in which employees worked were associated with differences in predicted oral health outcomes. In particular, employees working in state-owned enterprises had higher predicted likelihoods of residual roots (Estimate = 0.355, SE = 0.076, $P < 0.001$) and other dental diseases (Estimate = 0.242, SE = 0.105, $P = 0.021$). Workers in private limited liability companies were predicted to have a higher likelihood of dental caries (Estimate = 0.196, SE = 0.092, $P = 0.034$), and dental deposits (Estimate = 0.263, SE = 0.119, $P = 0.026$). Other limited liability companies (Estimate = 0.133, SE = 0.065, $P = 0.042$) had higher predicted likelihoods of dental caries. Similarly, joint-stock companies were predicted to have a higher likelihood of dental caries (Estimate = 0.238, SE = 0.106, $P = 0.025$) and dental deposits (Estimate = 0.322, SE = 0.140, $P = 0.022$).

Enterprise size was also identified as an influential predictor of dental disease outcomes. Employees in larger enterprises had higher predicted likelihoods of residual roots (Estimate = 0.049, SE = 0.024, $P = 0.038$), missing teeth (Estimate = 0.141, SE = 0.039, $P < 0.001$), dental caries (Estimate = 0.195, SE = 0.047, $P < 0.001$), dental deposits (Estimate = 0.199, SE = 0.060, $P < 0.001$), and other dental diseases (Estimate = 0.144, SE = 0.036, $P < 0.001$).

Sex and age-related patterns emerged within the machine learning model. Male employees had lower predicted likelihoods of residual roots (Estimate = -0.370, SE = 0.024, $P < 0.001$), missing teeth (Estimate = -0.262, SE = 0.035, $P = 0.001$), the combined outcome of residual roots and missing teeth (Estimate = -0.276, SE = 0.027, $p < 0.001$), dental caries (Estimate = -0.326, SE = 0.040, $P < 0.001$), and periodontal disease (Estimate = -0.454, SE = 0.056, $P < 0.001$) compared to female employees. Males were predicted to be more likely to present with dental deposits (Estimate = 0.301, SE = 0.068, $P < 0.001$) and other dental diseases (Estimate = 1.225, SE = 0.087, $P < 0.001$) than female employees. These sex differences should be interpreted cautiously, as unmeasured factors such as health-seeking behaviour and occupational role differentiation may have influenced the observed patterns. Age was an influential predictor, however, associations varied by outcome category in the machine learning model and should be interpreted cautiously in the context of screening-based diagnoses and the low-prevalence outcomes.

4. Discussion

This study provides compelling evidence of the multifactorial nature of dental diseases within industrial populations, elucidating the intricate relationships between demographic and occupational factors. A key strength of this study is the large sample size and the focus on an underexplored occupational population, enabling a comprehensive assessment of workplace-related risk factors and enhancing the relevance of the findings for occupational oral health prevention and policy. Using data from 66,449 participants and machine learning-driven risk assessment, our findings offer novel insights into patterns of dental disease prevalence and risk profiles in occupational settings. This area has long been underexplored in the context of large-scale industrial workforces. By leveraging both demographic data and machine learning models, we have identified key occupational risk factors for dental diseases. Machine learning models were used to identify key predictors and evaluate classification performance, while exploring associations between

occupational exposures and specific dental disease outcomes, providing interpretable estimates to complement machine learning predictions.

Occupational risk factors appear to be associated with adverse dental disease outcomes. In particular, the associations observed between occupational noise exposure, whether alone or in combination with dust, and periodontal disease, highlight the potential role of environmental stressors to oral health. Noise is a pervasive environmental stressor, and has previously been linked to negative oral health outcomes.[18] One possible explanation is that noise may induce stress directly through hearing impairment and inner ear damage, or indirectly by disrupting sleep, hindering communication, and impairing daily functioning.[19] Evidence from human studies has linked noise exposure to adverse periodontal outcomes. For example, an earlier study reported an association between propeller aircraft pilots' flight hours, exposure to noise and vibration, with alveolar bone loss.[20] More recent research has established a dose-response relationship between periodontal disease and environmental noise, with the risk increasing as the duration of noise exposure increases.[11,21] It is plausible that industrial workers in this study, who are exposed to consistently high noise levels, may experience chronic environmental stress, which may adversely impact periodontal health through both behavioural and biological mechanisms. Behaviourally, stress may lead to detrimental lifestyle changes such as increased tobacco use and neglect of oral hygiene, promoting plaque and calculus formation, thereby exacerbating periodontal disease.[22,23] Biologically, stress activates the sympathetic nervous system and the endocrine system.[24] This stress can modify the host immune response, impacting salivary composition and gingival sulcus circulation, further compromising periodontal health.[23] Additionally, stress is associated with low-grade chronic inflammation, which may contribute to the development and progression of periodontal disease or vice versa.[25] These findings underscore the need for further investigations to examine potential pathways that may link occupational noise exposure to periodontal disease.

