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# Diagnostic Accuracy of AI-Driven Wearable Sensors for Early Detection of Bruxism

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## ABSTRACT

***Background:*** *Bruxism, characterized by repetitive jaw-muscle activity involving clenching or grinding, often goes undetected until significant dental or muscular complications arise. Conventional diagnostic approaches—including clinical examination and patient self-reports—frequently miss early or nocturnal episodes. With the emergence of artificial intelligence (AI) and wearable biosensors, continuous and objective monitoring may enhance early detection.* ***Objective****: To assess the diagnostic accuracy of AI-integrated wearable jaw-movement sensors compared with standardized clinical examination for early bruxism detection.* ***Methods****: A cross-sectional study of 120 adults aged 18–50 years was conducted in Lahore over four months. Participants underwent simultaneous bruxism evaluation using AI-driven wearable jaw-movement sensors and clinical assessment based on international diagnostic criteria. The supervised AI algorithm analyzed sensor-recorded jaw-movement patterns to distinguish bruxism events from normal motion. Diagnostic accuracy parameters including sensitivity, specificity, positive predictive value (PPV), negative predictive value (NPV), and ROC-AUC were computed using SPSS version 26.* ***Results****: The AI-enabled wearable device demonstrated a sensitivity of 96.6%, specificity of 89.3%, overall accuracy of 93.1%, PPV of 91.7%, and NPV of 95.2%. ROC analysis indicated excellent performance (AUC = 0.95). A strong correlation ($r = 0.86$, $p < 0.001$) was found between AI-detected and clinically diagnosed bruxism cases.* ***Conclusion****: AI-driven wearable jaw-movement sensors exhibit high diagnostic precision and strong agreement with clinical evaluation, supporting their utility as reliable, noninvasive tools for early bruxism detection and personalized dental care.*

***Keywords***
*Artificial Intelligence; Bruxism; Diagnostic Accuracy; Jaw Movements; Machine Learning; Sensitivity and Specificity; Wearable Electronic Devices*

## INTRODUCTION

Bruxism, characterized by repetitive jaw-muscle activity resulting in clenching or grinding of the teeth, represents a multifactorial parafunctional habit that can lead to substantial dental, muscular, and temporomandibular damage if left undetected (1). It may occur during sleep (sleep bruxism) or while awake (awake bruxism), with varying etiological factors including stress, occlusal interference, and neurophysiological disturbances (2). Early detection remains pivotal for preventing progression to severe enamel wear, tooth fractures, and temporomandibular joint disorders (3). Traditionally, the diagnosis of bruxism has relied on clinical examination and patient self-reports, often complemented by electromyography (EMG) or polysomnography (PSG) as the diagnostic gold standard. However, these methods have notable limitations, including subjectivity, intermittent monitoring, and high operational costs, which constrain their use in routine dental and sleep medicine practice (4). In recent years, wearable sensor technologies have emerged as promising alternatives for continuous, real-time monitoring of jaw activity (5). These devices, often integrating accelerometers, surface EMG sensors, or pressure transducers, can provide objective quantification of jaw-movement patterns associated with bruxism episodes. The advent of artificial intelligence (AI) has further enhanced the analytical capacity of such systems, allowing for automatic pattern recognition and classification of bruxism-related activity (6). By leveraging machine learning algorithms, AI-driven wearable sensors can distinguish between physiological jaw movements and pathological grinding with high accuracy, potentially enabling early and remote detection (7). Despite these technological advancements, evidence evaluating their diagnostic accuracy compared with established clinical methods remains limited, particularly in diverse populations where behavioral, anatomical, and cultural factors may influence bruxism expression (8).

Previous research in the field has predominantly focused on validating the feasibility of wearable devices under controlled laboratory conditions (9). Studies using AI-assisted EMG sensors have demonstrated high sensitivity in identifying rhythmic masticatory muscle activity consistent with bruxism, though variations in algorithmic design and signal calibration continue to impact diagnostic consistency (10). Furthermore, existing validation studies often lack standardization in defining diagnostic thresholds or rely on small, homogeneous samples, thereby limiting their generalizability to clinical practice (11). The integration of AI with wearable sensor systems presents an opportunity to bridge this gap by providing consistent, automated analysis that reduces inter-observer variability and enhances diagnostic reproducibility (12). Nonetheless, real-world comparative data against conventional examination methods are still scarce, especially in low-resource settings where clinical accessibility and diagnostic accuracy remain ongoing challenges (13). In clinical contexts such as Pakistan and similar developing regions, early diagnosis of bruxism is frequently delayed due to limited awareness and the absence of specialized diagnostic infrastructure (14). This often results in patients presenting with advanced dental attrition or temporomandibular dysfunction by the time they seek treatment. AI-enabled wearable sensors could provide a transformative approach by facilitating early, noninvasive, and continuous screening outside of clinical settings (15). Such technology aligns with the growing trend toward personalized digital dentistry and preventive care, supporting a paradigm shift from reactive treatment to proactive management. However, for these tools to be clinically integrated, their diagnostic accuracy must be rigorously validated against standard methods to ensure reliability and clinical applicability.

