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İÇİNDEKİLER

BÖLÜM 1

BRUXISM: ASSESSMENT METHODS, ASSESSMENT TOOLS, AND TREATMENT APPROACHES

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Introduction

The etiology of bruxism is known to be influenced by genetic, psychological, physiological, and lifestyle-related factors; however, the exact etiopathogenetic mechanisms have not yet been fully elucidated (Uchima Koecklin, Aliaga-Del Castillo, & Li, 2024). Bruxism is a masticatory muscle activity characterized during sleep by rhythmic (phasic) or non-rhythmic (tonic) muscle activity, and during wakefulness by repetitive or sustained tooth contact and/or by bracing or thrusting of the mandible (Frank Lobbezoo et al., 2018; Verhoeff et al., 2025). This parafunctional activity

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manifests as clenching or grinding of the teeth and may lead to serious oral and systemic health problems, including tooth wear, temporomandibular disorders (TMDs), and pain (Manfredini & Lobbezoo, 2009). Bruxism is considered motor behavior rather than a disease or disorder per se. It may occur in both healthy individuals and those with impaired health status, and may serve as a risk factor for specific clinical outcomes (Verhoeff et al., 2025).

Definition and Prevalence of Bruxism

Bruxism is broadly classified into two main subtypes: sleep bruxism and awake bruxism (Frank Lobbezoo et al., 2018). Sleep bruxism is characterized as rhythmic (phasic) or non-rhythmic (tonic) masticatory muscle activity occurring during sleep, whereas awake bruxism is defined as repetitive or sustained tooth contact and/or bracing or thrusting of the mandible (Manfredini, Serra-Negra, Carboncini, & Lobbezoo, 2017). Lobbezoo et al. (Frank Lobbezoo et al., 2018), define bruxism not as a disease or disorder in itself, but rather as a motor behavior.

Verhoeff et al. (Verhoeff et al., 2025) subsequently refined this definition by emphasizing that bruxism may occur in both healthy and unhealthy individuals, and proposed a threefold classification comprising primary bruxism, secondary bruxism, and bruxism as a sign of a disorder. In the same study, the relationship between bruxism and disorders was addressed in three distinct ways: (1) primary bruxism, in which the association with a disorder remains unclear or both conditions coexist; (2) secondary bruxism, in which bruxism is demonstrably associated with a specific disorder, treatment, or lifestyle factor; and (3) bruxism as a sign of a disorder, in which the disorder itself gives rise to jaw-muscle activities, and bruxism is therefore regarded as part of that disorder (Verhoeff et al., 2025).

The global prevalence of bruxism varies considerably depending on the assessment method employed and the population studied. According to the systematic review and meta-analysis conducted by Zieliński et al. (Zieliński, Pająk, & Wójcicki, 2024) the prevalence of overall bruxism (sleep and awake bruxism combined) was 22.22%, whereas the prevalence rates were 21% for sleep bruxism and 23% for awake bruxism. In assessments based on polysomnography (PSG), the prevalence of sleep bruxism increased to 43%. Geographically, the highest prevalence was reported in North America (31%), and a more pronounced prevalence was observed among women (Zieliński et al., 2024). In an earlier systematic review, the reported prevalence ranged from 8.0% to 31.4% for overall bruxism, was 12.8% ± 3.1 for sleep bruxism, and ranged from 22.1% to 31.0% for awake bruxism; similar rates were found between sexes, and a decline in bruxism with increasing age was observed (Manfredini, Winocur, Guarda-Nardini, Paesani, & Lobbezoo, 2013).

The principal reason for this wide range in prevalence estimates is the heterogeneity of the diagnostic methods used across studies. Manfredini et al. (Manfredini et al., 2013), emphasized that studies based solely on self-report exhibit limited internal validity, whereas epidemiological data derived from objective methods such as polysomnography or electromyography remain extremely scarce.

In pediatric and adolescent populations, the prevalence of bruxism follows a pattern distinct from that observed in adults and exhibits marked variation across age groups. The prevalence of probable sleep bruxism has been reported to range from 25.2% to 34.5% in school-aged children and to reach 52.9% in adolescents aged 10–19 years. When evaluated by age group, the prevalence of probable sleep bruxism has been reported as 47.6% in preschool children, 10%–16% in school-aged children, and 5% in adolescents older than 13 years (Nelly Huynh & Fabbro, 2024). In children and adolescents, bruxism has been associated with anxiety, hyperactivity, sleep disturbances, and breathing difficulties (Guo et al., 2018). The association between gastroesophageal reflux and bruxism has also been supported by separate studies (Y. Li et al., 2018). In addition, the adverse impact of the COVID-19 pandemic on pediatric bruxism has been documented, with a marked increase in sleep-related problems and bruxism observed during the pandemic period (Lima et al., 2022).

It has been noted that the diagnostic method used (parental report, clinical examination, or polysomnography) and the level of diagnostic certainty applied (possible, probable, or definite) are among the main factors contributing to the wide range of bruxism prevalence estimates reported in the literature (Zieliński et al., 2024).

Etiology and Pathophysiology of Bruxism

Bruxism is a multifactorial condition arising not from a single cause, but from the combined influence of genetic, neurobiological, psychological, and behavioral factors (Frank LOBBEZOO, Van Der Zaag, Van Selms, Hamburger, & Naeije, 2008). For many years, peripheral malocclusion was regarded as the principal cause of bruxism; however, this view is no longer supported by current scientific evidence (F Lobbezoo & Naeije, 2001). Current evidence suggests that bruxism is more strongly associated with central neurophysiological mechanisms than with peripheral occlusal factors, although its exact pathophysiology has not yet been fully elucidated (F Lobbezoo & Naeije, 2001; Thomas et al., 2024; Uchima Koecklin et al., 2024). Stress and psychological factors are among the most frequently cited contributors, particularly in the etiology of awake bruxism, and the association of bruxism with anxiety, depression, and personality traits has been demonstrated in numerous studies (Manfredini & Lobbezoo, 2009).

Neurobiological Mechanisms

Dopaminergic and serotonergic neurotransmitter systems are thought to play a critical role in the neurobiological basis of bruxism (Pavlou, Spandidos, Zoumpourlis, & Papakosta, 2024). Dopamine is known to play an important role in motor control, and dysregulation of this system has been proposed to increase susceptibility to bruxism (George, Joy, & Roy, 2021). Serotonergic neurons are known to project from the raphe nuclei to the ventral tegmental area (VTA), where they form synapses with dopaminergic neurons. This two-neuron pathway constitutes the neuroanatomical basis of masticatory muscle modulation. Central bruxism may occur in hyperdopaminergic states induced by agents such as amphetamines and levodopa, in the presence of cholinergic hypofunction, and also in hypodopaminergic states observed in extrapyramidal system dysfunction (Pavlou et al., 2024).

Genetic Factors

Evidence supporting a hereditary component in bruxism is steadily increasing. Self-reported sleep bruxism has been associated with genes involved in serotonergic (5HTR2A) and dopaminergic pathways (DRD2, DRD3, ANKK1), as well as with genes encoding enzymes (COMT and MMP9) and proteins (ACTN3 and ANKK1). Sleep bruxism identified by objective measurement tools has been reported to be associated only with the telomerase reverse transcriptase gene (TERT), whereas self-reported awake bruxism has been associated with the ACTN3 and ANKK1 genes (de Oliveira et al., 2024).

Stress, Anxiety, and Psychological Factors

Bruxism has been strongly associated with chronic stress and allostatic load, defined as the cumulative physiological burden imposed by repeated stress responses, and this burden has been suggested to trigger weakening of critical neuronal pathways that contribute to involuntary orofacial muscle activity. Under stress conditions, lesions of the ventral tegmental area (VTA) have been shown to alter hypothalamic–pituitary–adrenal (HPA) axis responses, indicating that the dopaminergic system exerts a significant influence on the hypothalamic–pituitary–adrenal axis (Pavlou et al., 2024). Salivary cortisol levels have also been reported to be higher in individuals with bruxism (Fritzen et al., 2022). Children with higher levels of anxiety have been reported to experience bruxism more frequently; this association suggests that psychological assessment should constitute an integral component of the diagnostic evaluation of bruxism (Guo et al., 2018).

Medication-Induced Bruxism

Certain medications have been reported to trigger bruxism or exacerbate pre-existing bruxism. Although antidepressants—particularly selective serotonin reuptake inhibitors (SSRIs)—as well as antipsychotics and stimulant agents are among the most frequently reported drug classes, it has been emphasized that the current evidence is based largely on case reports and that controlled studies are still needed (George et al., 2021). SSRIs have been proposed to induce bruxism by exerting serotonergic effects on mesocortical neurons in the VTA, thereby indirectly suppressing dopaminergic activity. Fluoxetine is the SSRI most frequently associated with bruxism, followed by sertraline; however, it should not be overlooked that this finding may partly reflect the widespread use of these medications (George et al., 2021).

Conditions Associated with Bruxism and Concomitant Clinical Presentations

Sleep bruxism, in particular, has been reported more frequently in association with various sleep-related and neurological conditions, including obstructive sleep apnea (OSA), restless legs syndrome, periodic limb movements, sleep-related gastroesophageal reflux, REM (rapid eye movement) sleep behavior disorder, Parkinson's disease, and sleep-related epilepsy; however, the pathophysiological mechanisms underlying these associations have not yet been fully elucidated (Kuang et al., 2022). Regarding the relationship between bruxism and sleep quality, subjective sleep quality has been reported to be associated with both sleep bruxism and awake bruxism, whereas objective sleep parameters assessed by polysomnography have not shown a consistent association with sleep bruxism (de Holanda, de Holanda, & Casarin, 2025).