Although dental caries was not significantly associated with occupational X-ray radiation exposure, residual roots, which represented the significant outcome observed in this occupational group, are commonly the result of extensive tooth destruction due to caries. Previous studies have shown that head and neck radiotherapy can impair salivary gland function, resulting in hyposalivation.[26] Reduced salivary flow is a well-established risk factor for dental caries.[27] Salivary dysfunction may represent an indirect pathway contributing to the development of residual roots.

Workers in different industries, such as power supply, paint manufacturing, metal structure manufacturing, electronic circuits, and general hospitals, experienced adverse oral health outcomes, which is consistent with findings in other studies linking occupational exposures to oral diseases.[6,28-30] Specifically, the power supply sector demonstrated an increased likelihood of both dental caries and periodontal disease. One possible explanation is that working conditions in some settings (e.g., heat, shift work, limited hydration opportunities) may influence salivary function and oral health. However, these pathways could not be directly evaluated in this dataset and should be considered hypothesis generating. Reduced salivary flow has been proposed as a potential mechanism linking dehydration and dental caries,[31] but no direct causal relationship can be inferred from the current findings. In addition, occupational metal exposure may contribute to adverse oral health outcomes. Prior research has reported higher levels of dental caries associated with metal exposure, which may help explain the increased burden of dental caries and missing teeth observed in the metal structure manufacturing sector.[32,33]

In contrast, workers in the nuclear power generation sector consistently exhibited more favourable oral health outcomes. This may reflect protective occupational factors, such as regular health surveillance, early intervention, and preventive care.

Oral health outcomes varied by enterprise size, with poorer oral health outcomes observed in larger enterprises, potentially suggesting that larger, more complex operational environments carry an increased risk of oral health deterioration. This underscores the importance of considering enterprise size when designing workplace health interventions aimed at improving oral health.

Gender differences in oral health outcomes were observed in this study. The higher prevalence of dental deposits among men may be associated with poorer oral hygiene habits or differences in salivary composition that influence plaque accumulation and dental calculus formation.[34] In contrast, the lower prevalence of residual roots, missing teeth, dental caries, and periodontal disease among men varies from global data showing no gender difference in the disease burden caused by oral disorders.[35]

This discrepancy may have several explanations. One possibility is underreporting or delayed diagnosis among male workers in industrial settings. Another factor could be occupational role differentiation and exposure misclassification. For instance, in many industries, men are more likely to occupy supervisory or technical roles with reduced direct exposure to hazardous agents, while women are engaged in tasks with higher cumulative exposure. This could bias the observed gender comparison.

Additionally, men with poorer health may leave physically demanding or hazardous jobs earlier, resulting in a relatively healthier male workforce at the time of assessment. Conversely, women may experience greater cumulative stress from balancing work and domestic responsibilities, have less autonomy in accessing preventive care, or face nutritional deficiencies, all of which can negatively impact health.

These findings underscore the need for further investigations into the impact of workplace conditions on oral health and for gender-specific oral health interventions to address occupational oral health risks among male and female workers.

Most age-related patterns observed in this study were consistent with the cumulative oral deterioration commonly experienced with aging, often due to lifelong exposures to risk factors such as poor oral hygiene, smoking, and biological changes, including hyposalivation.[36] Additionally, salivary gland hypofunction may be exacerbated by polypharmacy and comorbid conditions in older populations.[37] This may contribute to the increasing prevalence of dental diseases in this age group.

However, the inverse association observed between age and periodontal disease should be interpreted with caution. This unexpected finding contrasts with the well-established pattern of declining periodontal health over time.[38] One likely explanation relates to the age distribution of the study population, which was predominantly composed of younger and middle-aged adults, with only a small proportion aged 60 years and older. This limited representation of older workers may have limited statistical power to detect age-related increases in periodontal disease.

The machine learning models applied in this study were useful for exploring the complex occupational exposure patterns associated with dental disease. Bootstrap Forest outperformed others in predictive accuracy, indicating their utility for screening in occupational health settings. These results align with previous studies advocating for machine learning in healthcare risk modeling, particularly for chronic or multifactorial conditions. The model demonstrated reasonable discriminatory performance (AUC = 0.72), which is acceptable given the exploratory nature of this study. Model performance is expected to improve in future research through refinement of predictor variables, enlargement of the sample size, and the use of independent validation datasets.