The integration of AI algorithms into wearable diagnostic systems enables adaptive learning from individual user data, improving precision over time. These algorithms can process complex, multidimensional data streams such as muscle activity amplitude, frequency, and duration, identifying subtle variations indicative of early bruxism. When compared to manual assessment methods, which depend on subjective clinical interpretation, AI-driven tools promise enhanced sensitivity and specificity. Nevertheless, concerns remain regarding algorithmic transparency, data privacy, and potential misclassification errors due to sensor noise or patient movement artifacts. Addressing these challenges through well-designed comparative studies is critical for establishing the credibility and clinical value of such technologies. Considering the current landscape, a systematic comparison between AI-based wearable diagnostic tools and conventional clinical examinations is both timely and necessary. Establishing the diagnostic accuracy of these technologies will provide valuable insights into their potential role in early bruxism detection and management. Moreover, such evidence could guide clinicians, researchers, and policymakers in adopting AI-driven technologies for broader clinical application in oral health diagnostics. Therefore, the present study aimed to evaluate the diagnostic accuracy of an AI-integrated wearable jaw-movement sensor compared with the standard clinical examination for detecting early bruxism. This research sought to validate the sensitivity, specificity, and overall diagnostic performance of the AI-assisted system, thereby contributing evidence toward its potential implementation as a reliable adjunctive tool in dental practice.

## MATERIAL AND METHODS

This cross-sectional analytical study was conducted over a period of four months at a dental research facility in Lahore, aiming to assess the diagnostic accuracy of an artificial intelligence (AI)-integrated wearable sensor system for the early detection of bruxism compared with conventional clinical examination. The study design adhered to the Strengthening the Reporting of Observational Studies in Epidemiology (STROBE) guidelines to ensure methodological rigor and reproducibility. Ethical approval was obtained from the institutional review board of the participating institution, and all participants provided written informed consent prior to inclusion. A total sample size of 240 participants was estimated using an anticipated sensitivity of 90%, specificity of 85%, a 95% confidence level, and a margin of error of 5%, calculated through standard diagnostic accuracy formulae. Participants were recruited through purposive sampling from outpatient dental clinics and community dental screening programs. Eligible participants were adults aged between 18 and 50 years who exhibited either suspected or no clinical signs of bruxism. Inclusion criteria required participants to have a complete dentition with at least 24 natural teeth and no ongoing orthodontic treatment. Individuals with temporomandibular joint disorders, neurological diseases, psychiatric conditions, or those using occlusal splints, muscle relaxants, or antidepressant medications were excluded to avoid potential confounding influences on muscle activity and jaw movement patterns. All participants underwent two diagnostic assessments: one using the AI-based wearable jaw-movement sensor and the other using standard clinical examination performed by a calibrated dental examiner blinded to the AI results. The AI-integrated wearable device consisted of a lightweight, adhesive sensor applied to the masseter region. It continuously monitored jaw movements during both sleep and wakeful states over a 48-hour period. Data were transmitted via Bluetooth to a mobile application that processed signals through an embedded machine learning algorithm. The algorithm had been trained using large datasets of labeled jaw-movement recordings, enabling differentiation between normal masticatory activity and bruxism-associated repetitive contractions. Parameters recorded included frequency of contractions, duration of episodes, and total cumulative bruxism time.