Awake bruxism, in contrast, appears to be more closely associated with psychosocial factors than sleep bruxism and is more frequently evaluated in conjunction with anxiety, depressive symptoms, emotional stress, TMDs, and headaches (Stanisic et al., 2025; Voß, Basedau, Svensson, & May, 2024). It has been reported that individuals with high trait anxiety exhibit increased masseter muscle activity and greater severity of tooth-clenching episodes during wakefulness; moreover, mandibular bracing and clenching behaviors have shown moderate-to-strong correlations with symptoms of anxiety and depression (Rofaeel, Chow, & Cioffi, 2021; Saracutu et al., 2024). On the other hand, salivary cortisol levels have been found to be elevated in individuals with bruxism, suggesting a possible association with the stress response; however, the available evidence does not, by itself, establish a causal relationship (Fritzen et al., 2022).

Bruxism is generally regarded as one of the leading contributing factors to TMDs (Fernandes, Franco, Siqueira, Gonçalves, & Camparis, 2012; Schiffman et al., 2014). In the systematic review and meta-analysis by Mortazavi et al. (Mortazavi, Tabatabaei, Mohammadi, & Rajabi, 2023) the presence of bruxism was shown to be significantly associated with TMD, with an increased likelihood of TMD occurrence. In the same study, this association was reported to be stronger for awake bruxism, while remaining lower but still significant for sleep bruxism (Mortazavi et al., 2023). Nevertheless, the magnitude and direction of this association vary substantially depending on the method used to assess bruxism (Manfredini & Lobbezoo, 2021). In the scoping review by Manfredini and Lobbezoo (Manfredini & Lobbezoo, 2021) questionnaire- and self-report–based assessments of sleep bruxism were generally found to show a positive association with TMDs, whereas instrumental assessments, such as electromyography (EMG) and polysomnography (PSG), were reported to show weaker or even negative associations.

Methods of Bruxism Assessment

The assessment of bruxism is a multidimensional process that encompasses both non-instrumental approaches, such as self-report and clinical examination, and instrumentally based methods, such as EMG and PSG (Frank Lobbezoo et al., 2018). According to current consensus statements, because bruxism is regarded as a motor behavior rather than a disease entity per se, the assessment process should extend beyond the mere identification of the behavior itself to include the evaluation of concomitant clinical consequences, associated conditions, and risk indicators (Manfredini et al., 2024; Verhoeff et al., 2025). Accordingly, bruxism assessment tools are used primarily for structured inquiry, screening, and clinical observation, whereas devices serve to characterize the nature, frequency, and severity of masticatory muscle activity more objectively (Frank Lobbezoo et al., 2018; Manfredini et al., 2024).

Because no single standard method that is valid, accessible, and cost-effective across all clinical and research settings is available for the assessment of bruxism, a diagnostic grading system comprising the categories of possible, probable, and definite bruxism was proposed (Frank Lobbezoo et al., 2013). Possible bruxism is based on a positive self-report only, probable bruxism on a positive clinical inspection, with or without a positive self-report, and definite bruxism on a positive instrumental assessment, with or without a positive self-report and/or a positive clinical inspection (Frank Lobbezoo et al., 2018).

In the assessment of bruxism, both historical grading systems and contemporary multidimensional frameworks should be considered. Earlier consensus statements categorized bruxism as possible, probable, and definite according to the combination of self-report, clinical examination, and instrumental assessment findings (Frank Lobbezoo et al., 2013; Frank Lobbezoo et al., 2018). More recent consensus documents, however, emphasize describing bruxism according to the assessment modality employed—subject-based, clinically based, and device-based assessment—and recommend interpreting these findings together with possible consequences, associated conditions, and risk indicators (Manfredini et al., 2024; Verhoeff et al., 2025).

Subject Based Assessment and Questionnaires

Questionnaires and other self-report instruments used in the assessment of bruxism are useful for initial screening, as they allow a structured evaluation of symptoms, potential triggers, and concomitant clinical features. However, because these tools cannot objectively verify the presence, frequency, or severity of bruxism, they are not sufficient on their own to establish a definitive diagnosis. For this reason, questionnaire findings should be interpreted in conjunction with clinical examination and, when indicated, instrumentally based assessment methods (Manfredini et al., 2024; Manfredini et al., 2020).

Sleep bruxism may be addressed clinically by inquiring whether the individual or a bed partner reports tooth-grinding sounds during sleep, as well as by assessing symptoms such as muscle fatigue, temporal headache, masticatory muscle pain, and jaw locking upon awakening; however, the diagnostic accuracy of these findings is limited, and they are more appropriately regarded as screening indicators. In particular, because self-report–based assessment does not reliably identify true sleep bruxism as confirmed by polysomnography, polysomnography is considered the reference standard for definitive evaluation (Palinkas et al., 2015; Raphael et al., 2015).

In the assessment of sleep bruxism in children, screening is generally based on parental reports and clinical examination because of the limited utility of self-report. However, as the agreement of these methods with objective measurements may be limited, they are not considered sufficient on their own to establish a definitive diagnosis. Therefore, although questionnaires and other non-instrumental screening tools are useful in first-line clinical assessment, instrumentally based methods, such as PSG and/or EMG recordings, should be employed when necessary to confirm the diagnosis (NT Huynh, Desplats, & Bellerive, 2016; Nelly Huynh & Fabbro, 2024; Restrepo et al., 2017).

In the assessment of awake bruxism, non-instrumental approaches based on self-report, questionnaires, and clinical examination may be employed; however, because these methods cannot quantitatively determine the intensity and duration of muscle activity, they are not sufficient on their own for definitive evaluation. For this reason, real-time assessment approaches and, when indicated, electromyographic recordings are recommended as complementary methods for a more comprehensive assessment of awake bruxism (Bracci et al., 2022; Emodi-Perlman et al., 2021).

In recent years, greater emphasis has been placed on the development of standardized instruments that integrate self-report, clinical examination, and associated risk factors within a single assessment framework for bruxism (Manfredini et al., 2024). Among the tools developed for the standardized assessment of bruxism, STAB (Standardised Tool for the Assessment of Bruxism) and BruxScreen (Bruxism Screener) are particularly noteworthy. STAB is a comprehensive instrument designed to evaluate bruxism behavior, its possible consequences, associated conditions, and risk factors in a multidimensional manner. In contrast, BruxScreen is a shorter, screening-oriented assessment tool developed primarily for use in large-scale research and general dental practice (Frank Lobbezoo et al., 2024; Manfredini et al., 2024).

Clinical Examination

Clinical examination represents an important step in the assessment of bruxism, as it allows findings obtained from self-report and history taking to be supported by physical signs. According to international consensus, clinical examination, together with self-report, is used particularly in the assessment of possible and probable bruxism. In this context, findings such as tooth wear, cracked teeth, restoration failure, masseter muscle hypertrophy, tooth indentations on the tongue or buccal mucosa, and linea alba may be evaluated. Symptoms including temporomandibular joint pain and pain, fatigue, or morning stiffness in the masticatory muscles are also taken into consideration. However, none of these clinical findings is specific to bruxism when considered in isolation. Tooth wear in particular, although it may be associated with bruxism, can also develop as a result of erosion, abrasion, and other etiological factors; therefore, clinical examination alone should not be regarded as sufficient for a definitive diagnosis (Cunha-Cruz et al., 2010; KOYANO, Tsukiyama, Ichiki, & Kuwata, 2008; Frank Lobbezoo et al., 2018).

Instrumentally Based Assessment Methods

While audio-video–supported polysomnography (PSG-AV) remains the reference standard for the assessment of sleep bruxism, ambulatory polysomnography and portable EMG-based systems are regarded as complementary options aimed at improving clinical feasibility; for awake bruxism, ecological momentary assessment and smartphone-based digital tools are gaining increasing importance (Abe et al., 2023; Bracci et al., 2022; Cid-Verdejo et al., 2024).

Polysomnography

Polysomnography is regarded as the gold standard for the diagnostic confirmation of sleep bruxism, as it enables the combined evaluation of sleep architecture, audio-video recording, and masticatory muscle EMG activity (Abe et al., 2023; Stuginski-Barbosa, Porporatti, Costa, Svensson, & Conti, 2017). This method allows not only the detection of masticatory muscle activity, but also the assessment of concomitant sleep events, thereby contributing to the differentiation of sleep bruxism episodes from other motor or respiratory sleep-related events (Abe et al., 2023).

Attended in-laboratory audio-video polysomnography (type 1 PSG) is considered the reference standard for identifying sleep bruxism episodes and quantitatively assessing their severity (Abe et al., 2023; Stuginski-Barbosa et al., 2017). However, although full PSG setups without video recording may still provide a certain level of diagnostic accuracy, the reliability of EMG-only configurations is lower. Therefore, audio-video PSG remains the superior method for the classification of bruxism events (Miettinen et al., 2020).

