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Predicting Tongue Pressure in Elderly Head and Neck Tumor Patients Using Machine Learning: A Cross-Sectional Investigation

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Abstract

This study aimed to revalidate determinants influencing the restoration of tongue pressure in older individuals following therapy for head and neck malignancies, utilizing advanced machine learning approaches. Logistic regression, support vector regression, random forest, and extreme gradient boosting models were trained on variables such as age, surgical category, dental condition, and demographic characteristics, derived from detailed patient records and direct tongue pressure measurements. Results: Logistic regression provided the highest predictive accuracy, yielding an accuracy of 0.630 [95% CI: 0.370–0.778], an F1 score of 0.688 [95% CI: 0.435–0.853], a precision of 0.611 [95% CI: 0.313–0.801], a recall of 0.786 [95% CI: 0.413–0.938], and an AUC of 0.626 [95% CI: 0.409–0.806]. The most significant predictors included glossectomy ($p = 0.039$), the number of functional teeth ($p = 0.043$), and patient age ($p = 0.044$), with significance set at $p < 0.05$. The findings confirmed that glossectomy, functional dentition, and age were key variables influencing tongue pressure in logistic regression, while the presence of natural teeth and tumors situated on the tongue remained consistent predictors across all algorithms assessed.

Keywords: Tongue pressure, Head and neck tumors, Machine learning, Oral performance, Random forest, XGBoost, Logistic regression, support vector machine

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Introduction

A national survey from 2022 showed that nearly half of community-dwelling seniors in Japan experience oral hypofunction [1]. Those who have undergone head and neck tumor resections are particularly susceptible to oral functional decline, reduced food variety, compromised chewing capacity, and consequently, malnutrition, weight loss, sarcopenia, dysphagia, and decreased quality of life compared with their healthy peers [2–10]. The maximum tongue pressure (MTP) serves as both a crucial indicator of lingual strength and a diagnostic parameter for oral hypofunction, as defined by the Japanese Society of Gerodontology (JSG). It also acts as a marker of swallowing difficulty, frailty, and nutritional risk [4,6,11,12]. Fujikawa *et al.* reported that tongue pressure contributes more to chewing efficacy in denture users than in those with their natural teeth, highlighting the clinical importance of maintaining tongue strength [7].

MTP values below 20 kPa are typically observed in dysphagia or pneumonia-related deaths [5,8], while Hasegawa *et al.* identified 15 kPa as a threshold for diagnosing post-surgical swallowing impairment in head and neck cancer cases [10]. Studies have demonstrated that tongue pressure diminishes with age following maturity, with greater decline in men below 60 years. This decline is further influenced by nutrition, muscle mass, physical parameters (height, weight), grip strength, chewing behavior, dental condition, and cognitive status [6,13,14]. Fujikawa and de Groot observed that MTP decreased following oncological surgeries, and that higher occlusal units correlated with greater pressure. Nonetheless, the influence of defect size, configuration, and prosthesis stability remains uncertain [7,12]. Considering the anatomical complexity and multifactorial determinants of lingual function in maxillofacial patients, it becomes essential to identify how surgical types, reconstruction techniques, residual teeth, and prosthetic rehabilitation predict changes in MTP to aid multidisciplinary clinical planning.

To optimize prediction accuracy, logistic regression (LR), support vector machine (SVM), random forest (RF), and extreme gradient boosting (XGB) were applied [15–17]. These algorithms, increasingly used in prosthodontics [18], are recognized for robust diagnostic precision and cross-validation of clinical risk variables [19–24]. RF and XGB, in particular, demonstrate superior sensitivity and specificity compared with conventional regression analysis [16–24]. RF, a nonlinear ensemble approach, integrates multiple decision trees to enhance robustness against collinearity, while XGB strengthens weak predictors through gradient boosting [16,19–24]. Though prior work used multiple regression to assess MTP in healthy populations [7,14,25], machine learning applications in predicting oral function—especially in elderly individuals with head and neck tumors—remain limited.

