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A predictive model for arthrogenous temporomandibular disorders based on clinical signs and symptoms

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ABSTRACT

This study aimed to develop and internally evaluate a multivariable statistical model to identify arthrogenous temporomandibular disorders (TMD) using routinely collected clinical data. The model's performance was compared with the Fonseca Anamnestic Index (FAI) alone, using an imaging-based classification as the reference standard. This cross-sectional observational study included 1170 consecutive patients attending their first consultation at a tertiary TMD center between August 2019 and August 2024. Arthrogenous TMD was determined using combined clinical and imaging assessment according to the Dimitroulis classification. Clinical variables, including age, maximum mouth opening (MMO), individual FAI items, and joint-related complaints, were extracted from the EUROTMJ database. Generalized additive models (GAMs) were used to develop predictive models. Performance was assessed using receiver operating characteristic (ROC) curves, area under the curve (AUC), sensitivity, and specificity in training (60%) and test (40%) datasets. The final Fonseca–Dimitroulis (FD-Class) model incorporated age, MMO, selected FAI items (Q2, Q6, Q7), crepitus, and temporomandibular joint (TMJ) locking. The model achieved an AUC of 0.761 in the training dataset and 0.742 in the test dataset, outperforming the FAI alone (AUC = 0.662). This model may support the early identification of arthrogenous TMJ disease and improve decision-making regarding referral for advanced imaging in maxillofacial practice.

1. Introduction

Temporomandibular disorders (TMD) encompass a heterogeneous group of conditions affecting the temporomandibular joint (TMJ) and associated musculoskeletal structures. They are characterized by pain, functional limitation, joint sounds, or muscle tension, and can significantly impair quality of life (Kapos et al., 2020; Ângelo et al., 2023; Matheson et al., 2023). Among these conditions, arthrogenous

TMD—originating within the joint—represents a clinically distinct and therapeutically relevant subgroup. Its recognition is essential because its management strategies and prognosis differ from those of muscular or myofascial disorders (Christidis et al., 2024). In routine clinical practice, the initial evaluation of patients with suspected TMD is based on self-reported symptoms and basic physical examination findings (Ângelo et al., 2023). These data are easily collected, low-cost, and non-invasive. However, it is difficult to distinguish arthrogenous from

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non-arthrogenous disorders at this early stage. Clinical presentation is often nonspecific and overlapping (Christidis et al., 2024; Nagi et al., 2025). This makes early decisions regarding imaging and referral more challenging.

The Dimitroulis classification provides a comprehensive framework for diagnosing and grading TMJ disorders. It includes clinical, functional, and imaging assessments (Dimitroulis, 2013). However, imaging data are required. Therefore, it can only be applied at a later stage of diagnostic workup, after all investigations are completed (Dimitroulis, 2013). Consequently, a reliable method for predicting Dimitroulis-defined joint disease using data from initial consultation would represent an important step toward earlier diagnosis and targeted intervention (Matheson et al., 2023; Angelo et al., 2024). Such an approach may support the rational use of imaging and surgical referral pathways in maxillofacial practice. It may also help clinicians stratify patients according to the likelihood of underlying joint pathology at the first visit.

The objective of this study was to determine whether TMJ disorders can be predicted from signs, symptoms, and simple clinical findings obtained during the first consultation. Initial clinical data were compared with the final Dimitroulis classification, which was used as the gold standard for the presence of articular TMJ disorders. A statistical model was developed and validated using these variables. The aim was to create a low-cost and minimally invasive tool to identify arthrogenous TMD at presentation (Mauro et al., 2024).

This study presents a data-driven approach that links symptom-based clinical screening with imaging-confirmed arthrogenous TMD diagnosis. The resulting model may support early triage, guide the use of advanced diagnostic imaging, and improve patient management in maxillofacial practice (Mauro et al., 2024; Nagi et al., 2025).

2. Materials and methods

2.1. Study design

A five-year cross-sectional observational study was conducted at the Instituto Português da Face (Lisbon, Portugal), between 1 August 2019 and 1 August 2024. The study was approved by the Ethics Committee of the Instituto Português da Face (PT/IPFace//PS/02408/01) and conducted in accordance with the Declaration of Helsinki. All participants provided written informed consent before enrolment. The inclusion criteria were: (1) complete data recorded at the first consultation; and (2) a definitive diagnosis combining clinical and imaging evaluation. Exclusion criteria were severe systemic disease, previous TMJ surgery, or cognitive impairment that could interfere with the assessment process. All eligible patients meeting these criteria during the study period were included.

2.2. Data source and collection

Data were retrieved from the EUROTMJ database, a secure and standardized digital registry for patients with TMD. The platform records demographic data, symptom characteristics, functional findings, imaging results, and questionnaire responses (Angelo et al., 2023).

Patients completed the Portuguese version of FAI, which consists of 10 self-reported items (Q1–Q10) addressing pain, functional limitation, joint sounds, and psychosocial symptoms. Each item was scored as “No” (0), “Sometimes” (5), or “Yes” (10). For analysis, items were recorded into binary variables (0 = absent, 1 = present) (Pires et al., 2018; Cervans et al., 2024). The total FAI score was also used. Patients were classified into four categories of dysfunction severity: 0–15: No dysfunction (asymptomatic); 20–40: Mild dysfunction; 45–65: Moderate dysfunction; 70–100: Severe dysfunction. For modelling purposes, each category was subsequently recoded into binary format (0 = absence of dysfunction, 1 = presence of dysfunction). The total FAI score was included as a continuous variable in the models.

This instrument provided the baseline symptom data used to construct the predictive model.

At the same visit, patients also reported the presence of the following symptoms: TMJ pain, TMJ clicking, TMJ crepitus, limited mouth opening, masticatory and cervical muscle tension, tinnitus, edema and vertigo.

All data were collected at the first consultation, prior to any treatment.

2.3. Clinical evaluation and diagnostic criteria

All examinations were performed by the same clinician (D.F.A.) to ensure diagnostic consistency. Maximum mouth opening (MMO) was measured between the upper and lower incisors using a TheraBite® Jaw ROM Scale. Myalgia was diagnosed following DC/TMD criteria. This required: (1) the presence of pain in the jaw, temple, or ear during the preceding 30 days, confirmed by palpation of the masseter and temporalis muscles; and (2) pain aggravated by jaw movement, function, or parafunction (Schiffman et al., 2014). Palpation was performed for 5 s with 1 kg of pressure, and pain was graded as 0 = none; 1 = mild; 2 = moderate; 3 = severe (Goiato et al. 2017). Arthralgia was diagnosed when both: (1) a history of TMJ pain was present; and (2) pain was elicited on palpation of the lateral pole or during mouth opening, lateral, or protrusive movements (Schiffman et al., 2014). Imaging evaluation included Magnetic Resonance Imaging (MRI) and/or Cone-Beam Computed Tomography (CBCT). These modalities were used to assess disc position, effusion, cortical bone integrity, and degenerative joint changes. The final diagnosis of arthrogenous TMD was derived from clinical and imaging findings. Each patient was classified according to the Dimitroulis classification, which stratifies TMJ pathology into five grades: Grade 1: Normal joint (no disease); Grade 2: Minor changes; Grade 3: Moderate changes; Grade 4: Severe changes; Grade 5: Catastrophic changes. For statistical modelling, this variable was dichotomized: 0 = No arthrogenous disease (Grade 1); 1 = Arthrogenous disease (Grades 2–5) (Dimitroulis, 2013).