On the other hand, marked night-to-night variability in sleep bruxism activity and, in some cases, a first-night effect have been reported; therefore, a single-night recording may be insufficient, particularly in individuals with low levels of activity (Lavigne, Guitard, Rompré, & Montplaisir, 2001; Miettinen et al., 2018; Van Der Zaag, Lobbezoo, Visscher, Hamburger, & Naeije, 2008). In addition, because of the need for multi-night recordings, the associated time and cost burden, and the requirement for expert scoring, PSG is not a feasible method for routine clinical use in every patient (Abe et al., 2023; C. Li et al., 2024).

Ambulatory Polysomnography

Ambulatory polysomnography devices are out-of-laboratory sleep monitoring systems that allow recordings to be obtained in the individual's usual sleep environment and may improve feasibility, particularly in multi-night assessments. According to the American Academy of Sleep Medicine (AASM) classification, type 2 PSG is defined as full unattended polysomnography with at least seven channels, performed outside the laboratory (Abe et al., 2023; Collop et al., 2007).

However, although full-channel ambulatory PSG systems offer the possibility of out-of-laboratory assessment, the diagnostic validity of simpler portable EMG-based devices has also been investigated for the evaluation of sleep bruxism in comparison with PSG (Cid-Verdejo et al., 2024; Yamaguchi et al., 2023). In this context, portable and wearable EMG-based devices suitable for home use have been developed as alternative tools for the more feasible monitoring of sleep bruxism (Yamaguchi et al., 2023).

In individuals with OSA, the performance of a portable EMG-ECG device for the diagnosis of sleep bruxism has been reported to show acceptable diagnostic agreement in those without OSA and in those with mild OSA; however, this agreement was found to decrease markedly in patients with moderate to severe OSA (Cid-Verdejo, Domínguez Gordillo, Sánchez-Romero, Ardizone García, & Martínez Orozco, 2023).

Instrument Based Assessment of Bruxism Using Intraoral and Portable Devices

The Bruxoff Device

Bruxoff is a portable assessment system that combines surface electromyography with cardiac signal recording. The fundamental rationale of the device is to detect sleep bruxism events under out-of-laboratory conditions by simultaneously recording masseter muscle activity and concomitant autonomic changes. In this respect, it provides a hybrid ambulatory recording approach that takes into account not only muscle activity, but also the physiological variables accompanying bruxism events (Cid-Verdejo et al., 2023; Yanez-Regonesi et al., 2023).

The clinical purpose of Bruxoff is primarily to enable preliminary screening in individuals at risk for sleep bruxism, to provide multi-night recordings in the home environment, and to yield objective ancillary data during follow-up. Although studies conducted simultaneously with PSG have reported acceptable levels of sensitivity and specificity for the device, systematic measurement differences between methods have also been demonstrated. Therefore, Bruxoff should be positioned in clinical practice as an adjunctive instrument-based assessment tool, rather than being presented as a definitive diagnostic method replacing PSG-AV (Cid-Verdejo et al., 2023; Yanez-Regonesi et al., 2023).

The BiteStrip Device

BiteStrip is a small, single-use surface EMG screening device applied over the masseter muscle. Its purpose is to detect masseter EMG events occurring during sleep in a practical format that is readily applicable in clinical settings. Accordingly, it was developed not as a substitute for comprehensive polysomnographic recordings, but rather as a tool primarily intended for preliminary assessment and clinical screening (Shochat et al., 2007).

The principal clinical application of BiteStrip is the rapid preliminary evaluation of individuals suspected of having sleep bruxism. Initial validation studies demonstrated a significant association between BiteStrip recordings and conventional masseter EMG events, whereas subsequent comparisons with polysomnography showed that the device is more useful for distinguishing the presence or absence of bruxism than for detailed severity grading. Therefore, BiteStrip should be regarded not as a definitive diagnostic tool, but as a simple screening instrument and an adjunctive aid for classification (C. Li et al., 2024; Shochat et al., 2007).

Biofeedback-Based Devices

Biofeedback is a behavioral intervention approach based on the delivery of real-time feedback or a counter stimulus when bruxism related jaw muscle activity occurs. The aim of this approach is to enhance awareness of parafunctional muscle activity and, over time, to reduce its frequency and/or intensity. Although biofeedback has been applied in both awake bruxism and sleep bruxism, the level of evidence regarding its efficacy varies across methods. In awake bruxism, short-term reductions in masticatory muscle activity have been reported with auditory or visual feedback based on surface electromyography. In sleep bruxism, biofeedback has been investigated primarily through contingent electrical stimulation and vibratory stimuli; although some studies have reported short-term benefits, the findings remain heterogeneous, and therefore these methods should not be presented as standard treatments with definitive efficacy (Jokubauskas & Baltrušaitytė, 2018; Maejima et al., 2024; Nakamura et al., 2019; Saito-Murakami et al., 2020; Vieira et al., 2023).

The GrindCare Device

GrindCare is a portable system that records single-channel surface EMG activity from the anterior temporal region and, in certain versions, delivers contingent electrical stimulation in response to detected muscle activity. Accordingly, the device functions not only as a recording instrument but also as an intervention platform operating on a biofeedback principle. Its primary aim is to detect specific patterns of masticatory muscle activity arising during sleep and to help reduce their intensity (Jadidi, Castrillon, & Svensson, 2008; Stuginski-Barbosa, Porporatti, Costa, Svensson, & Conti, 2016).

The clinical use of GrindCare can be summarized at two levels: first, multi-night home monitoring of masticatory muscle activity; and second, reduction of parafunctional activity through biofeedback. Studies evaluating GrindCare have shown that contingent electrical stimulation can significantly reduce temporalis EMG activity and that its discriminative performance relative to PSG improves when the device is used for three or five consecutive nights. Nevertheless, the device output is sensitive to the threshold setting, recording duration, and number of nights assessed. Therefore, GrindCare should be characterized as a portable EMG system intended for monitoring and biofeedback purposes, and its diagnostic validity should be interpreted in a context-dependent manner (Jadidi et al., 2008; Stuginski-Barbosa et al., 2016).

Single-Channel Wearable EMG Devices

Single-channel wearable EMG devices are portable systems that typically record activity from the temporalis or masseter muscle, can be used in the home environment, and impose a lower technical burden than laboratory-based EMG systems. The principal advantage of these devices is their ability to collect data over multiple nights in a natural setting, thereby allowing temporal variability to be monitored more effectively. Literature reviews indicate that, in recent years, ultraminiaturized and home-use EMG devices have increasingly been employed to record patterns of muscle activity during both sleep and wakefulness (Maeda et al., 2019; Yamaguchi et al., 2023).

The clinical applications of devices in this category include objective multi-night home recording, adjunctive screening, pre and post treatment monitoring, and the quantification of muscle activity patterns in research settings. Nevertheless, substantial inter-device differences exist with respect to algorithms, sensor placement, event definitions, and threshold values. In a systematic review and meta-analysis conducted by Cid-Verdejo et al. (Cid-Verdejo et al., 2024), portable EMG devices were reported to demonstrate promising diagnostic performance relative to PSG; however, the certainty of the evidence remained limited because of study heterogeneity and the risk of bias. Therefore, single-channel wearable EMG systems should most appropriately be used as adjunctive instrument-based tools for assessment and monitoring (Yamaguchi et al., 2023).

Acoustic and Sound Recording–Based Devices

Acoustic and sound recording–based systems are emerging technologies designed to use sounds generated by tooth grinding and other orofacial behaviors as biomarkers. In these systems, sound is recorded via transducers placed at different regions of the head or through in-ear (hearable) devices and is subsequently classified based on time and frequency-domain features. The principal appeal of this approach lies in its potential to provide more comfortable and non-invasive ambulatory monitoring. At present, the clinical application of these tools remains largely limited to research and technology development (Nahhas et al., 2024).

BruxChecker and Other Occlusal Disclosure Foil Methods

BruxChecker is a dental-level method based on the application of a thin colored occlusal foil to the dentition and the subsequent evaluation of the peeled or worn areas formed after use. This system does not directly measure muscle activity, autonomic variables, or sleep physiology; rather, it is intended to demonstrate, in a quantitative or semiquantitative manner, the traces left on the occlusal surfaces, particularly by the grinding component of bruxism. Accordingly, BruxChecker should not be evaluated at the same level of measurement as devices that provide physiological recordings (Ustrell-Barral, Zamora-Olave, Khoury-Ribas, Rovira-Lastra, & Martinez-Gomis, 2025).

The clinical applications of BruxChecker and similar occlusal foil methods include documenting patterns of dental contact and wear, visualizing grinding patterns, supporting occlusal analysis and restorative treatment planning, and comparing surface changes during follow-up examinations (Ustrell-Barral et al., 2025).

BruxApp and Digital Self-Reporting Tools

BruxApp is a digital self-reporting tool based on a smartphone-delivered ecological momentary assessment approach. By sending repeated prompts throughout the day, the application is intended to record jaw posture, tooth contact, clenching, and related awake bruxism behaviors in real-life contexts. In this respect, BruxApp is not a system that records physiological signals, such as EMG or PSG; rather, it is a digital monitoring platform based on repeated sampling of behavior in the natural environment (Colonna et al., 2023; Nykänen et al., 2022).

The clinical applications of BruxApp and similar tools include behavioral monitoring of awake bruxism, enhancement of patient awareness, habit modification, and longitudinal self-report monitoring. Multicenter study data indicate that prior training in the relevant professional terminology is beneficial for the correct use of the application, whereas findings from scoping reviews suggest that such ecological momentary assessment-based applications may capture awake bruxism behaviors in daily life more sensitively than conventional retrospective self-reports. Therefore, BruxApp is particularly suitable as a behavioral screening and monitoring tool for awake bruxism, but it does not replace the physiological assessment of sleep bruxism (Colonna et al., 2023; Nykänen et al., 2022).