In this investigation, LR, SVM, RF, and XGB were implemented to create predictive models for MTP among elderly patients (≥65 years) with head and neck malignancies, aiming to cross validate variables associated with reduced tongue strength. The proposed models may offer clinicians, particularly prosthodontists, early diagnostic insight and enable individualized rehabilitation strategies to mitigate dysphagia and aspiration risks associated with tongue pressure loss. The goal of this study was to develop machine learning models that identify and validate predictors influencing tongue pressure following tumor treatment. The null hypothesis posited that no significant predictive variables exist among the studied factors for tongue pressure outcomes in patients aged 65 and older after head and neck cancer therapy.

Materials and Methods

Patient selection

This research involved 80 individuals who had received ablative treatment for tumors in the head and neck region and later underwent prosthetic rehabilitation with dento-maxillary devices at the dental hospital affiliated with our university. Ethical clearance was granted by the Tokyo Medical and Dental University Ethics Committee (Approval No. D2022-004; issued July 5, 2022). The study adhered to the ethical principles of the Declaration of Helsinki and its later updates. Participant agreement was obtained through an opt-out procedure, with details of the investigation made publicly available on posters within the clinical departments.

Eligibility and exclusion conditions

Participants qualified if they were 65 years or older, had undergone surgical removal of a head or neck tumor, had been using a properly fitting mandibular or maxillary denture for a minimum of three months, and had completed all required oral rehabilitation. Individuals were excluded if they exhibited cognitive disorders, degenerative neurological conditions that restricted tongue mobility, temporomandibular joint problems, or unstable general health.

Study outline

Demographic information—age and sex—along with dental characteristics was collected from patient charts and oral evaluations. Teeth were counted if crowns had erupted and were in contact; non-occluding teeth, mobile roots, or residual roots were excluded. Occlusal units (with or without dentures), tumor location, and type of reconstructive procedure—either soft-tissue flap or hard-tissue restoration using bone and/or metallic reinforcement—were also recorded. The total number of functional teeth included all natural and restored teeth, such as crowns, implants, or bridgework, as well as those from removable prostheses. Third molars and remaining roots were not considered. Categorical data are reported as counts or percentages, and continuous variables are displayed as mean ± standard deviation (SD) **(Table 1)**.

Table 1. Characteristics of the study group and associated parameters

Characteristic	Value
Total patients	80
Primary tumor location	
Maxilla (%)	29 (36)
Mandible (%)	31 (39)
Tongue (%)	20 (25)
Age (years, mean ± SD)	71.98 ± 6.32
Gender	
Male (%)	42 (53)
Female (%)	38 (47)
Number of existing teeth (mean ± SD)	17.05 ± 6.73

Occlusal units (natural teeth, mean ± SD)	5.8 ± 3.98
Occlusal units (with denture, mean ± SD)	12.93 ± 1.44
Functional teeth (mean ± SD)	26.58 ± 2.02
Reconstruction type	
Flap reconstruction (%)	37 (46)
Bone and/or metal plate reconstruction (%)	20 (25)
Maxillary perforation (%)	16 (20)
No reconstruction (%)	7 (9)
Maximum tongue pressure ≥ 20 kPa (%)	43 (54)
Maximum tongue pressure < 20 kPa (%)	37 (46)

Data presented as mean ± SD or as number (percentage). MTP = maximum tongue pressure.

A balloon-based tongue pressure device (TPM-02, JMS Co. Ltd., Hiroshima, Japan) **(Figure 1)** was used to determine maximum tongue pressure (MTP) [4–6, 27]. Subjects wearing prosthetic appliances were instructed to sit upright and compress the inflated balloon between the anterior palate and tongue three times, including the denture base when applicable. The mean of the three trials was taken as the final reading [6,7]. A tongue pressure of 20 kPa served as the cutoff point; pressures ≥20 kPa were coded "1," while those below 20 kPa were coded "0" [5,8].