2.4. Statistical analysis

Descriptive statistics were calculated for all variables. Continuous variables were expressed as medians [interquartile range (IQR)], and categorical variables as n (%). Associations between categorical predictors and the presence of arthrogenous disease were evaluated using the Chi-square test ($p < 0.05$). To account for potential non-linear effects, Generalized Additive Models (GAMs) with a binomial logit link were applied. The dataset was randomly divided into training (60%) and testing (40%) subsets. The modeling process followed a stepwise approach.

1. Baseline model 1: MMO only.
2. Baseline model 2: MMO + Age.
3. Intermediate Model: Addition of qualitative predictors (Q2, Q6, Q7, Crepitus, TMJ locking).
4. Final model (FD-Class): Inclusion of interaction terms (TMJ clicking \times MMO and MMO \times Sex).

Model discrimination was evaluated using receiver operating characteristic (ROC) curves and the Area Under the Curve (AUC). Sensitivity, specificity, and predictive values (positive and negative) were also calculated. The optimal probability threshold was defined as the point maximizing sensitivity and specificity. All analyses were performed using R language (version 4.5.1) with the *mgcv* and *pROC* packages (2025) (R Core Team, 2025).

3. Results

A total of 1170 patients were registered in the EUROTMJ database,

of whom 1045 had complete data for all modelling variables. The median age was 39.0 years [28.0; 53.0], and 79.7% were female (Table 1). At the initial consultation, signs and symptoms consistent with TMD were recorded. The most frequent complaints were TMJ clicking (78.6%), TMJ pain (73.6%), and masticatory muscle tension (72.9%) (Table 2).

The FAI was used to evaluate disease severity using reported signs and symptoms. According to FAI, 3.10% of patients were considered free of disease, 23.54% had mild disease, 40.89% had moderate disease, and 32.48% had severe disease (Table 2).

Responses to the ten items of the FAI are presented in Fig. 1. The frequency of affirmative responses (“Yes”) across the questionnaire items ranged from 27% to 55%, indicating that many patients reported multiple signs or symptoms. Items related to joint sounds (Item 7, 55%), occlusal instability (Item 10, 49%), and ear or joint pain (Item 6, 48%) were the most frequently endorsed. Intermediate frequencies were observed for muscle fatigue during mastication (Item 3, 41%), headache (Item 4, 41%), and neck stiffness (Item 5, 38%). Lower frequencies were observed for difficulty opening (Item 1, 31%) and difficulty with lateral jaw movements (Item 2, 27%). Approximately one-third of respondents answered “Sometimes” across most items, reflecting variability in symptom intensity and frequency. This pattern suggests predominantly mild-to-moderate self-reported dysfunction at presentation.

Clinical parameters obtained during the first examination are summarized in Table 3. Arthralgia was present in 58.4% of patients, TMJ clicking in 46.2%, TMJ crepitus in 21.5%, and myalgia in 72.3%. The median MMO was 41.0 mm [IQR, 34.0–45.0]. After comprehensive clinical and imaging assessment, patients were classified according to the Dimitroulis Classification: 27.3% of joints were normal, 35.6% exhibited minor changes, 19.7% moderate changes, 16.9% severe changes, and 0.5% catastrophic alterations. This distribution indicates a predominance of mild-to-moderate structural joint involvement at the first consultation.

The prevalence of arthrogenous TMD was consistently higher among patients reporting joint-related complaints than among those without symptoms (Fig. 2). Among symptomatic patients (Fig. 2A), the frequency of arthrogenous TMD (TMD⁺) ranged from 69% to 89%, particularly for TMJ locking (89%), TMJ crepitus (85%), and mouth-opening limitation (84%). In contrast, among asymptomatic patients (Fig. 2B), the frequency of arthrogenous TMD ranged from 58% to 77%, with lower values in the absence of clicking (58%), mouth-opening limitation (60%) and pain (64%). These findings indicate that pain and joint sounds are strongly associated with underlying arthrogenous joint pathology.

The relationship between FAI questionnaire responses and the presence of arthrogenous TMD according to the Dimitroulis classification is shown in Fig. 3. Among patients who reported TMJ-related complaints (Fig. 3A), the proportion of TMD⁺ ranged from 74% to 83%. Among patients without perceived TMJ problems (Fig. 3B), the proportion of TMD⁺ cases remained more homogeneous (57%–76% across items). This suggests that absence of self-reported symptoms does not exclude joint disease. Overall, the comparison confirms that positive responses to Fonseca items—particularly those reflecting joint pain and

Table 1
Overall and gender-specific demographic data.

Variables	N (%) or median [P ₂₅ ;P ₇₅]	
Number of patients	1170	
Sex	Female	932 (79.7%)
	Male	238 (20.3%)
Age (years)	39.0 [28.0; 53.0]	
Sex	Female	40.0 [29.0; 54.0]
	Male	38.0 [26.0; 51.0]

noise—are closely associated with Dimitroulis-defined arthrogenous pathology, whereas the absence of self-reported symptoms shows limited discriminative value.

The association between qualitative variables and the presence of TMD⁺ according to the Dimitroulis classification was tested using the Chi-square test. Table 4 shows the differences in complaints between patients with and without arthrogenous disease. Significant associations were found for the following clinical complaints: edema (p = 0.025), TMJ crepitus (p < 0.001), TMJ locking (p < 0.001), TMJ clicking (p < 0.001), malocclusion (p = 0.039), masticatory muscle tension (p = 0.013), limitation in mouth opening (p < 0.001), TMJ pain (p < 0.001), and sex (p = 0.041).

Among the FAI items, significant associations with arthrogenous disease were found for: Q1 (difficulty opening the mouth, p < 0.001), Q2 (difficulty in jaw movement, p < 0.001), Q3 (pain or fatigue while chewing, p < 0.001), Q6 (ear or TMJ pain, p = 0.013), Q7 (joint sounds, p < 0.001), Q8 (bruxism, p = 0.033), Q9 (malocclusion, p = 0.044), and Q10 (stress or nervousness, p = 0.023). The FAI was also significantly associated with the Dimitroulis classification (p = 0.012).

