



REVIEW

Artificial Intelligence in Dentistry and Temporomandibular Disorders: Current Trends and Emerging Prospects—A Scoping Review

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ABSTRACT

Artificial Intelligence has grown tremendously in recent years, positioning as a transformative technology that uses algorithm-based systems to replicate human cognitive and behavioral processes. AI integrates machine learning (ML), deep learning (DL), and natural language processing (NLP) which have significantly transformed health care, including dentistry. AI models enabled efficient analysis of multidimensional datasets such as clinical and imaging records which improve diagnostic accuracy, predicting disease progression, and treatment outcomes. Temporomandibular disorders (TMD) are a chronic pain condition that affects temporomandibular joint, muscle of mastication and associated structures. TMD management requires multidisciplinary care; however, coordinated care for TMD is typically lacking due to clinician bias, limited training and differences in health care systems. In response to these challenges there is growing interest in using AI models to assist health care providers in diagnosing and managing TMD. AI models can assist health care providers by integrating heterogeneous data to provide tools for pattern recognition, strengthening evidence-based clinical decision-making and enhancing patient-centered care. In this narrative review we explore studies that utilize AI based algorithms for investigating dental conditions and TMD. This paper aims to explore fundamental AI methods, current AI applications in dentistry and underscore the potential of AI to support clinical decision making. By providing an overview of AI technologies and their integration into the dental practice this paper highlights the growing role of AI in diagnosing accuracy, treatment planning and optimizing patient outcomes.

Keywords: Artificial Intelligence; Algorithm; Machine Learning; Deep Learning; Dentistry; Temporomandibular Disorders

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ARTICLE INFO

Received: 6 January 2026 | Revised: 4 May 2026 | Accepted: 12 May 2026 | Published Online: 19 May 2026
 DOI: <https://doi.org/10.64797/rwas.v2i1.103>

CITATION

Shrivastava, M., Ye, L., 2026. Artificial Intelligence in Dentistry and Temporomandibular Disorders: Current Trends and Emerging Prospects—A Scoping Review. *Real-World AI Systems*. 2(1): 1–16. DOI: <https://doi.org/10.64797/rwas.v2i1.103>

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1. Introduction

Artificial Intelligence (AI) focuses on developing machines capable of executing tasks that usually require human intelligence. These activities include visual perception, speech recognition, experience-based learning, pattern identification, problem-solving, and decision-making^[1,2].

AI comprises a range of specialized technologies including machine learning (ML), deep learning (DL), and natural language processing (NLP)^[1,2]. ML primarily focuses on creating algorithms and statistical models that enable computers to learn from data without explicit programming, while necessitating features defined by humans. DL is a subset of ML that leverages artificial neural networks (ANN) and can learn directly from raw data without requiring feature definition from humans. Natural language processing (NLP) encompasses algorithms that allow machines to understand, decode, analyze, and translate human language in both spoken and written formats^[3,4].

Over the past decades, AI models have witnessed substantial advancements in all the sectors including healthcare. Recently, AI has garnered attention in dentistry, leading to significant advancements in different domains including facilitating diagnosis, predictive analysis, segmentation and treatment planning^[5–7]. AI models have demonstrated competency in interpreting radiographic images, predicting post-treatment response, and designing prosthetics and orthodontic aligners^[5,7,8]. Clinical and image data are used by AI models for an array of applications such as caries detection, bone loss assessment, diagnosis of odontogenic lesions and root fractures, categorization of dental implant systems, implant treatment planning, robotic surgical procedures and many other applications^[5,7,8]. AI models are boosting clinic operations more easily by reducing clerical tasks, augmenting documentation and improving practitioner-patient contact. AI models have also received significant attention in pain medicine, emphasizing their potential to enhance diagnostic accuracy, and optimize treatment strategies^[6,9] (**Figure 1**).

Chronic pain represents a substantial personal and socioeconomic burden, with prevalence estimates that range from 11 to 40%^[10,11]. Contributing factors to this increase include rising rates of depression and anxiety, changing work demands, lifestyle modifications, sleep disturbances, genetic predisposition, and heightened symptom awareness^[12]. Common

chronic orofacial pain conditions encompass musculoskeletal disorders, neuropathic pain, headaches, psychological disorders and others. Temporomandibular disorders constitute a cluster of musculoskeletal conditions affecting muscles of mastication, the temporomandibular joint (TMJ) and associated structures^[10,11,13]. TMD afflicts 10–15% of the population with symptoms severe enough to require medical attention^[10,11]. The etiology of TMD is multifactorial involving both biomechanical and biopsychosocial factors^[10,11,14,15]. The clinical presentation of chronic orofacial pain conditions including TMD varies with symptoms ranging from mild, transient, or recurrent episodes to severe disabling pain that can significantly impair quality of life. The diagnosis of TMD relies on a combination of clinical history and physical examination, with imaging required in selected cases, making the diagnostic process time-consuming^[11,13,16].