Intraoral Force and Occlusal Contact Detection Systems

Intraoral force and occlusal contact detection systems are devices intended to assess sleep bruxism not by directly recording masticatory muscle activity, but by analyzing patterns of tooth contact and force transmitted to an intraoral appliance. One of the principal examples in this category is the intra-splint force detector (ISFD) developed by Takeuchi et al.(Takeuchi, Ikeda, & Clark, 2001). In this device, signal changes associated with tooth–splint contact are recorded by means of a piezoelectric film positioned approximately 1–2 mm beneath the splint surface. In simulated bruxism studies, a significant correlation with masseter EMG has been reported in terms of event duration; however, the piezoelectric film has been shown to be limited in its ability to quantitatively reflect force intensity, particularly during sustained clenching. Therefore, the ISFD appears to be more useful for monitoring occlusal contact events and their duration than for absolute force measurement (Takeuchi et al., 2001).

Overview of Treatment Approaches for Bruxism

No single treatment modality has been shown to have universal and definitive superiority in the management of bruxism. Therefore, the treatment plan should be individualized, taking into account the type and severity of symptoms, the presence of concomitant temporomandibular disorders, sleep and psychosocial-related factors, medication use, and patient expectations (Riley et al., 2020). A recent systematic review on adult sleep bruxism classified the main treatment approaches into four categories: occlusal appliances, biofeedback, cognitive-behavioral approaches, and pharmacological interventions, and emphasized that the available evidence remains limited and heterogeneous across most categories (Minakuchi et al., 2022).

Occlusal Splint Therapy

Occlusal splints are among the most frequently used reversible and protective approaches in the management of bruxism (Riley et al., 2020). In clinical practice, their principal aims are to protect teeth and restorations from excessive loading, reduce occlusal trauma, and, in some cases, alleviate concomitant muscle pain or jaw fatigue. However, current evidence does not indicate that splints permanently eliminate bruxism activity (Minakuchi et al., 2022). Riley et al. (Riley et al., 2020) reported that uncertainty persists regarding the effects of splints on outcomes associated with bruxism or temporomandibular disorders, and that the overall quality of the evidence is low.

Botulinum Toxin Type A (BoNT-A) Injections

Botulinum toxin type A is commonly injected into the masseter and/or temporalis muscles to temporarily reduce muscle contraction force. For this reason, it has attracted particular interest in clinical presentations associated with pain, muscle hypertrophy, morning jaw fatigue, or excessive muscle force. Nevertheless, the role of BoNT-A in the treatment of bruxism remains controversial (Chen et al., 2023; Coelho et al., 2025).

In their systematic review focusing on temporomandibular symptoms associated with sleep bruxism, Buzatu et al. (Buzatu, Luca, Castiglione, & Sinescu, 2024) reported that BoNT-A may exert certain beneficial effects; however, the included studies were heterogeneous. Accordingly, BoNT-A should not be presented as a routine first line treatment, but rather as an option that may be considered with caution in selected cases refractory to conservative management (Buzatu et al., 2024; Coelho et al., 2025).

Biofeedback Therapy

Biofeedback is a behavioral intervention based on delivering a real time signal or counter stimulus when masticatory muscle activity occurs. Its aim is to increase the individual's awareness of parafunctional activity and, over time, to reduce the frequency and/or intensity of such activity (Ilovar, Zolger, Castrillon, Car, & Huckvale, 2014; Vieira et al., 2023). A systematic review on adult sleep bruxism reported that biofeedback therapy was associated with reductions in certain sleep bruxism parameters in some studies; however, the methods and protocols were heterogeneous (Minakuchi et al., 2022). The evidence base for awake bruxism appears to be somewhat more favorable, although it remains limited (Vieira et al., 2023). Vierira et al. (Vieira et al., 2023) indicated that auditory and visual EMG biofeedback appears promising in reducing masticatory muscle activity, but also noted that the included studies were few in number and carried a high risk of bias. Therefore, biofeedback should be regarded primarily as a supportive behavioral treatment for awake bruxism and as an adjunctive approach in selected cases of sleep bruxism (Minakuchi et al., 2022; Vieira et al., 2023).

Pharmacological Treatments

Pharmacological treatments should not be regarded as standard first line approaches in bruxism, but rather as adjunctive options for symptom control in selected cases (Minakuchi et al., 2022). Minakuchi et al. (Minakuchi et al., 2022) reported that certain agents, including rabeprazole, clonazepam, clonidine, and botulinum toxin type A, may be associated with reductions in specific PSG or EMG based parameters; however, the available studies were few and methodologically limited. In a placebo-controlled polysomnographic study, clonazepam was reported to reduce the bruxism index (Saletu et al., 2005), whereas a subsequent double-blind crossover trial demonstrated that clonidine was more effective than clonazepam in suppressing rhythmic masticatory muscle activity (Sakai et al., 2017).

There is no strong or well-established bruxism specific evidence base demonstrating that conventional muscle relaxants directly reduce sleep bruxism (Christidis et al., 2024; Minakuchi et al., 2022). Graham et al. (Graham et al., 2026), in their systematic review on the management of awake bruxism, reported that the available evidence is concentrated primarily around behavioral approaches such as biofeedback, reminder prompts, habit reversal, and self-management, whereas robust and standardized data on pharmacological treatments are lacking. Therefore, in awake bruxism, muscle relaxants should not be regarded as specific therapies targeting bruxism itself, but rather considered in a symptomatic context, particularly when concomitant pain or muscle tenderness is present (Christidis et al., 2024; Graham et al., 2026). Analgesics, especially oral NSAIDs, should be viewed not as treatments that suppress bruxism per se, but as adjunctive agents for the management of concomitant temporomandibular disorders and myofascial pain symptoms (Montinaro et al., 2024).

Cognitive-Behavioral Therapy

Cognitive-behavioral therapy (CBT) and related behavioral approaches are of theoretical relevance in situations associated with stress, anxiety, self-awareness, and habit control. However, the current systematic review specifically addressing adult sleep bruxism has shown that there is insufficient evidence to strongly support the potential benefits of cognitive-behavioral therapy. Therefore, for sleep bruxism, CBT should be regarded not as a specific treatment supported by strong evidence, but rather as an adjunctive approach that may be beneficial in the management of concomitant psychosocial factors (Graham et al., 2026; Minakuchi et al., 2022).

Physiotherapy

Physiotherapy is a broad category encompassing manual therapy, exercise, relaxation techniques, postural awareness, and certain physical modalities. In the context of bruxism, these approaches are primarily directed at concomitant muscle pain, restricted mandibular movement, head and neck posture, and symptoms involving the temporomandibular system. There is no strong evidence to indicate that physiotherapy directly and consistently reduces bruxism itself, particularly sleep bruxism activity (Amorim, Santo, Sommer, & Marques, 2018). Therefore, physiotherapy should be regarded not as a primary treatment for bruxism, but rather as a supportive symptom management approach, particularly in individuals presenting with myofascial pain, neck and jaw muscle tension, restricted movement, and concomitant TMD symptoms (Minakuchi et al., 2022; Mortazavi et al., 2023).

Treatment Approaches in Children

The evidence base for the management of sleep bruxism in children and adolescents is more limited than that available for adults (Minervini et al., 2024). Ierardo et al. (Ierardo et al., 2021) demonstrated that the available data on treatment in children are heterogeneous and limited. Likewise (Minervini et al., 2024) reported that comparative treatment data on childhood sleep bruxism remain insufficient. Therefore, the therapeutic approach in children should be based on sleep hygiene, stress reduction, evaluation of concomitant sleep-related breathing disorders, and the careful planning of conservative dental and orthodontic interventions in selected cases (Minervini et al., 2024; Restrepo-Serna & Winocur, 2023; Senff et al., 2023).

Conclusion

Bruxism is currently conceptualized not as a disorder per se, but as a masticatory muscle activity with distinct manifestations during sleep and wakefulness. Its pathophysiology is considered multifactorial and is best interpreted within a biopsychosocial framework involving neurobiological, behavioral, psychological, and sleep-related determinants. Accordingly, the clinical relevance of bruxism should be evaluated not solely based on muscle activity itself, but in relation to its potential consequences, associated comorbidities, and individual risk profile. In this context, contemporary assessment relies on a multidimensional approach integrating self-report, clinical examination, and, when indicated, instrument-based methods.

From a management perspective, current evidence does not support universally effective causal treatment for bruxism; therefore, clinical care should be consequence-oriented and individually tailored. Therapeutic strategies primarily aim to reduce adverse oral and musculoskeletal outcomes, alleviate pain or muscle overuse, and address modifiable contributing factors and comorbid conditions. Occlusal splints, behavioral and biofeedback-based interventions, selected pharmacological approaches, and botulinum toxin type A may be considered in carefully selected patients, although the overall level of evidence remains limited. Future progress will depend on further refinement of definitions, standardization of assessment protocols, and robust longitudinal and interventional studies capable of distinguishing bruxism as a motor activity from the clinically significant outcomes that warrant treatment.