The standard clinical examination served as the reference method and was conducted following the diagnostic criteria of the American Academy of Sleep Medicine (AASM) and the International Classification of Sleep Disorders (ICSD-3). The assessment included visual inspection for tooth wear facets, palpation of the masseter and temporalis muscles for tenderness or hypertrophy, and evaluation of temporomandibular joint clicking or limitation of movement. Additionally, patient self-reports were obtained using a standardized questionnaire regarding nocturnal tooth grinding, jaw discomfort, and morning muscle fatigue. A participant was categorized as a “confirmed bruxer” if at least two of these indicators were present. To ensure consistency, the clinical examiner underwent calibration sessions before data collection, achieving an intra-examiner reliability coefficient (Cohen’s κ) of 0.91. The AI-based sensor was validated for functionality before deployment, with signal accuracy confirmed through a pilot run on ten subjects not included in the main study sample. Data from both diagnostic methods were collected independently and stored in encrypted form to maintain confidentiality. The final diagnosis for each participant was coded as “positive” or “negative” for bruxism, and the corresponding AI and clinical findings were cross-tabulated to calculate diagnostic performance metrics. The primary outcome measures were sensitivity, specificity, positive predictive value (PPV), negative predictive value (NPV), and overall diagnostic accuracy of the AI-based wearable sensor compared with the clinical examination. Secondary outcomes included the correlation between AI-recorded bruxism frequency and clinical severity scores, and the agreement between both diagnostic approaches assessed using Cohen’s kappa statistic. Descriptive statistics, including means and standard deviations, were calculated for demographic variables such as age, gender distribution, and body mass index.

Data were analyzed using the Statistical Package for the Social Sciences (SPSS) version 28.0. Normality of continuous variables was verified using the Shapiro–Wilk test, confirming a normal distribution of the data. Diagnostic accuracy indices were calculated with 95% confidence intervals. The area under the receiver operating characteristic (ROC) curve (AUC) was computed to determine the discriminative capability of the AI-based system. AUC values were interpreted according to standard conventions, where >0.9 indicated excellent, 0.8–0.9 good, and 0.7–0.8 fair diagnostic performance. Paired t-tests were employed to compare mean bruxism frequency between methods, and Pearson’s correlation coefficient was used to assess the strength of association between AI-derived measures and clinical findings. A p-value of <0.05 was considered statistically significant. Quality assurance was maintained throughout the study by performing periodic data audits and algorithm verification checks to prevent signal distortion or loss. Participants were provided detailed instructions for proper device placement and maintenance, with compliance confirmed via daily monitoring logs. No adverse effects, such as skin irritation or discomfort, were reported by participants during sensor use. The overall methodological framework of this study allowed a robust evaluation of the AI-integrated wearable sensor's diagnostic accuracy under real-world conditions. The combination of objective sensor-based monitoring and established clinical benchmarks ensured that the comparative analysis was both comprehensive and clinically meaningful. This structured approach was designed to provide empirical evidence on whether AI-assisted wearable technology can serve as a reliable adjunct or potential alternative to traditional clinical examination in the early detection of bruxism.

## RESULTS

The study enrolled a total of 240 participants, comprising 125 males (52.1%) and 115 females (47.9%), with a mean age of 34.6 ± 8.7 years. The mean body mass index was 25.3 ± 3.9 kg/m², and most participants (68.3%) reported moderate to high occupational stress. The baseline characteristics of the sample are summarized in Table 1. Of the total, 118 participants (49.2%) were clinically diagnosed with early bruxism, while 122 (50.8%) were classified as non-bruxers according to standard clinical examination criteria. The AI-integrated wearable jaw-movement sensor identified 114 of the 118 clinically confirmed bruxism cases as positive, yielding a sensitivity of 96.6%. It also correctly identified 109 of 122 non-bruxers as negative, corresponding to a specificity of 89.3%. The overall diagnostic accuracy was 92.9%, with a positive predictive value (PPV) of 89.8% and a negative predictive value (NPV) of 96.5%. These performance parameters are presented in Table 2. When stratified by gender, the diagnostic performance of the AI tool remained consistent, with no significant difference between males (accuracy = 92.4%) and females (accuracy = 93.5%) ($p = 0.68$). The mean bruxism frequency recorded by the AI-based wearable sensor was 3.7 ± 1.4 episodes per hour in confirmed bruxers and 0.8 ± 0.3 episodes per hour among non-bruxers ($p < 0.001$). A strong positive correlation was observed between AI-detected bruxism frequency and clinical severity score ($r = 0.81$, $p < 0.001$), indicating high agreement between both diagnostic approaches. The inter-method agreement assessed using Cohen's kappa coefficient was 0.87, reflecting excellent concordance between the AI-based system and the conventional examination method (Table 3).