To assess the discriminative capacity of the FAI when used alone, a Generalized Linear Model (GLM) with a binomial logistic link was constructed using the ten Fonseca items as independent variables and the Dimitroulis classification as the reference outcome (presence of arthrogenous TMD). Significant predictors were: Q1 (difficulty opening the mouth) (p = 0.005), Q2 (difficulty in jaw movement) (p < 0.001), and Q7 (joint sounds) (p = 0.026). Items Q5 (neck stiffness) and Q3 (fatigue while chewing) showed borderline significance (p = 0.09 and p = 0.13, respectively). The overall model demonstrated a moderate discriminative ability, with an area under the ROC curve (AUC) of 0.662. Model accuracy was 63.2% (95% CI, 58.3–67.8), with sensitivity of 63% and specificity of 64%. The Positive Predictive Value (PPV) was 84%, and the Negative Predictive Value (NPV) was 36%. These results show that FAI alone has limited ability to identify arthrogenous TMD.

GAMs were applied to evaluate the non-linear association between the quantitative variables — Age and MMO — and the presence of arthrogenous TMD according to the Dimitroulis classification.

For Age, the partial-effect plots demonstrated a negative association with the probability of arthrogenous TMD (p = 0.0007) (Fig. 4A). The probability of joint disease decreased with increasing age. This pattern may reflect the greater clinical heterogeneity of older patients, where similar symptoms may be caused by other orofacial conditions.

The relationship between MMO and TMD was non-linear but significant (p < 0.001) (Fig. 4B). A protective threshold of approximately 39.8 mm was identified. Above this value, the probability of

Table 2
Signs and symptoms and Fonseca Anamnestic Index distribution.

Variables	N (%)		
Patient-reported complaint	TMJ clicking	919 (78.6%)	
	TMJ Pain	861 (73.6%)	
	Masticatory muscle tension	853 (72.9%)	
	Cervical muscle tension	823 (70.3%)	
	Headache	779 (66.6%)	
	Open mouth limitation	684 (58.5%)	
	Malocclusion	532 (45.5%)	
	Tinnitus	525 (44.9%)	
	Vertigo	407 (34.8%)	
	Edema	304 (26.0%)	
	TMJ locking	357 (30.5%)	
	TMJ crepitus	299 (25.6%)	
	Fonseca Anamnestic Index	Free	35 (3.1%)
		Mild	266 (23.6%)
Moderate		462 (40.9%)	
Severe		367 (32.5%)	

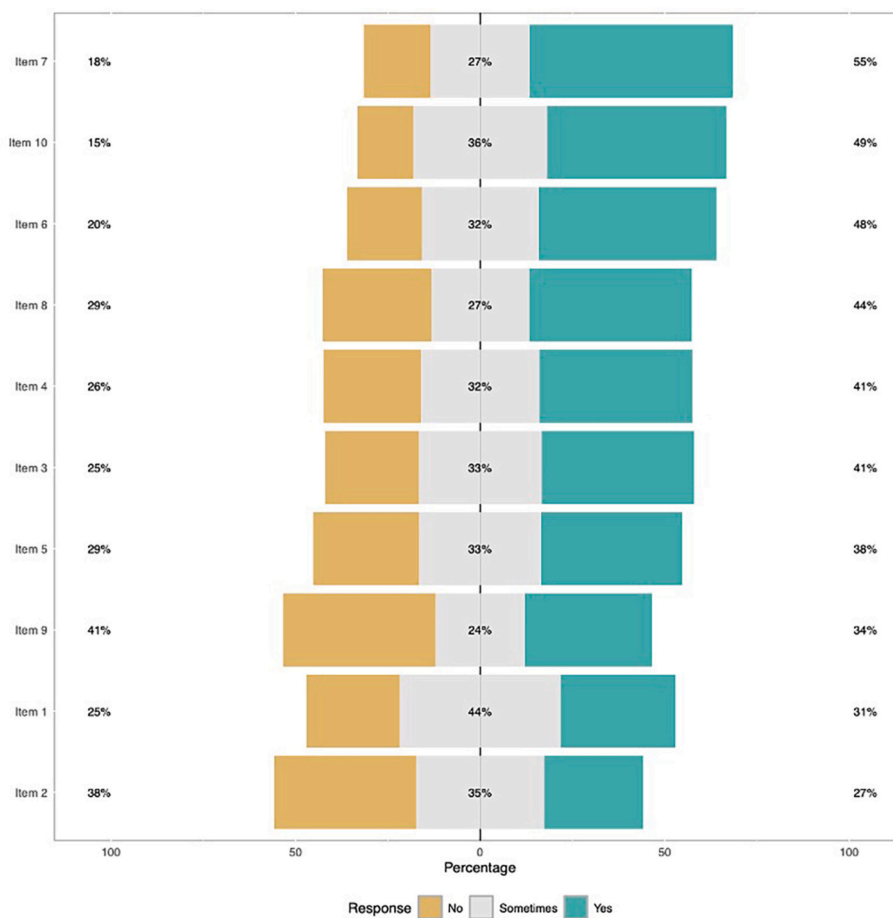


Fig. 1. Responses to the Fonseca Anamnestic Index. Proportion of patients answering “No,” “Sometimes,” or “Yes” to each of the ten FAI items, showing a predominance of affirmative responses (27–55%), particularly for joint sounds, occlusal instability, and ear or TMJ pain.

Table 3
Clinical evaluation.

Variables	N (%) or median [P ₂₅ ;P ₇₅]
Arthralgia	683 (58.4%)
TMJ clicking	541 (46.2%)
TMJ crepitus	251 (21.5%)
Myalgia	846 (72.3%)
MMO (mm)	41.0 [34.0; 45.0]
Dimitroulis Classification	
TMJ Normal	317 (27.3 %)
TMJ minor Changes	413 (35.6 %)
TMJ moderate Changes	228 (19.7%)
TMJ severe Changes	196 (16.9%)
TMJ catastrophic Changes	6 (0.5%)

arthrogenous disease decreased. These findings indicate that restricted mouth opening serves as a key clinical indicator of joint involvement.

A univariate GAM using MMO (Baseline Model 1) as the sole explanatory variable showed good discriminative ability, with an area under the ROC curve (AUC) of 0.659 in the training dataset and 0.602 in the test dataset. This model served as the baseline for subsequent multivariable modelling.

Age was then added to the model (Baseline Model 2). The resulting bivariate GAM demonstrated an area under the ROC curve (AUC) of 0.671 in the training dataset and 0.644 in the test dataset, indicating a small but measurable improvement in predictive accuracy compared with the univariate model (MMO only). This Baseline Model 2 configuration was therefore selected as the reference framework for subsequent modelling steps.

Qualitative variables were then tested based on their predictive value. The most relevant variables were Q2 (difficulty in jaw movement), Q6 (ear or TMJ pain), Q7 (joint sounds), TMJ crepitus, and TMJ locking. When these variables were added to the Baseline 2 Model (Age + MMO). The extended multivariable model achieved an AUC of 0.754 in the training dataset and 0.736 in the test dataset, with 13.9% deviance explained and an adjusted R² of 0.14. Among the added predictors, Q2, crepitus, and TMJ locking remained statistically significant (p < 0.05), confirming their independent association with the presence of arthrogenous joint disease.