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BÖLÜM 2

Contemporary Diagnostic and Surgical Management of Oral Potentially Malignant Disorders: An Evidence-Based and Clinical Perspective

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Introduction

Oral potentially malignant disorders (OPMDs) comprise a heterogeneous group of mucosal conditions associated with an increased risk of malignant transformation into oral squamous cell carcinoma (OSCC) (Warnakulasuriya et al., 2007; Warnakulasuriya, 2018). These disorders represent a biologically unstable spectrum rather than static clinical entities, with transformation risk influenced by both intrinsic epithelial alterations and extrinsic environmental factors (Speight et al., 2018).

Despite significant advances in diagnostic imaging, molecular pathology, and surgical techniques, early detection and optimal management of OPMDs remain among the most challenging aspects of oral medicine and oral and maxillofacial surgery (Speight et al., 2018). A major contributor to this challenge is the unpredictable biological behavior of these lesions; some clinically innocuous-appearing lesions may undergo malignant transformation, whereas others with advanced dysplasia may remain stable for prolonged periods (Bray et al., 2018).

Globally, the incidence of oral cancer continues to rise, particularly in regions with high tobacco, alcohol, and betel quid consumption (Bray et al., 2018). Delayed diagnosis remains one of the most important determinants of poor prognosis and reduced survival, with five-year survival rates remaining below 60% in many populations (van der Waal, 2009). In this context, OPMDs occupy a critical position at the interface between oral medicine and oral surgery, requiring close interdisciplinary collaboration, longitudinal patient monitoring, and evidence-based decision-making (Lodi et al., 2016).

This chapter provides a comprehensive and clinically oriented overview of contemporary diagnostic tools, etiopathogenetic mechanisms, risk stratification strategies, and surgical management principles for OPMDs, with particular emphasis on long-term outcomes, clinical decision-making, and future perspectives in preventive oral oncology.

Definition and Classification of Oral Potentially Malignant Disorders

The World Health Organization defines oral potentially malignant disorders as clinical presentations that carry a risk of malignant transformation either at the time of diagnosis or during follow-up (Warnakulasuriya et al., 2007; WHO Classification of Head and Neck Tumours, 2017). The adoption of this terminology marked a conceptual shift away from the earlier term “precancerous lesions,” acknowledging that malignant transformation risk may exist not only within the visible lesion but also in clinically normal-appearing mucosa (Napier & Speight, 2008).

Clinically relevant OPMDs include oral leukoplakia, oral erythroplakia, oral lichen planus (particularly erosive and atrophic subtypes), oral submucous fibrosis, actinic cheilitis, and proliferative verrucous leukoplakia (Villa & Woo, 2017; Warnakulasuriya, 2018). Among these, oral leukoplakia remains the most prevalent entity, whereas erythroplakia and proliferative verrucous leukoplakia exhibit the highest rates of malignant transformation (Blot et al., 1988).

Importantly, classification based solely on clinical appearance is insufficient. Increasing evidence suggests that OPMDs should be conceptualized as part of a continuum of epithelial instability influenced by genetic, epigenetic, and environmental factors (Gupta & Warnakulasuriya, 2002). This perspective underlines the necessity for dynamic risk assessment rather than static diagnostic labeling.

Etiopathogenesis and Risk Factors

Environmental and Behavioral Factors

Tobacco use remains the most significant etiological factor in the development of OPMDs, exerting both direct mutagenic effects and indirect immunomodulatory influences on the oral epithelium (Blot et al., 1988; Bray et al., 2018). Alcohol consumption acts synergistically with tobacco by increasing epithelial permeability and facilitating the penetration of carcinogens (Hunter, 2005).

Betel quid chewing, with or without tobacco, is strongly associated with oral submucous fibrosis and subsequent malignant transformation, particularly in South and Southeast Asia (Gupta & Warnakulasuriya, 2002). The arecoline component induces fibroblast activation, collagen deposition, and progressive mucosal stiffness, creating a microenvironment conducive to malignant change (Califano, 1996).

Biological and Genetic Influences

At the molecular level, OPMDs are characterized by cumulative genetic and epigenetic alterations affecting cell cycle regulation, apoptosis, and DNA repair mechanisms (Mao et al., 1996; Hunter, 2005). Dysregulation of tumor suppressor genes such as p53, overexpression of EGFR, and aberrant cyclin-dependent kinase activity contribute to epithelial dysplasia and malignant progression (Eisen, 2002).

Chronic inflammation plays a critical role in this process. Inflammatory cytokines and oxidative stress promote genomic instability, particularly in immune-mediated disorders such as oral lichen planus (Neville & Day, 2002). These findings support the concept that malignant transformation is not a singular event but the result of prolonged epithelial stress and molecular damage.

Clinical Presentation and Diagnostic Challenges

OPMDs frequently present as subtle, asymptomatic mucosal alterations, including color changes, surface irregularities, or textural variations (Neville & Day, 2002). As a result, many patients remain unaware of the lesion until it is incidentally detected during routine dental examination.

Clinical heterogeneity and overlap with benign reactive lesions significantly limit the predictive value of visual examination alone (Kujan et al., 2006). Non-homogeneous lesions, speckled leukoplakia, and erythroplakia are generally associated with higher risk; however, even homogeneous leukoplakia may harbor severe dysplasia (Awan et al., 2011). Consequently, reliance solely on clinical appearance may lead to underestimation of malignant potential.

Diagnostic Modalities in OPMDs

Adjunctive Optical and Imaging-Based Techniques

Adjunctive diagnostic tools such as autofluorescence imaging, chemiluminescence, and narrow-band imaging have been explored to improve early lesion detection (Lingen et al., 2008; Awan et al., 2011). These techniques may assist in identifying areas of epithelial alteration not readily visible under conventional illumination.

However, multiple studies have demonstrated that while sensitivity may be improved, specificity remains limited, leading to false-positive findings and unnecessary biopsies (Lingen et al., 2008). Therefore, these modalities should be regarded as adjunctive tools rather than diagnostic replacements.

Histopathology and Grading of Epithelial Dysplasia

Biopsy followed by histopathological evaluation remains the gold standard for diagnosis and risk assessment (Reibel, 2003). The degree of epithelial dysplasia is a key prognostic indicator, with increasing severity correlating with higher malignant transformation risk.

Nevertheless, interobserver variability and subjective interpretation remain significant limitations (Thomson, 2012). This has prompted ongoing efforts to refine grading systems and incorporate objective molecular markers.

Molecular and Immunohistochemical Markers in OPMDs

Recent advances in molecular pathology have expanded understanding of malignant transformation mechanisms in OPMDs. Immunohistochemical markers such as p53, Ki-67, cyclin D1, and podoplanin have been extensively investigated as predictors of dysplastic progression (Mao et al., 1996; Hunter, 2005; Arduino et al., 2009).

Overexpression of p53 reflects genomic instability and impaired DNA damage response, whereas elevated Ki-67 indices correlate with increased proliferative activity (Warnakulasuriya et al., 2011). Cyclin D1 amplification has been linked to early oncogenic transformation, particularly in leukoplakic lesions with moderate to severe dysplasia (Brouns et al., 2013).

Despite promising results, lack of standardized thresholds and inter-laboratory variability currently limit routine clinical implementation. Nonetheless, integration of molecular markers into risk stratification models represents a critical step toward personalized management (Schepman et al., 1998).

Risk Stratification and Clinical Decision-Making

Effective management of OPMDs requires individualized risk stratification incorporating clinical phenotype, histopathological grading, lesion size and anatomical location, patient-related risk factors, and recurrence history (Arduino et al., 2009; Thomson, 2012). Lesions involving the tongue and floor of the mouth demonstrate higher malignant transformation risk and warrant aggressive surveillance (Warnakulasuriya et al., 2011).

Field Cancerization and Multifocal Disease

The concept of field cancerization explains the presence of genetically altered epithelial fields predisposed to multifocal disease and recurrence (Slaughter et al., 1953; Braakhuis et al., 2003). Clinically, this phenomenon accounts for malignant transformation at sites distant from the original lesion and underscores the limitations of lesion-centered treatment approaches (Hansen et al., 1985; Cerero-Lapiedra, 2010).

Surgical Management of Oral Potentially Malignant Disorders

Indications for Surgical Intervention

Surgical management is generally indicated for moderate to severe epithelial dysplasia, non-homogeneous lesions, recurrent disease, and high-risk anatomical locations (Schepman et al., 1998; Brouns et al., 2013). Early surgical intervention aims to remove dysplastic epithelium before invasive transformation occurs.

Surgical Techniques

Conventional scalpel excision remains the reference technique, allowing precise histopathological margin assessment (Holmstrup et al., 2006). Laser excision offers advantages such as reduced intraoperative bleeding and postoperative discomfort but may limit margin evaluation when vaporization techniques are employed (Ishii et al., 2003; Suter et al., 2010).

Margin Assessment and Surgical Clearance

Adequate margin control is critical for reducing recurrence risk. Dysplasia-positive margins are associated with significantly higher recurrence rates, although complete excision does not eliminate malignant potential due to field cancerization (Schepman et al., 1998; Brouns et al., 2013).

Non-Surgical and Adjunctive Therapies

Medical therapies including topical corticosteroids, retinoids, and immunomodulators may alleviate symptoms, particularly in inflammatory OPMDs, but provide limited evidence for long-term malignant risk reduction (Eisenberg, 2000; Lodi et al., 2006).