Figure 1. Device for measuring tongue pressure using an air-inflated probe. The display shows (1) peak tongue pressure (kPa) and (2) real-time tongue pressure (kPa)

Data analysis

Machine learning algorithms were applied to predict MTP outcomes. Logistic Regression (LR) and Support Vector Machine (SVM) models were built using R software (version 4.3.0), employing the *glm()* command and *e1071* package. Random Forest (RF) and Extreme Gradient Boosting (XGB) models were executed in PyCharm (version 2023.2, JetBrains, Prague, Czech Republic) under the Python environment (version 3.11, Python Software Foundation, Wilmington, DE, USA), utilizing *scikit-learn* and *XGB* libraries. Two-thirds of the total samples (n = 53) were allocated for training, and one-third (n = 27) for testing [21,28]. The alpha level for significance was fixed at 0.05. All SVM, RF, and XGB models used fivefold cross-validation to fine-tune model parameters [28].

Optimized parameters for the RF model were as follows:
• "max_depth": 2, 3, 4, 5, 6, 8, 10, 20
• "min_samples_split": 2, 3, 5
• "n_estimators": 10, 20, 30, 50
• "max_features": "sqrt", "log2"
• "criterion": "gini", "entropy"

Parameters adjusted in the XGB model included:
• "max_depth": 2, 3, 5, 10
• "booster": "gbtree", "gblinear"
• "learning_rate": 0.01, 0.1, 0.3, 0.5
• "n_estimators": 10, 20, 30, 50
• "gamma": 0, 0.3, 1.0
• "reg_lambda": 0, 0.3, 0.8, 1
• "reg_alpha": 0, 0.3, 0.8, 1
• "silent": 1

Evaluation metrics such as accuracy, precision, recall, F1 score, and the area under the ROC curve (AUC) were used to assess each model's predictive strength [15]. In SVM, the top five predictors were identified using recursive feature elimination [29]. The most influential five features from RF and XGB models were also extracted to determine their respective importance in prediction.

Sample size validation

The adequacy of the dataset was judged using the criteria from Rajput *et al.* [30], defining an acceptable sample when (i) prediction accuracy exceeded 80% and (ii) Cohen's *d* value was above 0.5.

Results

Details of the participants and their associated parameters are summarized in **Table 1**, while **Table 2** displays the evaluation outcomes of all predictive models. Statistical examination provided clear support for discarding the null assumption. Within the logistic regression (LR) framework, three variables showed statistical significance for predicting MTP: glossectomy ($p = 0.039$; OR = 0.128; 95% CI = 0.018–0.898), count of functional teeth ($p = 0.043$; OR = 0.014; 95% CI = 0.000–0.882), and age ($p = 0.044$; OR = 5.335; 95% CI = 1.044–27.243). Variables with $p < 0.05$ were considered significant **(Table 3)**. Among all constructed algorithms, LR achieved the largest ROC-AUC value of 0.626 (95% CI: 0.409–0.806) **(Figure 2)**.

Using support vector machine (SVM) analysis combined with recursive feature elimination, the five attributes that contributed most to MTP prediction were: natural-tooth occlusal units, tongue malignancy, glossectomy, existing teeth, and number of functional teeth. The SVM achieved an ROC-AUC of 0.582 (95% CI: 0.390–0.761).

For the random forest (RF) classifier, the tuned settings were {'clf__criterion': 'gini', 'clf__max_depth': 5, 'clf__max_features': 'sqrt', 'clf__min_samples_split': 2, 'clf__n_estimators': 10}. Feature-importance analysis ranked the variables as follows: occlusal units of natural teeth (0.178), presence of teeth (0.173), age (0.132), tongue cancer (0.088), and occlusal units including dentures (0.081). The model's ROC-AUC reached 0.626 (95% CI: 0.385–0.843).