To further enhance model performance, several interaction terms were tested among the previously selected predictors. The resulting Fonseca–Dimitroulis model (FD-Class) was defined as:

$$\sim s(\text{Age}) + s(\text{MMO}) + Q2 + Q6 + Q7 + \text{CrepitusComplaint} + \text{TMJlocking} + (\text{TMJclicking} \times \text{MMO}) + (\text{MMO} \times \text{Sex})$$

where the variables Age and MMO are modelled using smoothing functions *s*().

This configuration was identified as the final predictive model for the presence of arthrogenous TMD according to the Dimitroulis classification.

In the training dataset, the model achieved an AUC of 0.761, and in the test dataset, an AUC of 0.742, corresponding to a mean discriminative capacity of approximately 0.75. The model explained 14.6% of deviance and had an adjusted R² of 0.143. At a threshold of 0.73, sensitivity and specificity were balanced (68% and 73%, respectively), although the negative predictive value (NPV) remained suboptimal (44%). Adjusting the threshold to 0.65, sensitivity increased to 81% while specificity remained acceptable (55%). This resulted in a positive predictive value (PPV) of 84% and an NPV of 51% in the test dataset.

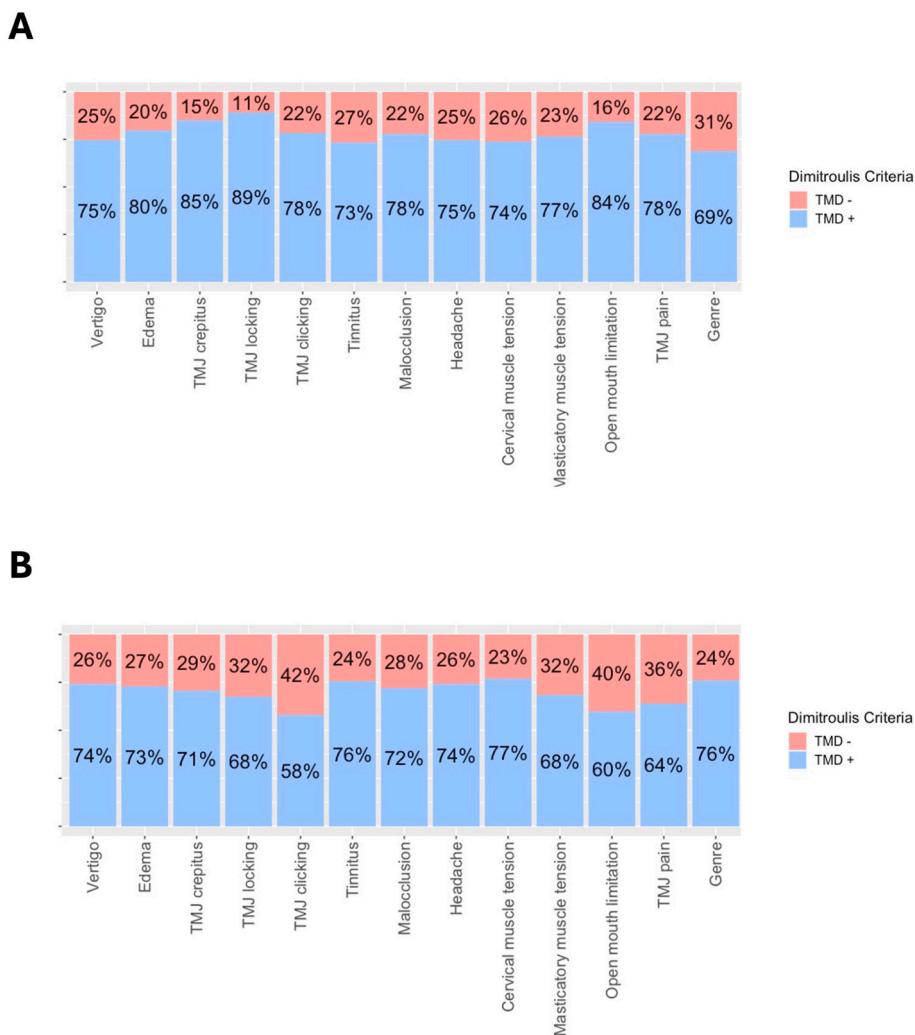


Fig. 2. Distribution of Clinical Complaints According to the Dimitroulis Classification. (A) shows the prevalence of each complaint among patients reporting its presence, and (B) shows the distribution among those reporting absence of complaints.

Overall model accuracy was 0.74 (95% CI, 0.71–0.78), with a Cohen's kappa statistic of 0.35, indicating moderate agreement with the Dimitroulis classification. These findings support that the FD-Class model is a reliable and sensitive tool for identifying arthrogenous TMD based on initial clinical evaluation.

The ROC curves for the Fonseca-only model (GLM) and the Fonseca–Dimitroulis model (FD-Class) are shown in Figs. 5 and 6. The FD-Class model achieved an AUC of 0.742, whereas the Fonseca-only model (blue curve) showed an AUC of 0.662 (Fig. 7).

This difference demonstrates a clear improvement in discriminative performance.

The FD-Class model also demonstrated higher sensitivity across most thresholds, confirming its better ability to identify patients with arthrogenous TMD.

4. Discussion

In this cross-sectional observational study, we developed the FD-Class model, a predictive algorithm that combines clinical and self-reported data from the first consultation to estimate arthrogenous TMD. The Dimitroulis classification, which integrates imaging and clinical assessment, was used as the reference standard. The model (with variables such as age, MMO, selected Fonseca items, crepitus, TMJ locking, and interaction terms) achieved an AUC of ≈0.75. It demonstrated superior sensitivity and overall accuracy compared to the FAI-

only model (AUC ≈ 0.66). These findings support the hypothesis that arthrogenous TMJ disease can be predicted through accessible, low-cost clinical data. The model provides a framework to support early decision-making and imaging referral in patients with suspected joint disease, bridging the gap between symptom screening and definitive diagnosis (Al Turkestani et al., 2024).

The spectrum of symptoms reported by patients at the first consultation reflects the heterogeneous nature of TMD. The predominance of female patients and the age distribution observed in our cohort are consistent with previous studies (Ângelo et al., 2023; Carapinha et al., 2024; Qin et al., 2024). The most frequent complaints were TMJ clicking, TMJ pain, and masticatory muscle tension. Other symptoms such as tinnitus and vertigo also showed relatively high prevalence. These variables were recorded as patient-reported complaints during the clinical history and should therefore be interpreted cautiously. Given the anatomical proximity between the TMJ and the ear, patients may sometimes interpret or describe preauricular discomfort, pressure, or pain as ear-related symptoms.