Photodynamic Therapy and Emerging Treatments

Photodynamic therapy has emerged as a minimally invasive option for selected lesions, offering favorable functional and aesthetic outcomes. However, long-term data regarding malignant transformation prevention remain inconclusive, and PDT should currently be considered an adjunct rather than a definitive treatment (Jerjes, et al., 2011; Sieron et al., 2013).

Postoperative Follow-Up and Long-Term Surveillance

High recurrence and malignant transformation rates necessitate lifelong surveillance with periodic clinical examination, photographic documentation, and repeat biopsy when indicated (Arduino et al., 2013; Warnakulasuriya et al., 2016). Follow-up strategies should be risk-adapted and patient-specific.

Digital Documentation and Longitudinal Monitoring

Digital lesion mapping and standardized photographic documentation facilitate early detection of morphological changes and support objective comparison over time (Arduino et al., 2013).

Malignant Transformation and Prognostic Indicators

Malignant transformation of OPMDs represents the most clinically relevant outcome and the primary determinant of patient prognosis. Transformation rates vary widely depending on lesion type, histopathological grade, anatomical localization, and patient-related risk factors (Hansen et al., 1985; Cerero-Lapiedra, 2010).

Oral leukoplakia demonstrates an average malignant transformation rate ranging from 1% to 5%, whereas erythroplakia and proliferative verrucous leukoplakia exhibit substantially higher risks, with reported rates exceeding 20% in long-term follow-up studies (Hansen et al., 1985; Cerero-Lapiedra, 2010). Lesions located on the lateral tongue and floor of the mouth are consistently associated with higher malignant potential, likely due to thinner epithelium and increased exposure to carcinogens (Warnakulasuriya et al., 2011).

Histopathological grading remains the most reliable prognostic indicator; however, transformation has been reported even in lesions without dysplasia, underscoring the limitations of histology alone (Reibel, 2003; Thomson, 2012). These observations support the necessity of combining histopathological findings with clinical and molecular risk factors to improve prognostic accuracy.

Oral Medicine–Oral Surgery Interface

The management of OPMDs exemplifies the necessity for close collaboration between oral medicine specialists and oral and maxillofacial surgeons (Lodi et al., 2012). Oral medicine clinicians often play a central role in early detection, longitudinal monitoring, and medical management, whereas surgeons are responsible for definitive diagnosis through biopsy and surgical intervention when indicated.

This interdisciplinary interface enables more accurate risk stratification, optimized surgical planning, and continuity of care throughout long-term surveillance. Multidisciplinary case discussions are particularly valuable in complex scenarios involving multifocal disease, recurrent lesions, or discordance between clinical and histopathological findings.

Importantly, coordinated care models have been shown to reduce diagnostic delay and improve patient adherence to follow-up protocols, ultimately contributing to improved clinical outcomes (Lodi et al., 2012).

Emerging Concepts and Future Directions

Rapid advances in biomedical research are reshaping the diagnostic and therapeutic landscape of OPMDs. Molecular diagnostics, salivary biomarkers, and computational risk prediction models are increasingly investigated as tools to complement conventional assessment (Kujan et al., 2013; Lee et al., 2018; Schwendicke et al., 2020).

Salivary biomarkers, including microRNAs, cytokines, and DNA methylation patterns, offer a non-invasive means of detecting molecular alterations associated with malignant transformation.

Although promising, variability in sampling methods and analytical techniques currently limits routine clinical application.

Artificial Intelligence–Assisted Risk Prediction

Artificial intelligence–based models trained on clinical, histopathological, and molecular datasets have demonstrated encouraging accuracy in predicting malignant transformation risk (Lee et al., 2018; Schwendicke et al., 2020). Machine learning algorithms may assist clinicians by integrating multidimensional data into probabilistic risk scores, thereby reducing subjective variability in clinical decision-making.

Nevertheless, challenges related to dataset heterogeneity, lack of external validation, and interpretability of algorithmic outputs must be addressed before widespread clinical adoption (Kujan et al., 2020). AI systems should therefore be regarded as decision-support tools rather than autonomous decision-makers.

Psychosocial and Ethical Considerations

The diagnosis of an OPMD imposes a significant psychological burden on patients, often characterized by anxiety, uncertainty, and fear of cancer development (Epstein et al., 2007). The chronic nature of these disorders, coupled with repeated biopsies and prolonged surveillance, may negatively impact quality of life and treatment adherence.

Ethically, clinicians must balance the need for early intervention with the risk of overtreatment and unnecessary morbidity. Transparent communication, shared decision-making, and clear explanation of uncertainty are essential to maintaining patient trust and promoting informed consent.

Psychological support and patient education should therefore be considered integral components of comprehensive OPMD management.

Limitations of Current Evidence

Despite extensive research, the evidence base guiding OPMD management remains limited. High-quality randomized controlled trials comparing surgical and non-surgical interventions are scarce, and heterogeneity in diagnostic criteria and outcome measures complicates comparison across studies (Warnakulasuriya, 2010).

Furthermore, long latency periods between diagnosis and malignant transformation necessitate prolonged follow-up, which is often logistically challenging. These limitations highlight the need for standardized diagnostic frameworks and collaborative multicenter research initiatives.

Extended Discussion

The management of OPMDs exemplifies the complexities inherent in preventive oncology within the oral cavity. Surgical excision remains the most effective intervention for high-risk lesions, yet it does not address the underlying biological instability of the oral mucosa.

The concept of field cancerization explains persistent malignant risk even after complete excision and underscores the limitations of lesion-centered treatment strategies (Slaughter et al., 1953; Braakhuis et al., 2003). Consequently, future management paradigms are expected to rely on integrated approaches combining surgical intervention, behavioral modification, molecular risk assessment, and technological innovation.

Personalized risk models incorporating histopathology, molecular biomarkers, and artificial intelligence may enable tailored surveillance intervals and targeted intervention, optimizing both clinical outcomes and resource utilization.

Clinical Implications for Daily Practice

From a practical standpoint, clinicians managing OPMDs should adopt structured, evidence-based protocols emphasizing early recognition, timely biopsy, individualized treatment planning, and lifelong follow-up (Thomson, 2012).

Routine documentation, standardized photographic records, and clear referral pathways between oral medicine and oral surgery services are essential for effective long-term care. Importantly, patient education regarding risk factors and the necessity of follow-up should be reinforced at every clinical encounter.

Educational and Training Perspectives

Improved education and training in OPMD recognition and management are critical to reducing diagnostic delay and improving patient outcomes (Patton et al., 2002). Undergraduate curricula should emphasize early detection and risk assessment, while postgraduate training should focus on interdisciplinary management and surgical decision-making.

Continuing professional development programs are equally important, particularly given the evolving nature of diagnostic technologies and management strategies.

Global Health Perspective

Globally, disparities in access to oral healthcare significantly influence OPMD outcomes. Low- and middle-income countries bear a disproportionate burden of oral cancer, largely due to limited access to preventive care and high prevalence of risk behaviors (Sankaranarayanan et al., 2005; Petersen, 2009).

Public health initiatives focusing on tobacco cessation, betel quid control, and community-based screening programs are essential components of global oral cancer prevention strategies. Integration of OPMD screening into primary healthcare systems may substantially reduce late-stage cancer diagnosis.

Final Conclusion

Oral potentially malignant disorders represent a critical interface between oral medicine and oral surgery. Contemporary management requires accurate diagnosis, appropriate surgical intervention, and vigilant, lifelong surveillance.

While significant advances have been made in understanding the biological behavior of these disorders, challenges related to risk prediction and long-term management persist. Future progress will depend on the integration of molecular diagnostics, artificial intelligence, and interdisciplinary collaboration into routine clinical practice (Warnakulasuriya et al., 2007; van der Waal, 2010; Kujan et al., 2015; Speight, 2018).

When implemented responsibly and guided by evidence-based principles, these innovations hold substantial promise for reducing malignant transformation risk and improving patient outcomes in oral potentially malignant disorders.

According to the current literature, AI applications in oral and maxillofacial surgery can be categorized as follows (Gupta & Warnakulasuriya, 2002; Villa & Woo, 2017):

- Radiological image analysis (CBCT, panoramic radiography) (Blot et al., 1988; Neville & Day, 2002; Kujan et al., 2006),
- Automated detection of pathological lesions (Holmstrup et al., 2006; Awan et al., 2011),
- Assessment of impacted teeth and their relationship with anatomical structures (Lingen et al., 2008; Thomson, 2012),
- Bone quality evaluation and risk analysis in implant surgery (Eisen, 2002; Brouns et al., 2013; Arduino et al., 2013),
- Prediction of surgical complications (Reibel, 2003; Warnakulasuriya et al., 2016),
- Patient education and clinical decision support systems (Slaughter et al., 1953; Gupta et al., 2002).

These applications are not intended to replace the surgeon's clinical expertise but rather to function as supportive tools that enhance the decision-making process (Gupta et al., 2002; Speight et al., 2018).