This study represents an exploratory predictive modeling investigation, and the core objective is to identify key variables with high discriminative power through feature selection to construct a screening-oriented risk prediction framework for oral diseases, thereby providing an efficient tool for early screening. The analysis is not intended to establish causal relationships between individual factors and disease occurrence. Although the key occupational health features identified by the model have demonstrated consistent predictive value within the machine learning models, the cross-sectional design and modeling framework limit causal interpretation, and these features should therefore be

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regarded as predictors rather than causal determinants of oral diseases. This study is exploratory, and future research using longitudinal designs is required to further evaluate these findings. To address this research limitation, future studies may utilize prospective cohort studies or randomized controlled trials and integrate causal inference models such as propensity score matching and Mendelian randomization to strengthen causal nature of these features, thereby providing more robust evidence to support their application in oral disease prevention and control.

Despite the strengths of a large sample size and the comprehensive inclusion of occupational variables, this study has further limitations. Key factors, including smoking status, alcohol consumption, oral hygiene behaviors, and systemic conditions such as diabetes, were not available for inclusion in the analysis. In addition, residual confounding and data imbalance may affect model training. Missing dental data (30.33%) may have affected the precision of the findings, and future studies should address this by using imputation or targeted sampling. Enterprise size was analysed as an ordinal variable, and differences between specific size categories could not be examined in detail. Moreover, the generalizability of these results may be limited to similar industrial populations rather than the broader community.

Some estimates, particularly for hazard factor categories in the dental caries outcome, exhibited large standard errors, due to missing data and the exploratory nature of the analysis, resulting in model instability, and should therefore be interpreted with caution. Importantly, the main findings of the study are supported by more prevalent dental outcomes and by the machine learning analyses.

While this study focuses on a single industrial workforce, the findings may have broader relevance. Many labor sectors are exposed to similar occupational hazards, including noise, heat, dust, and chemical agents. In this context, the findings suggest that occupational oral disease may be under-recognized and that workplace exposures may impact an individual's oral health trajectory.

The results of this study have practical implications for group-based intervention strategies, such as workplace health promotion, and may also inform policy considerations related to dental resource allocation and dental insurance coverage. Identifying modifiable risk factors among workers and high-risk groups provides direction for prevention and supports individual self-management. Overall, this study links individual behaviors, clinical practice, and workplace policy, highlighting opportunities to strengthen oral disease prevention and promote health equity in occupational settings.

Our study findings support the inclusion of oral health within occupational health frameworks. This may involve reducing exposures through improved work practices, appropriate personal protective equipment, and exposure monitoring. From a policy and practice perspective, these findings suggest opportunities to strengthen workplace oral health promotion initiatives, including employee oral health education, access to dental preventive strategies, and regular dental screenings. Future interdisciplinary collaboration between occupational physicians, dental professionals, and researchers will be important for strengthening preventive strategies and improving oral health outcomes in working populations.

5. Conclusion

The application of machine learning techniques, particularly the Bootstrap Forest model, demonstrated acceptable predictive performance and highlighted complex relationships between occupational exposures, demographic factors, and dental diseases within a large industrial workforce. Machine learning analyses indicated associations between dental disease outcomes and occupational exposures, enterprise size, and industry sector when incorporating multiple demographic and occupational variables. Workplace exposure to noise alone or in combination with dust was associated with a higher predicted likelihood of periodontal disease, while workers in the power supply and metal structure manufacturing sectors exhibited a higher predicted likelihood of

dental caries. These findings highlight occupational patterns in oral diseases among employees and underscore the importance of occupational dental health research and proactive workplace oral health prevention programs to address under-recognized oral health risks and reduce the burden of occupational dental disease.

The use of generative AI and AI-assisted technologies in scientific writing

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Ethical approval and consent to participate

The study was reviewed and approved by the Griffith University Human Research Ethics Committee (GU Ref No: 2023/325). Written informed consents were obtained from participants included in the study.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

CRediT authorship contribution statement

Xiaojing Meng: Writing – review & editing, Writing – original draft, Supervision, Project administration, Investigation, Data curation, Conceptualization. **Yvette Rainbow:** Writing – review & editing, Writing – original draft, Visualization, Validation, Data curation. **Meitao Tan:** Writing – review & editing, Resources, Project administration, Investigation, Data curation. **Yiming Shi:** Writing – review & editing, Resources, Project administration, Investigation, Data curation. **Zongjie Li:** Writing – review & editing, Resources, Project administration, Investigation, Data curation. **Jake Ball:** Writing – review & editing, Writing – original draft, Visualization, Validation, Data curation. **Jing Sun:** Writing – review & editing, Visualization, Validation, Supervision, Methodology, Formal analysis, Data curation, Conceptualization.

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