The FAI, first introduced in 1994, remains a widely used tool for initial assessment of TMD (Fonseca et al., 1994). More broadly, the FAI remains widely employed for epidemiological screening because of its ease of use, minimal resource requirements, and capacity to capture symptom burden (Mitro et al., 2024). However, it does not clearly distinguish between articular and muscular disorders. In general, the FAI shows high sensitivity but limited specificity. In contrast, the

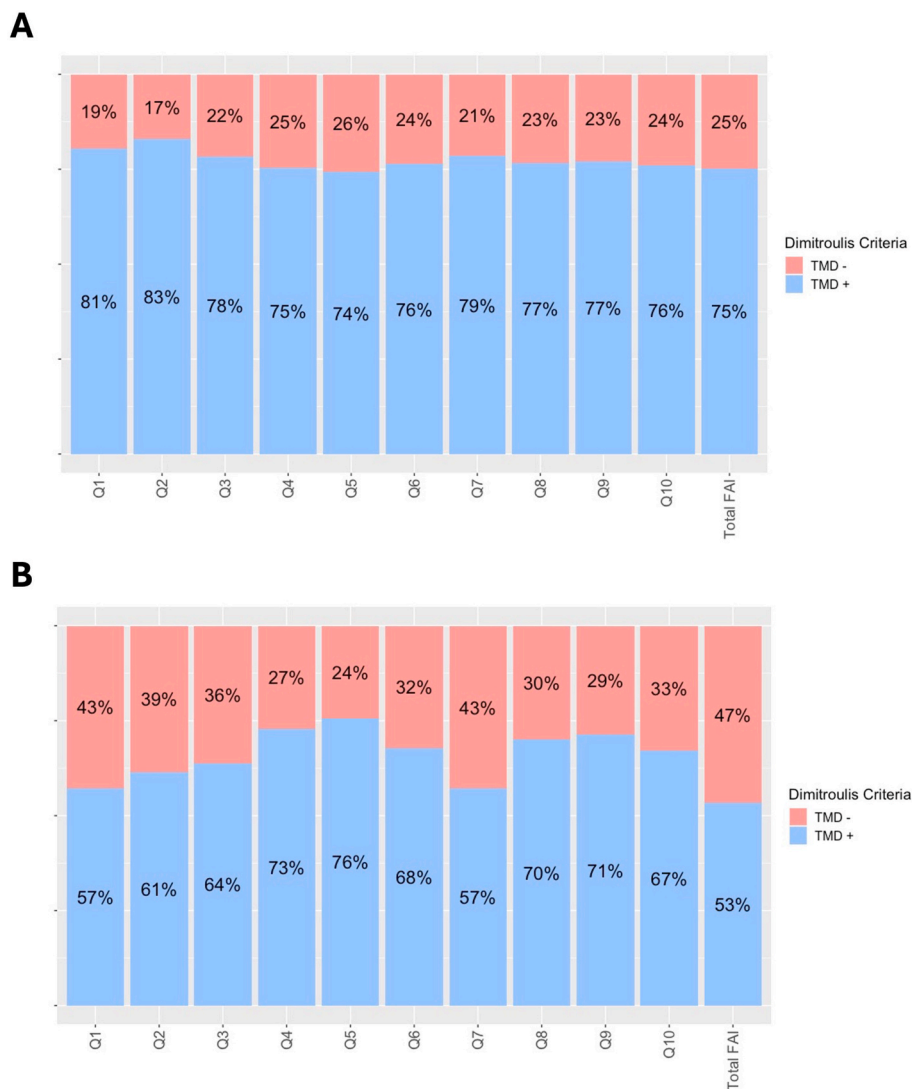


Fig. 3. Association Between Fonseca Questionnaire Responses and the Dimitroulis Classification. Each bar shows the proportion of patients with or without arthrogenous TMD (TMD⁺/TMD⁻) according to the Dimitroulis criterion. (A) The upper panel represents patients reporting positive answer in FAI; the lower panel, those reporting negative answer in FAI.

FD-Class model improves specificity, making it more suitable for clinical use. This differs from DC/TMD, which exhibit strong screening ability but limited specificity. In effect, the FD-Class model bridges the gap between a simple screening instrument and a more rigorous diagnostic classification (Schiffman et al., 2014), offering clinically actionable information that may assist maxillofacial clinicians in stratifying patients according to the likelihood of underlying joint disease.

Multiple investigations have documented both the strengths and limitations of the FAI. For instance, Stasiak et al. (2023) reported a sensitivity of 97.2% but a specificity of only 26.0% compared to RDC/TMD criteria, indicating that while the FAI effectively screens for possible TMD, it poorly discriminates non-cases. Similarly, in a study of the Short-Form Fonseca Index (SFAI), Yap et al. (2022) reported moderate diagnostic accuracy for the Short-Form Fonseca Index (SFAI) (AUCs ranging from 0.70 to 0.80 for pooled items), with limited discrimination at the item level. In our study, the FAI alone showed an AUC of 0.66, consistent with its role as a global symptom scale rather than a discriminant diagnostic tool. Nevertheless, its integration into the FD-Class model enhanced performance substantially. These findings indicate that structured symptom data remain useful when integrated with objective measures.

Emerging literature underscores a growing trend toward integrating

clinical, imaging, and computational methods for predicting TMJ pathology. For example, the EHPN tool, which combined clinical, imaging, and biomarker data into a nested ensemble model, achieved an accuracy of approximately 0.87 and an AUC of 0.72 in predicting TMJ osteoarthritis (Al Turkestani et al., 2024). Their work demonstrates the feasibility and potential of multidimensional models, albeit at the cost of requiring sophisticated biomarker and imaging inputs. Similarly, Artificial Intelligence (AI) models have been developed for radiographic diagnosis. Talaat et al. (2023) used convolutional neural networks on CBCT images to diagnose TMJ osteoarthritis, obtaining diagnostic performance surpassing radiologists in certain settings. Deep-learning and segmentation-based approaches have also been applied to MRI to detect articular disc displacement with AUCs around 0.88 (Jha et al., 2022; Lee et al., 2024). A recent systematic review of deep learning models in TMJ disorders confirms growing interest in such approaches but emphasizes their current limitations in generalizability and interpretability (Rokhshad et al., 2024). Another recent algorithm, published in 2025, enables simultaneous classification of multiple TMJ disease stages from imaging, improving prediction accuracy and streamlining interpretation (Su et al., 2025). These methods underscore that imaging-driven or AI-driven diagnosis is a rapidly evolving frontier. However, they are often resource-intensive, require high-quality imaging data and lack

Table 4
Qualitative variables significantly associated with arthrogenous temporomandibular Disorder (TMD).

Variables	N (%), or mean ± SD	
Demographic Data		
Sex		0.041
Complaints		
TMJ clicking		<0.001
TMJ Pain		<0.001
Masticatory muscle tension		0.013
Cervical muscle tension		0.356
Headache		0.992
Open mouth limitation		<0.001
Malocclusion		0.039
Tinnitus		0.454
Vertigo		0.930
Edema		0.025
TMJ crepitus		<0.001
TMJ locking		<0.001
Fonseca questionnaire items		
Q1		<0.001
Q2		<0.001
Q3		<0.001
Q4		0.467
Q5		0.686
Q6		0.013
Q7		<0.001
Q8		0.033
Q9		0.044
Q10		0.023
Fonseca Anamnestic Index (FAI)		
		0.012

integration with first-visit symptom data. By contrast, our FD-Class model emphasizes clinical parsimony: using only data collected at first consultation, it attains discriminative performance approaching that of more complex multimodal approaches. In doing so, it may serve as a “gatekeeper” to more advanced diagnostics, supporting rational use of MRI or CBCT and optimizing referral pathways in maxillofacial practice, reserving imaging or AI evaluation for the higher-risk cohort (Al Turkestani et al., 2024; Mehta et al., 2025).