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BÖLÜM 3

ARTIFICIAL INTELLIGENCE-ASSISTED DIAGNOSIS, TREATMENT PLANNING, AND SURGICAL DECISION-MAKING PROCESSES: CURRENT APPROACHES IN ORAL AND MAXILLOFACIAL SURGERY

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Introduction

Oral and maxillofacial surgery is a discipline that requires advanced diagnostic and planning processes due to complex anatomical structures, limited surgical visibility, and a high risk of complications. For many years, traditional clinical evaluation, two-dimensional radiographic imaging, and surgeon-dependent decision-making constituted the foundation of clinical practice. However, over the past decade, advances in imaging technologies and the rapid digitalization of healthcare have enabled artificial intelligence (AI)–based systems to assume a transformative role in many aspects of oral and maxillofacial surgery (Topol, 2019a; Schwendicke et al., 2020b; Rajpurkar et al., 2022)

Artificial intelligence, through its subfields such as machine learning (ML), deep learning (DL), and natural language processing (NLP), is capable of learning from large datasets, identifying complex patterns, and supporting clinical decision-making processes (LeCun et al., 2015; Goodfellow et al., 2016; Litjens et al., 2017). Particularly in the analysis of cone-beam computed tomography (CBCT) data, AI-based applications have gained increasing clinical relevance by enabling automatic segmentation of anatomical structures, identification of pathological lesions, and prediction of surgical risks (Abdolali et al., 2017; Miki et al., 2017; Yoo et al., 2021).

The aim of this book chapter is to comprehensively review AI-assisted diagnostic, treatment planning, and surgical decision-making processes in oral and maxillofacial surgery in light of current literature, to discuss their potential for clinical integration, and to provide a future-oriented perspective (Shortliffe & Sepúlveda, 2018).

Fundamental Concepts of Artificial Intelligence and Its Applications in Oral Surgery

Artificial Intelligence, Machine Learning, and Deep Learning

Artificial intelligence is a broad concept aimed at enabling computer systems to exhibit human-like cognitive functions such as learning, reasoning, and problem-solving (LeCun et al., 2015; Esteva et al., 2017). Machine learning allows algorithms to learn from data without being explicitly programmed, whereas deep learning, utilizing multi-layered artificial neural networks, offers superior performance particularly in image recognition and classification tasks (Esteva et al., 2017; Samek et al., 2019).

AI models employed in oral and maxillofacial surgery are predominantly based on:

- Supervised learning using labeled radiological datasets (Hung et al., 2020; Yoo et al., 2021)
- Unsupervised learning for pattern recognition (Samek et al., 2019; Schwendicke et al., 2019),
- Deep convolutional neural networks (CNNs) for image analysis (Chartrand et al., 2017; Orhan et al., 2020).

Applications of AI in Oral and Maxillofacial Surgery

According to the current literature, AI applications in oral and maxillofacial surgery can be categorized as follows (Hung et al., 2020; Shortliffe & Sepúlveda, 2018):

- Radiological image analysis (CBCT, panoramic radiography) (Scarfe & Farman, 2008; Kamburoğlu, 2015),
- Automated detection of pathological lesions (Lee et al., 2020),

- Assessment of impacted teeth and their relationship with anatomical structures (Hiraiwa et al., 2019; Guerrero et al., 2014),
- Bone quality evaluation and risk analysis in implant surgery (Kirnbauer et al., 2022; Albrecht et al., 2021; Rios et al., 2009),
- Prediction of surgical complications (Renton & Yilmaz, 2012; (Schultze-Mosgau & Reich, 1993),
- Patient education and clinical decision support systems (Shortliffe & Sepúlveda, 2018; Schwendicke et al., 2020).

These applications are not intended to replace the surgeon's clinical expertise but rather to function as supportive tools that enhance the decision-making process (Schwendicke et al., 2020; Shortliffe & Sepúlveda, 2018).

AI-Assisted Radiological Diagnostic Processes

Automated Analysis and Segmentation of CBCT Data

CBCT is an indispensable imaging modality in oral and maxillofacial surgery (Scarfe & Farman, 2008; Kamburoğlu, 2015). However, manual segmentation is time-consuming and highly operator-dependent (Chartrand et al., 2017). Deep learning-based algorithms now enable automatic segmentation of:

- The mandibular canal (Yoo et al., 2021; Park et al., 2020; Orhan et al., 2020),
- The maxillary sinus (Abdolali et al., 2017),
- Tooth roots (Miki et al., 2017),
- Cystic and tumoral lesions (Lee et al., 2020)

with high accuracy.

Studies demonstrate that AI-assisted CBCT segmentation provides more consistent results than manual methods and significantly reduces surgical planning time (Orhan et al., 2020; Kirnbauer et al., 2022).

Detection and Classification of Pathological Lesions

Odontogenic cysts, benign tumors, and malignant lesions can be distinguished at early stages using AI-based systems (Lee et al., 2020; Ezhov et al., 2021; Patel et al., 2009). Models developed using CNN architectures show potential in delineating lesion borders and predicting biological behavior (Schwendicke et al., 2019; (Lee et al., 2020).

This capability offers substantial clinical benefits in determining biopsy timing and defining surgical margins (Patel et al., 2009; (Carter & Farman, 2008).

Artificial Intelligence and Surgical Risk Analysis

Prediction of Nerve Injury Risk in Third Molar Surgery

Mandibular third molar surgery is one of the most frequently performed procedures in oral surgery, and inferior alveolar nerve injury represents one of its most serious complications (Renton & Yilmaz, 2012; Schultze-Mosgau & Reich, 1993; Pogrel, 2004). AI-based models can classify nerve injury risk by analyzing:

- Root–canal relationship (Hiraiwa et al., 2019; Guerrero et al., 2014),
- Cortical bone integrity (Yoo et al., 2021; Orhan et al., 2020),
- Radiographic risk indicators (Hiraiwa et al., 2019; Guerrero et al., 2014).

These systems support surgical decision-making by guiding the choice between coronectomy and total extraction (Pogrel, 2004; Renton, 2013).

AI-Assisted Risk Assessment in Implant Surgery

AI-driven software integrates bone volume, bone density, anatomical boundaries, and systemic risk factors to predict implant failure risk (Kirnbauer et al., 2022; (Albrecht et al., 2021; Rios et al., 2009). This approach enhances predictability in complex implant cases (Jemt et al., 2018; Tonetti & Chapple, 2018).

AI-Assisted Treatment Planning and Surgical Simulation

Virtual Surgical Planning and Digital Workflow

One of the most significant contributions of AI to oral and maxillofacial surgery is the comprehensive management of digital workflows (Widmann & Berggren, 2016; Tahmaseb et al., 2014). Integration of CBCT, intraoral scans, and facial scans enables patient-specific virtual surgical planning (Dawood et al., 2015; Vercruyssen et al., 2014). AI algorithms identify anatomical limitations, propose optimal surgical approaches, and predict potential complications during the simulation phase (Widmann & Berggren, 2016; (Schwendicke et al., 2020a).

In implant and reconstructive surgery, AI-assisted planning allows more predictable determination of osteotomy lines, implant positions, and angulations, thereby reducing surgical time, intraoperative stress, and postoperative complication rates (Tahmaseb et al., 2014 ; Vercruyssen et al., 2014).

Artificial Intelligence and Clinical Decision Support Systems

The Role of Artificial Intelligence in Clinical Decision-Making Processes

Clinical decision-making represents one of the most complex stages in oral and maxillofacial surgery and often requires the simultaneous evaluation of multiple variables (Shortliffe & Sepúlveda, 2018; Schwendicke et al., 2020a). AI-assisted clinical decision support systems integrate radiological findings, clinical examination data, systemic conditions, and evidence-based risk factors to provide structured recommendations to the surgeon (Schwendicke et al., 2020a; (Jiang et al., 2017; (Patel et al., 2009).

By organizing complex clinical information into interpretable outputs, AI-based decision support systems contribute to more transparent, reproducible, and traceable clinical decision-making processes (Shortliffe & Sepúlveda, 2018; Schwendicke et al., 2020a; (Shortliffe, 1987).

Ethical and Legal Considerations in Artificial Intelligence Applications

Data Security and Patient Privacy

The effective functioning of artificial intelligence systems requires access to large volumes of patient-related data, rendering data security and patient privacy critical concerns in oral and maxillofacial surgery (European Parliament, 2016; London, 2019). Radiological images, clinical records, and biometric data used for training and operating AI algorithms must be anonymized and stored within secure digital infrastructures to prevent unauthorized access or misuse (Kelly et al., 2019).

International regulatory frameworks, particularly the General Data Protection Regulation (GDPR), impose strict legal obligations regarding the collection, processing, storage, and sharing of health-related data (European Parliament, 2016). Consequently, AI-based clinical applications must be developed and implemented in compliance with these regulations to ensure ethical integrity and legal accountability (London, 2019; Kelly et al., 2019).

Legal Responsibility and Shared Clinical Decision-Making

The integration of AI-supported systems into clinical workflows introduces new medico-legal considerations related to accountability and professional responsibility (London, 2019). Within existing legal frameworks, the clinician remains the ultimate decision-maker and bears responsibility for outcomes resulting from AI-assisted recommendations (Shortliffe & Sepúlveda, 2018; (Schwendicke et al., 2020a).

Accordingly, responsible clinical use of AI systems necessitates comprehensive documentation of decision-making processes, integration of AI-generated outputs into clinical records, and explicit disclosure of AI utilization during the informed consent process (Shortliffe & Sepúlveda, 2018; London, 2019). Such measures enhance transparency and provide legal protection for both clinicians and patients (Kelly et al., 2019).