In the extreme gradient boosting (XGB) model, optimal hyperparameters were {'classifier__booster': 'gbtree', 'classifier__gamma': 0.3, 'classifier__learning_rate': 0.01, 'classifier__max_depth': 3, 'classifier__n_estimators': 50, 'classifier__reg_alpha': 0, 'classifier__reg_lambda': 0, 'classifier__silent': 1}. The most dominant factors were occlusal units of natural teeth (0.395), glossectomy (0.233), tongue cancer (0.165), age (0.105), and existing teeth (0.103). The AUC value was 0.618 (95% CI: 0.405–0.826). The proportion between groups was 0.453 to 0.547 (MTP < 20 kPa : MTP ≥ 20 kPa).

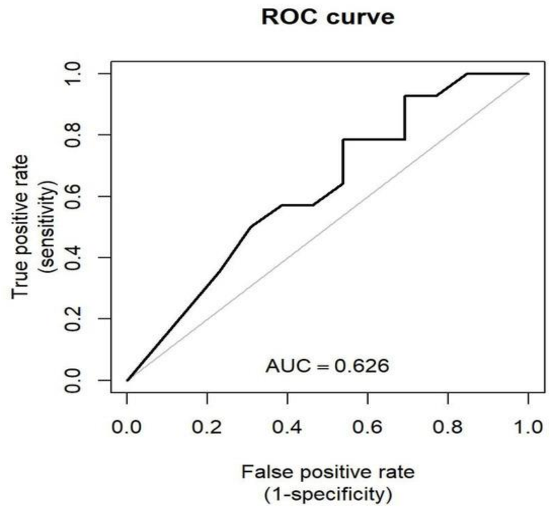

Figure 2. ROC curve of the logistic regression model applied to the testing data

Table 2. Model performance indices for the four algorithms on the testing dataset

Model	Accuracy	F1 Score	Precision	Recall	AUC
Logistic Regression (LR)	0.630 [95% CI: 0.370–0.778]	0.688 [95% CI: 0.435–0.853]	0.611 [95% CI: 0.313–0.801]	0.786 [95% CI: 0.413–0.938]	0.626 [95% CI: 0.409–0.806]
Support Vector Machine (SVM)	0.593 [95% CI: 0.370–0.741]	0.645 [95% CI: 0.400–0.811]	0.588 [95% CI: 0.301–0.800]	0.714 [95% CI: 0.385–0.889]	0.582 [95% CI: 0.390–0.761]
Random Forest (RF)	0.556 [95% CI: 0.370–0.741]	0.571 [95% CI: 0.320–0.762]	0.571 [95% CI: 0.294–0.833]	0.571 [95% CI: 0.308–0.846]	0.626 [95% CI: 0.385–0.843]
XGBoost (XGB)	0.630 [95% CI: 0.444–0.815]	0.667 [95% CI: 0.435–0.833]	0.625 [95% CI: 0.375–0.857]	0.714 [95% CI: 0.462–0.929]	0.618 [95% CI: 0.405–0.826]

Abbreviations: LR = logistic regression; SVM = support vector machine; RF = random forest; XGB = extreme gradient boosting; AUC = area under the curve; F1 score = 2/([1/Recall] + [1/Precision]); Accuracy = (TP + TN)/(TP + TN + FP + FN); Precision = TP/(TP + FP); Recall = TP/(TP + FN); FN = false negatives; FP = false positives; TN = true negatives; TP = true positives.

Table 3. Multivariable logistic-regression outcomes for the training data ($p < 0.05$)

Characteristic	β Coefficient	p-Value
Tongue resection surgery	−2.059	0.039 *
Number of functional teeth	−4.251	0.043 *
Age of patient	1.674	0.044 *
Occlusal units with denture	4.166	0.052
Occlusal units without denture	2.405	0.150
Male gender	0.731	0.221
Hard tissue reconstruction	1.174	0.252
Tongue malignancy	−0.263	0.750
Soft tissue reconstruction	0.198	0.811
Presence of natural teeth	−0.179	0.901
Glossectomy (repeated)	−0.206	0.993
Maxillary perforation	−9.306	0.994

Discussion

Previous studies have frequently analyzed the determinants of reduced tongue-pressure strength among dentate or elderly cohorts through conventional statistical frameworks. Nevertheless, influences such as tumor localization, defect extension, and type of reconstructive approach in head-and-neck tumor cases still require validation through machine-learning paradigms with improved predictive accuracy [6, 13, 14].