In this study, two quantitative variables—age and MMO—showed non-linear relationships with arthrogenous disease. Younger age was associated with a higher predicted probability of joint disease. A finding that may reflect the clearer manifestation of primary articular disease in younger individuals, whereas older patients may present mixed or nonspecific orofacial pain syndromes. This age effect has been reported in several epidemiologic studies suggesting that symptomatic TMD

peaks between the second and fourth decades of life and declines thereafter (Qin et al., 2024; Zieliński et al., 2024). The non-linear protective pattern observed for MMO, with an inflection near 40 mm, is physiologically plausible and consistent with the clinical definitions of limited mouth opening used in DC/TMD and other diagnostic frameworks (Schiffman et al., 2014; Angelo et al., 2025). Restricted opening likely reflects intra-articular mechanical constraints, whereas preserved mobility above this threshold correlates with muscular or functional limitations rather than structural joint disease (Goiato et al., 2017).

The inclusion of interaction terms between TMJ clicking and MMO, and between MMO and sex, further improved the model's discriminative capacity. These interactions suggest that the effect of joint sounds depends on the degree of opening, and that the relationship between mobility and pathology differs between sexes. Female patients are known to have higher prevalence and severity of TMD, potentially due to hormonal and biomechanical factors affecting joint laxity and inflammatory response (Hirsch et al., 2023; Zieliński and Pająk-Zielińska, 2024). The model's ability to capture these interactions supports its biological plausibility and clinical coherence.

The results also align with Dimitroulis's original concept of TMJ degeneration as a progressive continuum, beginning with minor functional alterations and advancing toward osteoarthritis. By using the Dimitroulis classification as the gold standard, this study bridges subjective symptomatology with objective structural outcomes, effectively translating a pathophysiologic continuum into a statistical prediction framework. This integration is particularly relevant given that most clinical tools—including the FAI, Helkimo Index, and RDC/TMD—capture symptoms and function but do not correlate directly with underlying joint pathology.

Clinically, the FD-Class model offers several advantages. It is non-invasive, inexpensive, and based entirely on information obtainable during the first visit. Its high sensitivity and moderate specificity make it especially suitable for screening or triage purposes, where missing true cases is more detrimental than over-referral. In settings with limited access to imaging, the model could help prioritise patients for MRI or CBCT, improving resource allocation and reducing unnecessary imaging in patients unlikely to have structural joint disease. When integrated into systems as the EUROTMJ database, the model could be used as a real-time decision-support tool, automatically estimating the probability of arthrogenous disease (Angelo et al., 2023; Al Turkestani et al., 2024). It may also support standardized triage in maxillofacial outpatient clinics. Beyond immediate clinical use, such predictive modelling may also enhance research efficiency by enabling patient stratification according to joint-disease probability, reducing heterogeneity in future trials.

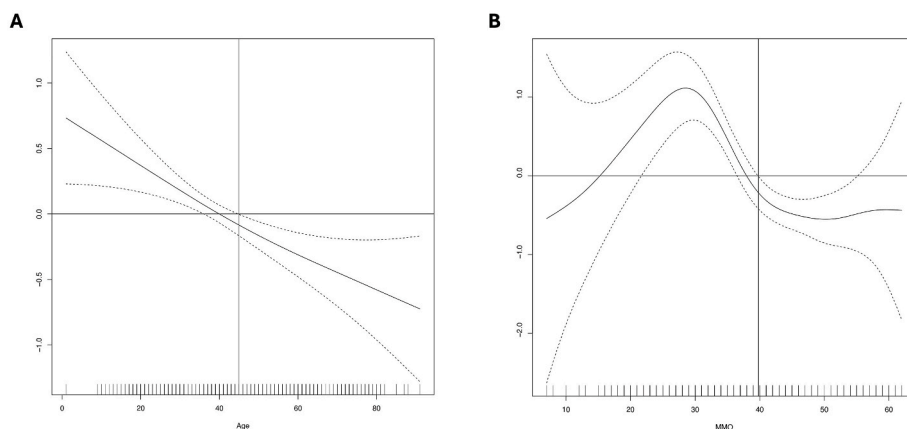


Fig. 4. Estimated effects of continuous predictors on the probability of arthrogenous temporomandibular disorder (TMD). (A) Effect of age and (B) effect of maximum mouth opening (MMO) on the predicted probability of arthrogenous TMD. The solid line represents the estimated effect, while the dashed lines indicate the 95% confidence intervals. The horizontal line at zero represents no effect on the log-odds of arthrogenous TMD. Vertical reference lines mark the value of 45 years for age and 39.8 mm for MMO.

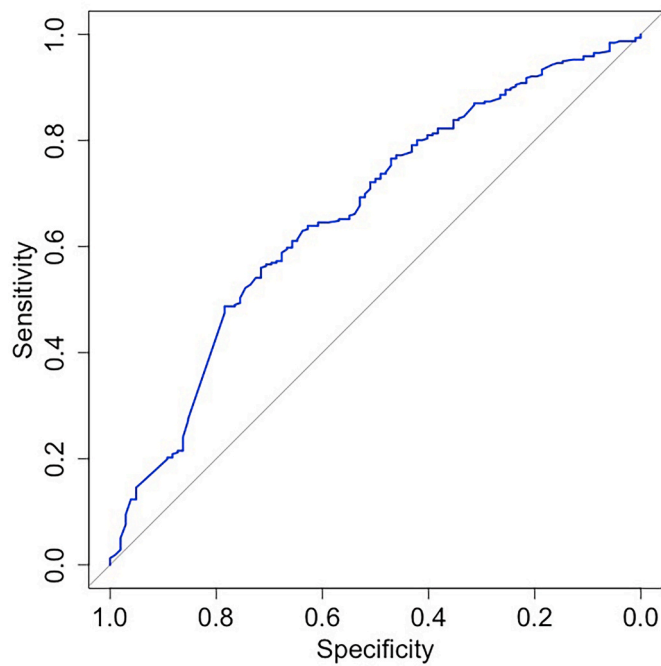


Fig. 5. Receiver-Operating Characteristic (ROC) Curve for the Fonseca Model. The curve illustrates the discriminative performance of the model built exclusively from the ten Fonseca questionnaire items in predicting arthrogenous TMD according to the Dimitroulis classification (AUC = 0.662).