Additionally, epidemiological studies demonstrate a high prevalence of comorbidities among individuals with chronic TMD^[10,11,16]. For example, widespread central pain conditions such as fibromyalgia, chronic pelvic pain, back pain, psychological and sleep disorders, frequently co-occur in this population. These comorbid conditions not only coexist with TMD but also contribute to the onset and persistence of chronic pain^[15,16]. Given the diverse nature of pain complaints, limited understanding of underlying mechanisms and frequent co-occurrence of multiple pain conditions in a single individual diagnosing and managing chronic orofacial pain conditions including TMD poses a significant challenge to health care professionals. Furthermore, differences in the clinical presentation between the individuals at diverse points of time contribute to delays in diagnosis and ineffective management^[11,15,16].

AI has been progressively employed in the detection and quantification of TMD, with the objective of emulating human decision-making and reasoning processes through the acquisitions of data sets. Recent literature has demonstrated the potential of AI in predictive modeling and precision healthcare^[5,9]. Retrospective studies have demonstrated the utility of AI in image interpretation identifying risk factors, diagnosis, and evaluation of treatment outcomes^[8–10,17–19]. Similarly, NLP and AI algorithms have been employed to extract relevant information from clinical notes and patient records, enabling the diagnosis and classification of distinct TMD phenotype^[10,17–19]. Despite substantial breakthroughs in AI applications in both imaging and clinical data, research in this area is limited^[10].

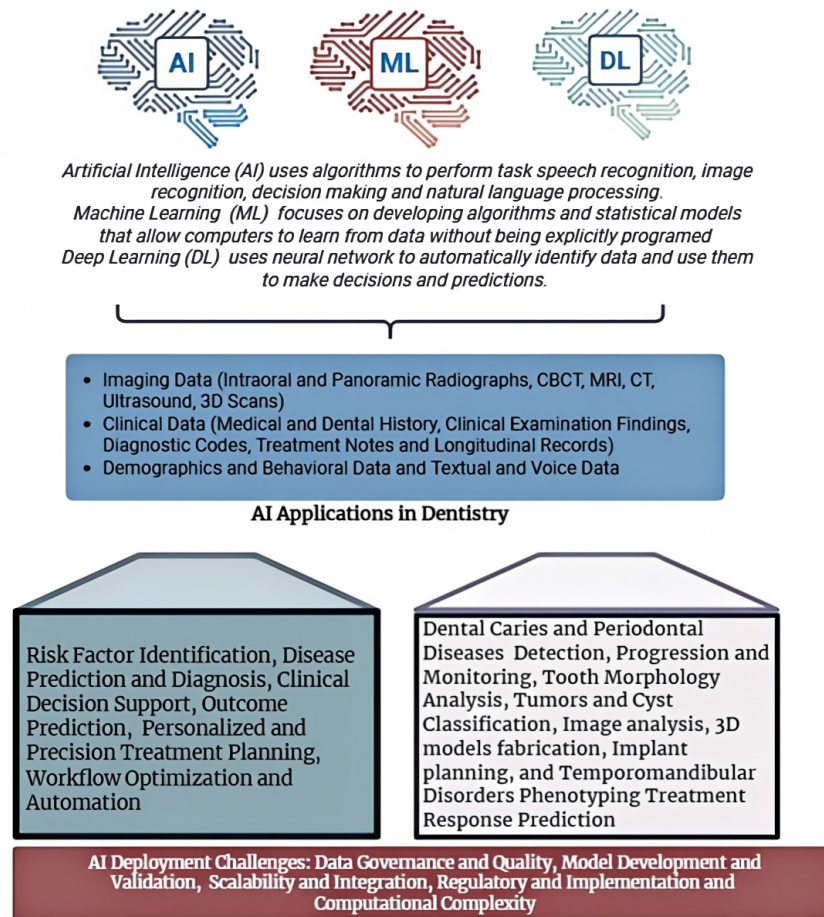


Figure 1. Overview of the Relationship between Artificial Intelligence and Dental Conditions and Temporomandibular Disorders.

It is observed that AI systems are still evolving, and they have a limited grasp of understanding of oral health. The existing literature focuses either on technical performance or high-level conceptual difficulties in analyzing the data^[5–8]. Moreover, conclusions drawn from the existing studies are constrained by specific research conditions including study design, data analysis approaches, input data characteristics, diagnostic applications and outcome measures used for the performance evaluation^[5–7,18–20]. Furthermore, the wide range of clinical data in dentistry complicates the scalability and generalizability of AI methods. Therefore, this review aims to bridge the gap between controlled and real-world contexts and familiarize the investigators with AI-based methods including ML, and DL, and provide an overview of their applications in dentistry. It further explores how AI can disentangle the complexity of TMD by developing diagnostic and prognostic models and predicting responses. Finally, the review highlights the potential challenges and provides a brief perspective on future aspects of AI in this area.