In this investigation, four predictive algorithms were developed using the independent variables summarized in **Table 1**. According to the results shown in Table 2, the LR model surpassed the others when evaluated on the testing data, producing an ROC-AUC of 0.626 (95% CI: 0.409–0.806) **(Figure 2)**. Within this model, glossectomy ($p = 0.039$), functional teeth ($p = 0.043$), and age ($p = 0.044$) emerged as statistically relevant factors influencing maximum tongue pressure **(Table 3)**.

The LR algorithm achieved the greatest values for accuracy (0.630), F1 index (0.688), recall (0.786), and AUC (0.626). These metrics indicate its ability to recognize positive cases efficiently, balance precision with recall, and differentiate between outcome categories at multiple thresholds. Although machine-learning approaches such as RF, SVM, and XGB typically manage nonlinear interactions and intricate datasets more effectively, LR retains benefits like transparency, faster computation, straightforward implementation, and interpretability within linearly separable data [16, 17].

Choosing the optimal model depends largely on the research objectives, dataset complexity, and the need for interpretability [16, 17]. For empirical use, it is advisable to evaluate multiple models and apply cross-validation to identify the most appropriate one for a given context. In LR, discrepancies observed between recall and precision could be linked to issues such as multicollinearity or limited sample volume. Since none of the algorithms reached an accuracy above 0.8, the relatively small sample size may have restricted performance, indicating that broader studies with more participants are essential to substantiate these findings (see Section 2.5 for methodological specifications).

From a clinical standpoint, tongue pressure plays an increasingly pivotal role in maintaining oral function among elderly individuals affected by head and neck malignancies [9]. The outcomes derived from the four predictive models were in strong alignment with earlier findings [6,7,25,31], reinforcing known determinants of tongue-pressure reduction and emphasizing its diagnostic specificity in this patient population. These results indicate that even with limited datasets, machine-learning–based approaches can provide valuable reference insights. Dental practitioners, particularly those specializing in maxillofacial prosthodontics, should prioritize the prompt recognition of tongue tumors and their potential recurrence, even when tissue defects are minor. In addition, early identification of decreased oral efficiency and physiological performance, followed by interventions—such as isometric exercises and targeted suprahyoid muscle strengthening to enhance tongue pressure [25,32]—can be instrumental in preventing progressive functional decline.

Implementing such preventive measures not only preserves swallowing effectiveness but also improves overall quality of life by minimizing complications associated with weakened tongue pressure. Achieving these outcomes requires collaborative coordination with surgical teams to ensure correct occlusal relationships and adequate prosthetic space, supporting the retention of functional dentition. During clinical visits, prosthodontists must also account for the unique anatomical and functional challenges faced by patients aged 65 years and older who have undergone glossectomy. Particular attention should be paid to their swallowing ability, along with the provision of personalized dietary counseling and the use of prosthetic devices—such as palatal augmentation prostheses—to aid rehabilitation [33]. Consequently, tongue performance should be routinely evaluated during follow-up appointments, with timely adjustments made to denture fit when necessary.

The mean age of participants in this study was 71.98 ± 6.32 years, and the average MTP value was 21.7 kPa, which is notably below the 26.22 kPa recorded among individuals in their seventies from the general population (measured via a wireless tongue-pressure device) and the 25.9 kPa reported in maxillectomy patients in prior studies [7,34]. The present analysis also verified an age-associated decline in tongue pressure. This reduction in older adults is intricately linked to aging-related disorders such as oral hypofunction, sarcopenia, and sarcopenic dysphagia, all of which contribute to frailty [5]. The decline adversely influences food intake capacity, often resulting in malnutrition and nutrient deficiencies that further aggravate systemic health problems [35].