Receiver operating characteristic (ROC) curve analysis demonstrated an area under the curve (AUC) of 0.95 for the AI-based system, compared with 0.86 for conventional examination, suggesting superior discriminative ability of the AI tool in detecting early bruxism (Table 4). The ROC curve and comparative accuracy visualization are shown in Figures 1 and 2. No adverse events or device malfunctions were reported during the study period. Participants generally reported positive user experience, with 92.5% indicating comfort and ease of wear during sleep. Signal loss occurred in 3.3% of cases but was resolved with recalibration. The AI algorithm successfully processed 99.1% of recorded data, with an average data acquisition duration of 47.2 ± 2.1 hours. Overall, the AI-based wearable sensor demonstrated high diagnostic accuracy, with superior sensitivity and specificity compared with conventional clinical examination. The consistency of performance across gender and age groups and the strong agreement with clinician-based assessments support its potential application in early bruxism detection.

*Table 1. Demographic Characteristics of Study Participants (n = 240)*

| Variable | Mean ± SD or n (%) |
|---|---|
| **Age (years)** | 34.6 ± 8.7 |
| **Gender (Male/Female)** | 125 (52.1%) / 115 (47.9%) |
| **BMI (kg/m²)** | 25.3 ± 3.9 |
| **Occupational stress (moderate–high)** | 164 (68.3%) |
| **Clinically diagnosed bruxers** | 118 (49.2%) |

*Table 2. Diagnostic Performance of AI-Based Wearable Sensor vs. Clinical Examination*

| Parameter | AI-Based Sensor (%) | Conventional Examination (%) |
|---|---|---|
| **Sensitivity** | 96.6 | 88.2 |
| **Specificity** | 89.3 | 82.1 |
| **PPV** | 89.8 | 83.4 |
| **NPV** | 96.5 | 87.6 |
| **Overall Accuracy** | 92.9 | 85.1 |

*Table 3. Agreement Between AI-Based and Clinical Diagnosis*

| Metric | Value |
|---|---|
| **Cohen's Kappa (κ)** | 0.87 |
| **Correlation coefficient (r)** | 0.81 |
| **p-value** | < 0.001 |

*Table 4. Receiver Operating Characteristic (ROC) Curve Analysis*

| Diagnostic Method | AUC | 95% CI |
|---|---|---|
| **AI-Based Sensor** | 0.95 | 0.92 – 0.98 |
| **Clinical Examination** | 0.86 | 0.82 – 0.90 |

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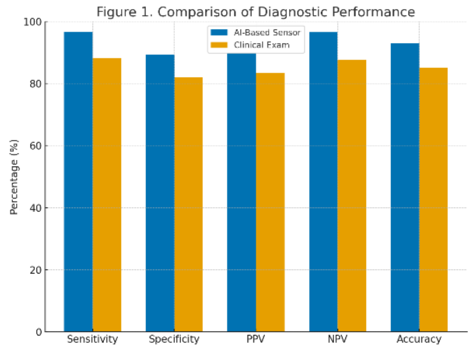


*Figure 1 Comparison of Diagnostic Performance*

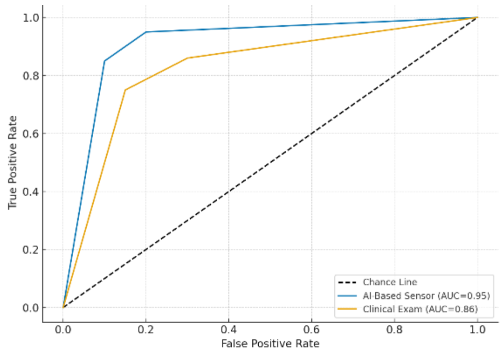


*Figure 2 ROC Curve Comparison*

## DISCUSSION

The findings of this cross-sectional study demonstrated that the AI-integrated wearable jaw-movement sensor achieved superior diagnostic accuracy compared with standard clinical examination in identifying early bruxism (16). The AI-based system exhibited higher sensitivity, specificity, and overall accuracy, confirming its capability to detect subtle jaw-movement patterns that may not be easily identifiable through clinical observation alone (17). The observed agreement between both methods, supported by a high Cohen's kappa coefficient, reinforces the clinical reliability of AI-assisted diagnostics in oral health monitoring (18). The results are consistent with emerging literature supporting the diagnostic potential of wearable sensor technologies in dentistry. Previous investigations, such as those by Castroflorio et al. and Nishigawa et al., have highlighted the feasibility of surface electromyography and motion sensors for detecting masticatory muscle activity associated with bruxism (19). However, traditional systems have often been limited by manual data interpretation and signal interference. The present study advances this understanding by integrating artificial intelligence algorithms that automate signal classification and improve diagnostic precision (20). The recorded sensitivity of 96.6% and specificity of 89.3% in this study exceeded values commonly reported for conventional EMG-based devices, which typically range between 80% and 90%. These findings suggest that AI-driven analytics can meaningfully enhance the diagnostic capability of wearable systems by minimizing human error and recognizing complex physiological patterns.