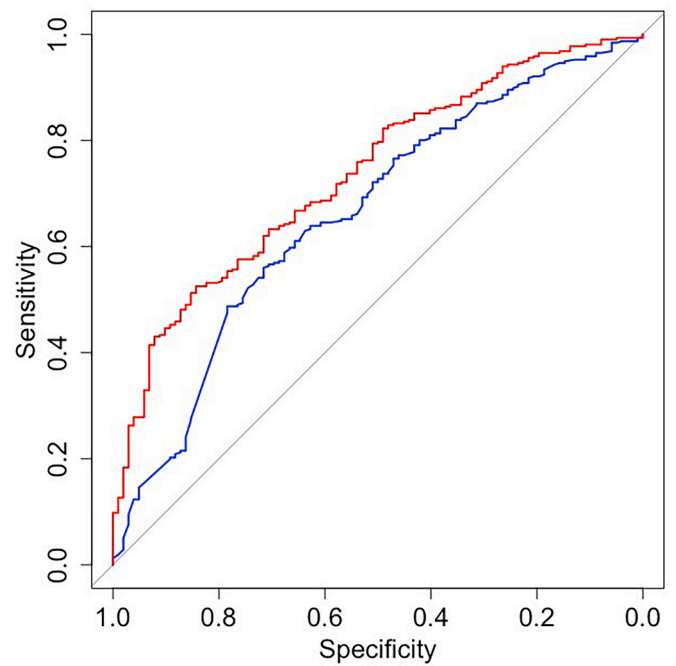


Fig. 7. Comparison of ROC Curves for the Fonseca and Fonseca–Dimitroulis Models. The red line represents the final Fonseca–Dimitroulis model (AUC = 0.742) and the blue line the Fonseca model (AUC = 0.662). (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)

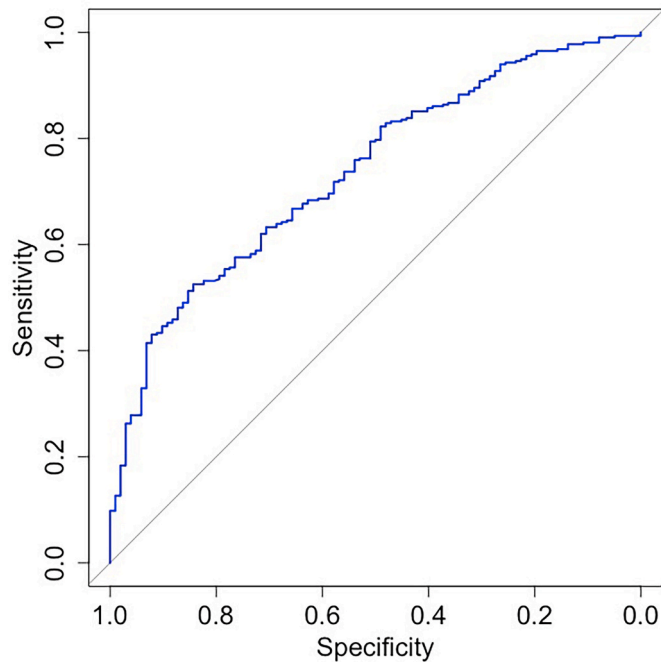


Fig. 6. Receiver-Operating Characteristic (ROC) Curve for the Fonseca–Dimitroulis Model (FD-Class). The curve shows the performance of the final predictive model combining smooth functions for Age and MMO), Fonseca items, and clinical variables for identifying arthrogenous TMD according to the Dimitroulis classification (AUC = 0.742).

Despite its promising results, the model has inherent limitations. The dataset was derived from a single specialized centre, and although the sample size was large, external validation is necessary to confirm generalizability. Imaging modalities were not uniform across cases, which could introduce variability in the reference classification. The

cross-sectional design precludes assessment of the model's longitudinal predictive power or its ability to monitor disease progression. Moreover, while the sensitivity–specificity balance was optimized for screening, moderate specificity implies some risk of false-positive classifications. Future research should include multicentric validation, prospective evaluation of temporal stability, and integration with complementary data—such as muscle electromyography, occlusal dynamics, and biochemical markers—to further refine model performance.

In a broader context, the FD-Class model reflects a paradigm shift in TMJ diagnostics: moving from symptom-based questionnaires toward integrated, quantitative prediction. As AI and imaging automation advance, models can provide interpretable, low-cost solutions that complement more sophisticated machine-learning systems. Unlike complex “black-box” AI systems, generalized additive modelling offers transparency—clinicians can visualize how each predictor contributes to disease probability, preserving interpretability while maintaining predictive strength. This remains an essential consideration for clinical adoption, where explainability and accountability are paramount.

5. Conclusion

The FD-Class model demonstrates that arthrogenous TMJ disease can be estimated using clinical data from the first consultation, before imaging confirmation. The model outperformed the FAI alone and achieved good discriminative performance. It provides a practical and sensitive tool for early detection. It acts as a bridge between simple screening and advanced diagnostics, offering an interpretable, cost-effective solution for TMD assessment in maxillofacial practice. By integrating key clinical variables and a short questionnaire into a digital system, this approach may support clinicians during the first visit, standardize triage, and enable large-scale screening. It may also help maxillofacial surgeons in guiding imaging decisions and prioritize patients for further diagnostic assessment and potential surgical evaluation. Future work should focus on developing this statistical model into a clinical decision-support tool capable of real-time risk estimation of

arthrogenous TMD.

Data availability statement

The data supporting the findings of this study are available from the corresponding author upon reasonable request.

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Conflict of 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 article.