Evidence suggests that the age-related drop in tongue pressure primarily stems from diminished muscular strength [35]. This weakening process is driven by both loss of muscle mass and reduced neuromuscular efficiency [25]. With advancing age, neural performance deteriorates—manifested by a gradual reduction in motor unit count, particularly beyond the sixth decade of life [6,25]. Older adults also exhibit a substantial decrease in the cross-sectional area of the geniohyoid muscle, a key component in the swallowing mechanism [25]. In addition, marked atrophy of the suprahyoid musculature and increased intramuscular fat infiltration are frequently observed [25]. The concurrent rise in visceral adiposity in the elderly can further enlarge the tongue, exacerbating deglutition difficulties [25].

Furthermore, age progression is associated with atrophy of type II (fast-twitch) muscle fibers**,** which account for nearly **60%** of the suprahyoid muscles, resulting in reduced power and functional performance [36]. Systemic inflammation is another major contributor to this phenomenon. Prior studies have reported strong correlations between elevated inflammatory cytokines—such as interleukin-6 (IL-6) and tumor necrosis factor-alpha (TNF-α)—and muscle atrophy and weakness. Monocytes in aged individuals have been shown to release higher levels of IL-1, IL-6, and TNF-α than those in younger counterparts, underscoring the heightened inflammatory state accompanying aging [35]. This chronic, low-grade inflammatory process—often referred to as *"inflammaging"*—further accelerates muscular degeneration and functional loss, thereby diminishing tongue pressure and negatively influencing general health and quality of life among elderly populations [35].

Taken together, these findings highlight the necessity of early screening and timely rehabilitation to mitigate the cascading effects of aging on oral muscular strength and function.

Younger individuals and those with favorable occlusal conditions tend to compensate for diminished maximum tongue pressure (MTP), whereas the absence of occlusal units and the use of removable partial dentures contribute to reduced MTP levels [7,8,12,31,35]. Conversely, fixed restorations such as bridges or implants have been shown to help restore and maintain adequate tongue pressure [14]. In the present study, the mean number of natural occlusal units was 5.8, and the corresponding mean MTP was 21.7 kPa—lower than the 26.4 kPa MTP reported by

Fujikawa *et al.* [7] in participants with an identical mean occlusal unit count of 5.8. Some studies have linked decreased tongue pressure in individuals with fewer occlusal units to impaired oral stereognostic ability, a function controlled by the central nervous system, which also regulates chewing rhythm [12]. Others attribute the decline to reduced muscular strength and loss of occlusal function following tooth loss [8,35]. However, these investigations generally found no significant correlation between tongue pressure and remaining tooth count, despite expectations that tongue strength would increase compensatorily to sustain chewing ability [37]. Attaining stable occlusion is essential for safe swallowing [31]. Such stability depends on maintaining a greater number of teeth, maximizing occlusal contact, and enlarging the supporting area. During deglutition, the mandible remains fixed as the hyoid bone moves upward and forward via its associated muscles, while the tongue simultaneously presses against the palate. This coordinated muscular activity underpins the relationship between tongue pressure and oral health factors such as dentition and systemic frailty. The interdependence between dental integrity and muscular coordination highlights the need to preserve oral health to ensure efficient swallowing and general well-being, particularly in aging individuals. Despite differing viewpoints, evidence consistently indicates that functional tooth count and occlusal unit number remain key factors, even among patients fitted with maxillofacial prostheses. Further investigation is warranted to clarify how occlusal condition, masticatory rhythm, and tongue pressure interrelate.