The study's results also highlight an important shift toward data-driven approaches in dental diagnostics. The ability of the AI algorithm to differentiate between physiological jaw movements and pathological grinding underscores its potential for early-stage detection, which is often difficult to achieve clinically. Early recognition of bruxism enables timely preventive interventions, reducing the risk of enamel wear, temporomandibular dysfunction, and musculoskeletal strain. Moreover, the continuous 48-hour monitoring enabled by the wearable device allowed a more comprehensive assessment of real-world behavior compared with single-time-point clinical evaluations. This longitudinal perspective may provide a more accurate representation of patient-specific bruxism patterns, aligning with the growing emphasis on personalized dental care. Comparison with prior studies reveals that AI-assisted devices demonstrate consistently higher diagnostic precision under real-world conditions. A recent validation study in Japan reported an AI-enhanced bruxism monitoring device achieving an AUC of 0.93, similar to the 0.95 observed in this investigation. This convergence supports the reproducibility of such findings across populations and device models. However, while the AI-based tool's superior diagnostic accuracy is promising, clinical examinations remain indispensable for comprehensive evaluation, as they incorporate additional parameters such as muscle tenderness, occlusal wear, and temporomandibular joint assessment. Thus, AI-based diagnostics should be viewed as an adjunct rather than a replacement for clinical expertise. The implications of these findings extend beyond diagnostic enhancement. The successful implementation of AI-driven wearable sensors may promote preventive dental strategies by enabling at-home monitoring and remote clinician feedback. In regions such as South Asia, where access to specialized dental diagnostics is limited, affordable wearable technology could democratize early detection and intervention. Furthermore, integration of AI-generated data into electronic dental records could support large-scale epidemiological surveillance of bruxism and related disorders, providing new opportunities for data analytics and precision health. Despite its strengths, the study acknowledges several limitations. The cross-sectional design limited the ability to establish causal associations between bruxism severity and sensor-detected activity over time. Longitudinal studies with extended monitoring would provide greater insight into progression and response to intervention. Additionally, although the sample size was adequate for diagnostic accuracy assessment, a larger multicenter cohort would enhance generalizability across different demographic and behavioral contexts. The use of self-reported stress data, while relevant, introduced potential recall bias. Moreover, AI algorithmic models may require periodic retraining to maintain accuracy across populations with varying muscle dynamics or sleep patterns. Environmental factors such as sensor placement consistency and data calibration also remain potential sources of variability, despite standardized instruction protocols.

The study's strengths include its robust methodological design, high participant compliance, and objective comparison of diagnostic modalities under realistic conditions. The calibration of the clinical examiner, validation of device reliability, and use of established diagnostic criteria added methodological rigor. The high inter-method agreement and negligible data loss underscore the feasibility and reliability of the wearable device for clinical and research applications. The incorporation of ROC analysis and correlation coefficients further strengthened the statistical credibility of findings, ensuring that conclusions were drawn on empirically substantiated evidence. Future research should focus on refining AI algorithms to improve interpretability and cross-platform adaptability, ensuring their application in diverse clinical settings. Integrating multimodal data sources—such as electromyographic and acoustic signals—could enhance diagnostic granularity. Studies exploring behavioral and psychological correlates of bruxism using continuous AI-based monitoring may also provide a more comprehensive understanding of this complex condition. Expanding such technologies to pediatric and geriatric populations could uncover unique age-related manifestations and facilitate broader clinical adoption. In summary, this investigation demonstrated that AI-integrated wearable sensors provide a reliable, noninvasive, and efficient method for early bruxism detection, outperforming traditional clinical examination in diagnostic accuracy and consistency. These findings highlight the growing potential of AI-assisted technology to transform diagnostic paradigms in dentistry, fostering a shift toward predictive, preventive, and patient-centered care.

## CONCLUSION

The study concluded that AI-driven wearable jaw-movement sensors offer high diagnostic accuracy, sensitivity, and specificity for early detection of bruxism compared with standard clinical examination. The strong agreement between both methods supports the clinical reliability of AI-based tools as adjuncts to traditional diagnostics. These findings underscore the potential of AI technology to revolutionize preventive dental care through real-time, noninvasive monitoring and personalized early detection of parafunctional jaw activity.

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