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References

- Al Turkestani, N., Li, T., Bianchi, J., Gurgel, M., Prieto, J., Shah, H., Benavides, E., Soki, F., Mishina, Y., Fontana, M., Rao, A., Zhu, H., Cevidanes, L., 2024. A comprehensive patient-specific prediction model for temporomandibular joint osteoarthritis progression. *Proc. Natl. Acad. Sci. U. S. A.* 121, e2306132121.
- Ângelo, D.F., Mota, B., João, R.S., Sanz, D., Cardoso, H.J., 2023. Prevalence of clinical signs and symptoms of temporomandibular joint disorders registered in the EUROTMJ database: a prospective study in a Portuguese center. *J. Clin. Med.* 12.
- Ângelo, D.F., Lopes, C.S., Sanz, D., Faria-Teixeira, M.C., Marques, R., Maffia, F., Cardoso, H.J., 2024. Temporomandibular joint minimally invasive procedures in the pediatric population: a prospective study. *J. Clin. Med.* 13.
- Ângelo, D.F., Cardoso, H.J., João, R.S., Brás-Geraldes, C., Sanz, D., Maffia, F., Salvado, F., 2025. Gender differences in mouth opening on temporomandibular disorder patients-implications for diagnosis. *J. Clin. Med.* 14.
- Carapinha, I.H.A., De la Torre Canales, G., Poluha, R.L., Câmara-Souza, M.B., Christidis, N., Ernberg, M., de Almeida, A.M., Manso, A., 2024. Sociodemographic profile: a forgotten factor in temporomandibular disorders? A scoping review. *J. Pain Res.* 17, 393–414.
- Cervaens, M., Pereira, J., Magalhães, A., Esteves, M., Vilarinho, R., Abreu, V., Amaral, L., 2024. Portuguese translation, cultural adaptation and psychometric properties of the temporomandibular joint scale: a cross-sectional study. *Oral Maxillofac. Surg.* 29 (3).
- Christidis, N., Al-Moraissi, E.A., Barjandi, G., Svedenlöf, J., Jasim, H., Christidis, M., Collin, M., 2024. Pharmacological treatments of temporomandibular disorders: a systematic review including a network meta-analysis. *Drugs* 84, 59–81.
- Dimitroulis, G., 2013. A new surgical classification for temporomandibular joint disorders. *Int. J. Oral Maxillofac. Surg.* 42, 218–222.
- Fonseca, DMD, Bonfante, G., Valle, ALD, Freitas, SFTD, 1994. Diagnóstico Pela Anamnese Da Disfunção Craniomandibular: RGO. Porto Alegre, pp. 23–28.
- Goiato, M.C., Zuim, P.R.J., Moreno, A., Dos Santos, D.M., da Silva, E.V.F., de Caxias, F.P., Turcio, K.H.L., 2017. Does pain in the masseter and anterior temporal muscles influence maximal bite force? *Arch. Oral Biol.* 83, 1–6.
- Hirsch, C., Schierz, O., Körner, A., Kiess, W., Biemann, R., Schrock, A., Türp, J.C., 2023. Sex hormones associated with temporomandibular pain on palpation in Male adolescents—Results of the epidemiologic LIFE child study. *J. Oral Rehabil.* 50, 972–979.
- Jha, N., Lee, K.S., Kim, Y.J., 2022. Diagnosis of temporomandibular disorders using artificial intelligence technologies: a systematic review and meta-analysis. *PLoS One* 17, e0272715.
- Kapos, F.P., Exposto, F.G., Oyarzo, J.F., Durham, J., 2020. Temporomandibular disorders: a review of current concepts in aetiology, diagnosis and management. *Oral surgery* 13, 321–334.
- Lee, Y.H., Jeon, S., Won, J.H., Auh, Q.S., Noh, Y.K., 2024. Automatic detection and visualization of temporomandibular joint effusion with deep neural network. *Sci. Rep.* 14, 18865.
- Matheson, E.M., Fermo, J.D., Blackwelder, R.S., Temporomandibular Disorders: Rapid Evidence Review, 2023. *Am. Fam. Physician* 107, 52–58.
- Mauro, G., Verdecchia, A., Suárez-Fernández, C., Nocini, R., Mauro, E., Zerman, N., 2024. Temporomandibular disorders management-what's new? A scoping review. *Dent. J.* 12.
- Mehta, V., Tripathy, S., Noor, T., Mathur, A., 2025. Artificial intelligence in temporomandibular joint disorders: an umbrella review. *Clin Exp Dent Res* 11, e70115.
- Mitro, V., Caso, A.R., Sacchi, F., Gilli, M., Lombardo, G., Monarchi, G., Pagano, S., Tullio, A., Fonseca's Questionnaire Is a Useful Tool for Carrying Out the Initial Evaluation of Temporomandibular Disorders in Dental Students, 2024. *Clinics and Practice* 14, 1650–1668.
- Nagi, R., Kumar, S.S., Kalladka, M., Khan, J., 2025. Diagnosis and management of arthrogenous temporomandibular joint disorders: a literature review. *Front. Oral Maxillofac. Med.* 7.
- Pires, P.F., de Castro, E.M., Pelai, E.B., de Arruda, A.B.C., Rodrigues-Bigaton, D., 2018. Analysis of the accuracy and reliability of the short-form fonseca anamnestic index in the diagnosis of myogenous temporomandibular disorder in women. *Braz. J. Phys. Ther.* 22, 276–282.
- Qin, H., Guo, S., Chen, X., Liu, Y., Lu, L., Zhang, M., Zhang, H., Zhang, J., Yu, S., 2024. Clinical profile in relation to age and gender of patients with temporomandibular disorders: a retrospective study. *BMC Oral Health* 24, 955.
- R Core Team, 2025. *A Language and Environment for Statistical Computing*. R Foundation for Statistical Computing, Vienna, Austria.
- Rokhshad, R., Mohammad-Rahimi, H., Sohrabniya, F., Jafari, B., Shobeiri, P., Tsolakis, I. A., Ourang, S.A., Sultan, A.S., Khawaja, S.N., Bavarian, R., Palomo, J.M., 2024. Deep learning for temporomandibular joint arthropathies: a systematic review and meta-analysis. *J. Oral Rehabil.* 51, 1632–1644.
- Schiffman, E., Ohrbach, R., Truelove, E., Look, J., Anderson, G., Goulet, J.P., List, T., Svensson, P., Gonzalez, Y., Lobbezoo, F., Michelotti, A., Brooks, S.L., Ceusters, W., Drangsholt, M., Ettlin, D., Gaul, C., Goldberg, L.J., Haythornthwaite, J.A., Hollender, L., Jensen, R., John, M.T., De Laat, A., de Leeuw, R., Maixner, W., van der Meulen, M., Murray, G.M., Nixdorf, D.R., Palla, S., Petersson, A., Pionchon, P., Smith, B., Visscher, C.M., Zakrzewska, J., Dworkin, S.F., 2014. Diagnostic criteria for temporomandibular disorders (DC/TMD) for clinical and research applications: recommendations of the international RDC/TMD consortium network* and orofacial pain special interest group. *Journal of oral & facial pain and headache* 28, 6–27.
- Stasiak, G., Maracci, L.M., de Oliveira Chami, V., Pereira, D.D., Tomazoni, F., Bernardon Silva, T., Ferrazzo, V., Marquezan, M., 2023. TMD diagnosis: sensitivity and specificity of the fonseca anamnestic index. *Cranio J. Craniomandib. Sleep Pract. : J. Cranio-Mandibular Pract.* 41, 199–203.
- Su, T.-Y., Wu, J.C.-H., Chiu, W.-C., Chen, T.-J., Lo, W.-L., Lu, H.H.-S., 2025. Automatic classification of temporomandibular joint disorders by magnetic resonance imaging and convolutional neural networks. *Journal of dental sciences* 20, 393–401.
- Talaat, W.M., Shetty, S., Al Bayatti, S., Talaat, S., Mourad, L., Shetty, S., Kaboudan, A., 2023. An artificial intelligence model for the radiographic diagnosis of osteoarthritis of the temporomandibular joint. *Sci. Rep.* 13, 15972.
- Yap, A.U., Zhang, M.-J., Lei, J., Fu, K.-Y., 2022. Diagnostic accuracy of the short-form fonseca anamnestic index in relation to the diagnostic criteria for temporomandibular disorders. *J. Prosthet. Dent* 128, 977–983.
- Zieliński, G., Pająk-Zielińska, B., 2024. Association between estrogen levels and temporomandibular disorders: an updated systematic review. *Int. J. Mol. Sci.* 25, 9867.
- Zieliński, G., Pająk, A., Wójcicki, M., 2024. Global prevalence of sleep bruxism and awake bruxism in pediatric and adult populations: a systematic review and meta-analysis. *J. Clin. Med.* 13.