Clinical Limitations and Bias in Artificial Intelligence Systems

The clinical performance of artificial intelligence systems is intrinsically linked to the quality, diversity, and representativeness of the datasets used for algorithm training (Kahn, 2020; (Beam & Kohane, 2018). Models developed using single-center data or homogenous patient populations may demonstrate reduced accuracy when applied to diverse demographic or clinical settings (Beam & Kohane, 2018; (Holzinger et al., 2019).

In oral and maxillofacial surgery, limitations to AI generalizability arise from variability among CBCT devices, differences in imaging resolution, and heterogeneity in clinical protocols and treatment philosophies [16,17]. These factors may introduce systematic bias, potentially affecting diagnostic accuracy and clinical reliability (Kahn, 2020; (Holzinger et al., 2019).

Therefore, AI models trained on multicenter, standardized datasets with diverse patient populations offer superior robustness and broader clinical applicability (Beam & Kohane, 2018).

Future Perspectives and Integration into Clinical Practice

In the foreseeable future, artificial intelligence is expected to play an increasingly active role in oral and maxillofacial surgery through the development of real-time surgical navigation systems, integration with robotic surgical platforms, and intraoperative prediction of complications (Maier-Hein et al., 2017; Hashimoto et al., 2018).

Furthermore, continuously learning AI systems may evolve alongside accumulating clinical experience, facilitating adaptive treatment planning and personalized surgical strategies (Topol, 2019; Rajpurkar, 2022). Nevertheless, sustainable integration into routine clinical practice requires clinicians to critically evaluate AI-generated outputs and adhere strictly to evidence-based principles [Schwendicke et al., 2020a; Schwendicke et al., 2020b).

Conclusion

Artificial intelligence is assuming an increasingly significant role in diagnostic evaluation, treatment planning, and surgical decision-making processes in oral and maxillofacial surgery (Topol, 2019; Schwendicke et al., 2020b). From advanced radiological image analysis and surgical risk prediction to virtual surgical planning and patient communication, AI-based technologies serve as valuable adjuncts that enhance clinical expertise and patient safety (Hung et al., 2020; Schwendicke et al., 2020a).

However, ethical, legal, and clinical limitations must be carefully considered, and AI systems should be integrated in a controlled, transparent, and informed manner (European Parliament, 2016; Kelly et al., 2019). When responsibly implemented, artificial intelligence holds substantial potential to improve predictability, safety, and personalization in oral and maxillofacial surgical practice (Miller & Brown, 2018; Rajpurkar el al., 2022).

Clinical Deepening of AI-Assisted Imaging Analysis

Automated Identification of Anatomical Structures and Surgical Safety

Accurate identification of anatomical structures constitutes a fundamental determinant of surgical success in oral and maxillofacial surgery (Scarfe & Farman, 2008; Kamburoğlu, 2015). Manual identification of critical anatomical landmarks such as the mandibular canal, mental foramen, maxillary sinus floor, and nasopalatine canal is highly operator-dependent and subject to inter-observer variability (Yoo et al., 2021; Orhan et al., 2020).

Deep learning–based convolutional neural network models have demonstrated high accuracy in delineating cortical boundaries of the mandibular canal on CBCT images, thereby supporting nerve injury risk prediction and enhancing surgical safety in third molar surgery, implant placement, and cyst–tumor procedures (Yoo et al., 2021; Orhan et al., 2020).

Prediction of Lesion Behavior Using Artificial Intelligence

Recent AI models extend beyond lesion detection to provide predictive insights into biological behavior (Schwendicke et al., 2019; Lee et al., 2020). By analyzing parameters such as border irregularity, internal density heterogeneity, and effects on surrounding bone, AI systems assist in differentiating benign from aggressive lesions (Patel et al., 2009; Lee et al., 2020).

This capability offers clinically meaningful advantages in determining surgical margins, resection extent, and postoperative follow-up protocols in the management of odontogenic cysts and tumors (Carter & Farman, 2008; Patel et al., 2009).

Artificial Intelligence and Personalized Surgical Approaches

Development of Patient-Specific Risk Profiles

While traditional surgical planning primarily focuses on local anatomical factors, AI-supported systems enable simultaneous integration of multiple patient-specific variables (Rios et al., 2009; Schwendicke et al., 2020b). Demographic characteristics, systemic diseases, smoking status, medications influencing bone metabolism, and radiological findings are collectively analyzed to generate individualized risk profiles (Rios et al., 2009; Abdolali et al., 2017).

This approach facilitates objective patient selection and outcome prediction, particularly in implant surgery and bone augmentation procedures (Jemt et al., 2000; Tonetti & Chapple, 2018).

Comparison of Personalized Treatment Alternatives

Artificial intelligence systems allow simulation of multiple treatment alternatives for the same patient and provide comparative outcome predictions (Schwendicke et al., 2020b; Rajpurkar, 2022). In implant dentistry, for example, immediate implantation, delayed implantation, and the need for bone grafting can be evaluated based on predicted complication and success rates (Rios et al., 2009; Tonetti & Chapple, 2018; Albrecht et al., 2021).

Such comparative analyses strengthen clinical decision-making and promote transparent, patient-centered communication (Jiang et al., 2017; Shortliffe & Sepúlveda, 2018).

AI-Assisted Postoperative Follow-Up and Complication Management

Early Prediction of Postoperative Complications

AI-based systems are increasingly applied in postoperative monitoring by analyzing follow-up radiographs, clinical photographs, and patient-reported outcomes (Jemt et al., 2018; Albrecht et al., 2021). Early detection of complications such as infection, implant loss, soft tissue dehiscence, and nerve injury enables timely intervention before clinical deterioration becomes evident (Rios et al., 2009; Renton & Yilmaz 2012).

Analysis of Long-Term Clinical Outcomes

Long-term clinical follow-up data constitute valuable learning resources for artificial intelligence algorithms (Jemt et al., 2018; Albrecht et al., 2021). Parameters including implant survival, peri-implant bone loss, and patient satisfaction are analyzed to develop predictive models for future cases, thereby reinforcing evidence-based surgical practice (Rios et al., 2009; Rajpurkar, 2022).

Artificial Intelligence in Education, Residency Training, and Continuing Professional Development

The Role of AI in Oral Surgery Education

Artificial intelligence–supported simulation systems offer substantial potential in oral and maxillofacial surgery education (Maier-Hein et al., 2017; Hashimoto et al., 2018). Virtual case scenarios, three-dimensional surgical simulations, and automated feedback mechanisms allow residents and trainees to develop surgical skills in a controlled and safe environment (Maier-Hein et al., 2017).

Such educational tools shorten learning curves while enhancing patient safety and procedural confidence (Hashimoto et al., 2018).

Clinical Performance Assessment

AI-based analytics enable objective assessment of surgical performance using metrics such as operative duration, complication rates, and clinical outcomes (Schwendicke et al., 2020b; Rajpurkar, 2022). These analyses support continuous quality improvement initiatives at both individual and institutional levels (Miller & Brown, 2018).

Practical Challenges in Clinical Integration of Artificial Intelligence

Clinical integration of AI systems entails technical, economic, and cultural challenges (Kaplan & Porter, 2011; Kahn, 2020). High software and hardware costs, lack of data standardization, and variability in clinician acceptance represent major barriers to widespread adoption (Beam & Kohane, 2018; Kahn, 2020).

Moreover, excessive reliance on AI-generated recommendations may diminish clinical intuition; therefore, a balanced human–machine collaboration model remains essential (Schwendicke et al., 2020b; Rajpurkar, 2022).

Future Vision of Oral and Maxillofacial Surgery and Artificial Intelligence

The future of oral and maxillofacial surgery is expected to be shaped by real-time AI-supported navigation systems, robotic integration, and fully personalized treatment algorithms (Hashimoto et al., 2018; Maier-Hein et al., 2017). However, the success of this transformation depends not only on technological advancement but also on ethical awareness, scientific validation, and professional responsibility (London, 2019; Rajpurkar, 2022).

Extended Discussion

The rapid expansion of AI-assisted systems in oral and maxillofacial surgery represents not merely a technological evolution but a fundamental paradigm shift in surgical reasoning (Topol, 2019; Schwendicke et al., 2020b). By integrating multidimensional datasets, AI algorithms provide systematic and predictive decision support mechanisms that extend beyond traditional experience-based approaches (Schwendicke et al., 2020b; Rajpurkar, 2022).

Nevertheless, AI performance is not absolute and remains strongly dependent on training data quality and diversity (Beam & Kohane, 2018; Kahn, 2020). Multicenter, standardized datasets are therefore essential to enhance generalizability and clinical reliability (Beam & Kohane, 2018). Ethical and legal considerations further reinforce the clinician's ultimate responsibility and the necessity of critically evaluating AI-generated outputs (London, 2019; Kelly, 2019).

Final Conclusion

Artificial intelligence represents a powerful technological tool with the potential to transform diagnostic accuracy, treatment planning, and surgical decision-making in oral and maxillofacial surgery (Topol, 2019; Schwendicke et al., 2020b). By supporting rather than replacing clinical expertise, AI enhances patient safety, treatment predictability, and procedural efficiency (Hung et al., 2020; Schwendicke et al., 2020b).

Future success depends on evidence-based implementation, rigorous clinical validation, and multidisciplinary collaboration (Miller & Brown, 2018; Rajpurkar et al., 2022). When aligned with these principles, AI-assisted systems will contribute substantially to safer, more predictable, and more personalized oral and maxillofacial surgical care (Rajpurkar et al., 2022).

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