Compared to surgical procedures such as mandibulectomy or maxillectomy, glossectomy appears to have a stronger impact on tongue pressure. This finding aligns with studies by Hasegawa *et al.* and Hamahata *et al.*, who observed that reduced tongue pressure was associated with tongue cancer, implicating the suprahyoid and intrinsic tongue muscles as the primary contributors to pressure generation [10,38]. In contrast, the mandibular and palatal structures act as dual support anchors for MTP following mandibulectomy or maxillectomy. The hard palate, therefore, not only provides support for obturators but also acts as a resistance base for tongue movement [7]. Nevertheless, the degree to which such structural defects influence MTP remains debated. Fujikawa *et al.* noted functional deterioration of the tongue after oncologic oral surgery due to loss of tissue support or postoperative complications [7,10], whereas de Groot *et al.* found no reduction in tongue pressure following treatment for maxillary tumors, likely because the tongue itself was not affected [12]. In edentulous patients using complete dentures or obturators, the tongue contributes not only to food propulsion and mixing but also to comminution and denture stabilization, effectively compensating for the absence of natural teeth and potentially enhancing MTP [6,7]. Among individuals who have undergone ablative maxillofacial surgery and rely on flaps or skin grafts for prosthetic support, sufficient occlusal force and tongue pressure are critical for maintaining denture stability and oral performance [12]. For extensive defects, diminished obturator support leads to reduced retention [7]; thus, further study is needed to determine whether repetitive use can elevate tongue pressure to sustain denture stability or whether muscle atrophy from larger defects ultimately decreases tongue strength.

In terms of the limitations of this research, although the sample size was relatively small and some potential confounding factors were not incorporated into the analysis, it remains important to consider participants' treatment histories—such as exposure to chemotherapy, radiotherapy, and surgical procedures of the neck—as well as their socioeconomic background. Previous investigations have shown that lower socioeconomic conditions are linked to poorer occlusal health and decreased MTP [31]. Additionally, tongue pressure in this study was not classified based on denture type—fixed or removable—which may influence the degree of tongue pressure recovery. Hence, future research should separately assess the effects of different denture retention types [8,14]. Tongue pressure testing requires stabilization of the anterior teeth with the pressure balloon centered on the tongue; however, several participants had missing anterior teeth or underwent subtotal glossectomy. For these cases, the balloon was positioned according to individual comfort, underscoring the need for specific protocols for head and neck tumor patients. Therefore, standardized methods for tongue pressure evaluation in such populations should be established. Another important variable is the denture adaptation period, which can impact tongue pressure, since muscular control during denture use provides consistent training for perioral and lingual muscles [6]. Additional studies are necessary to determine optimal adaptation periods—especially for individuals with complex maxillofacial defects—to improve measurement consistency and interpretation. Moreover, the retrospective nature of this study limited its ability to observe changes over time.

Looking ahead, future investigations would greatly benefit from prospective, longitudinal designs using large-scale datasets that include a wider age distribution, multiple denture retention categories, and additional variables such as complications from adjuvant therapy. Such comprehensive research could help define clearer causal and temporal relationships, improving both the precision and clinical utility of predictive modeling. Expanding and refining machine learning algorithms could enhance their application to broader groups of elderly patients with head and neck tumors, ensuring that findings remain valid across diverse datasets. As automated machine learning systems and electronic health records continue to advance, the relevance of artificial intelligence in assessing and managing oral function will likely increase. These developments are expected to drive innovation in dental diagnostics and care, supporting more accurate and efficient management of complex oral health challenges. Furthermore, incorporating manually validated classifications from larger groups of dental specialists could strengthen the verification of AI-generated predictive outcomes. This interdisciplinary collaboration would not only improve the reliability of predictive models but also enrich understanding of oral health mechanisms, facilitating more individualized and effective care strategies for aging populations. The synergy of expert knowledge and intelligent technology has the potential to reshape dental care, making it more precise, responsive, and patient-specific.

Conclusions

Taking into account the limitations of this investigation, the main conclusions are as follows:

- Among patients aged 65 years and older with head and neck tumors, glossectomy, the number of functional teeth, and age were the major factors affecting MTP according to the LR model.
- The LR model outperformed the other two models analyzed in this limited sample, demonstrating the practicality and potential of applying machine learning for predicting tongue pressure.
- The variables of natural tooth presence and tumor localization in the tongue consistently influenced MTP across all four models, suggesting their potential role as early predictive indicators of reduced tongue pressure.

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