2. Overview of Artificial Intelligence Methods

The data presented in this paper were collected from a comprehensive search of multiple databases and dental-specific peer-reviewed scientific journals. The studies presented are unique to AI models that extensively reported a range of variables such as imaging, clinical findings and patient-reported outcomes in dentistry.

The foundational work of AI started in 1943, but the term “artificial intelligence” was formally introduced in 1956 by John McCarthy^[21]. It means creating a machine that has a kind of meta consciousness and thinks like human or something that captures the imagination^[22,23]. So far, there are three generations of AI. Artificial narrow intelligence (ANI) is often referred to as the first generation that is engineered to execute a specific task or limited range of tasks extremely well, for example, facial recognition and virtual voice assistants. The second generation of AI, known as artificial general intelli-

gence (AGI) aims to emulate human intelligence by possessing the ability to understand, learn, reason, apply knowledge and solve problems across a broad range of tasks. Currently, the most advanced generation is artificial super intelligence, a self-aware machine that might render people and their contributions obsolete in some certain situations^[22,23].

ML, a subfield of AI, focuses on developing algorithms that learn hidden statistical patterns within the data, thereby enabling accurate predictions on novel information. ML models learn patterns directly from data. For example, ML models can examine thousands of scans and discover patterns that humans might not recognize. It is prudent to highlight that ML and traditional statistics are overlapping disciplines, yet their methods and tools are different^[23–25]. ML rules are learned automatically from data examples, while traditional statistics use rules and models established prior to data analysis. Unlike traditional statistical approaches ML models (Random Forest, SVM, Gradient Boosting) can identify nonlinear relationships between multiple variables, enabling them to capture the complex interactions commonly noticed in biological and clinical data^[26]. Furthermore, ML can progressively refine their performance by iteratively optimizing their parameters during training by minimizing prediction errors^[26,27].

Another important concept of ML methodologies is deployment. It is the process of integrating ML models into the real world so that models can provide predictions and automate tasks^[28]. This technique includes transforming the trained models into a production-ready system, connecting it with software infrastructure such as databases, electronic health records, imaging systems and testing its ability to process new data efficiently. After a model is developed and validated, it can be deployed into apps, clinical systems and digital platforms allowing users to interact with its outputs. It is a critical step in transforming research models into practical tools capable of assisting in clinical decision making, increasing workflow efficiency and boosting real-world applications^[26,28]. Scalability, computational efficiency, and data governance are all critical challenges for successful deployment of AI models, especially in healthcare contexts outlined in the recommendation and limitation section.

In general, ML methodologies can be categorized into supervised learning (SL), unsupervised learning (UL) and reinforcement learning (RL) (**Figure 2**).

Among these, SL involves training models on labelled

data sets, wherein each observation is associated with corresponding label. The labels may be categorical, such as nociceptive or neuropathic pain, or a continuous variable, like change in pain intensity. These models require supervision in the form of labelled samples, which is where the term “supervised learning” originates^[23–25]. The core objective of SL is to use several input characteristics to predict the value of one or more outcomes. It is used when a training data set clearly delineates the relationship between each input and the anticipated output. SL has been identified as the most successful type of ML; however, it is time-consuming and necessitates a significant volume of label data. The primary challenges in developing such models arise from difficulties associated with large-scale data collection, which hinders the full utilization of SL potential^[23–25]. Additionally, many traditional ML models require careful featured engineering, which relies on domain knowledge and may introduce human bias.

Unlike SL, UL is employed when labeled data is unavailable. UL uses unlabeled data to train machines in the absence of known output. It is predicted that the algorithms can recognize concealed patterns or clusters within the data^[23–25,29,30]. Examples of UL are clustering, which means grouping patients with similar pain profiles or simplifying complex data sets. Unlike SL, UL does not require labeled data, reducing time and effort. These methodologies facilitate the identification of previously unrecognized patterns within the data set. While domain knowledge can be readily integrated into the SL models, its incorporation into UL methods presents greater challenges^[23–25,30–33].

While semi-supervised learning leverages a limited subset of labeled data along with a substantial amount of unlabeled data, integrating aspects of both SL and UL. The primary objective of semi-supervised learning is to enhance model functionality in settings where labeled samples are limited, while a substantial number of unlabeled samples are accessible. RL is a subset of ML in which a software agent learns decision-making by interacting with an environment and receiving feedback in the form of rewards and penalties. Unlike SL, RL does not rely on predefined outcomes for each input; instead, it uses quantifiable feedback to guide learning. This model is generally used when the inputs are environmentally stimulated rather than compiled data sets, enabling learning through trial and error. While this eliminates the need for data labelling, it limits RL to applications that can

be effectively simulated through iterative interactions. Examples of RL are where decisions must be made sequentially, and strategies need to adapt over time, such as personalized treatment optimization^[25,34,35]. Moreover, RL models face

challenges related to the need for extensive training through repeated interactions with an environment that can require a large number of simulations and considerable computational power.

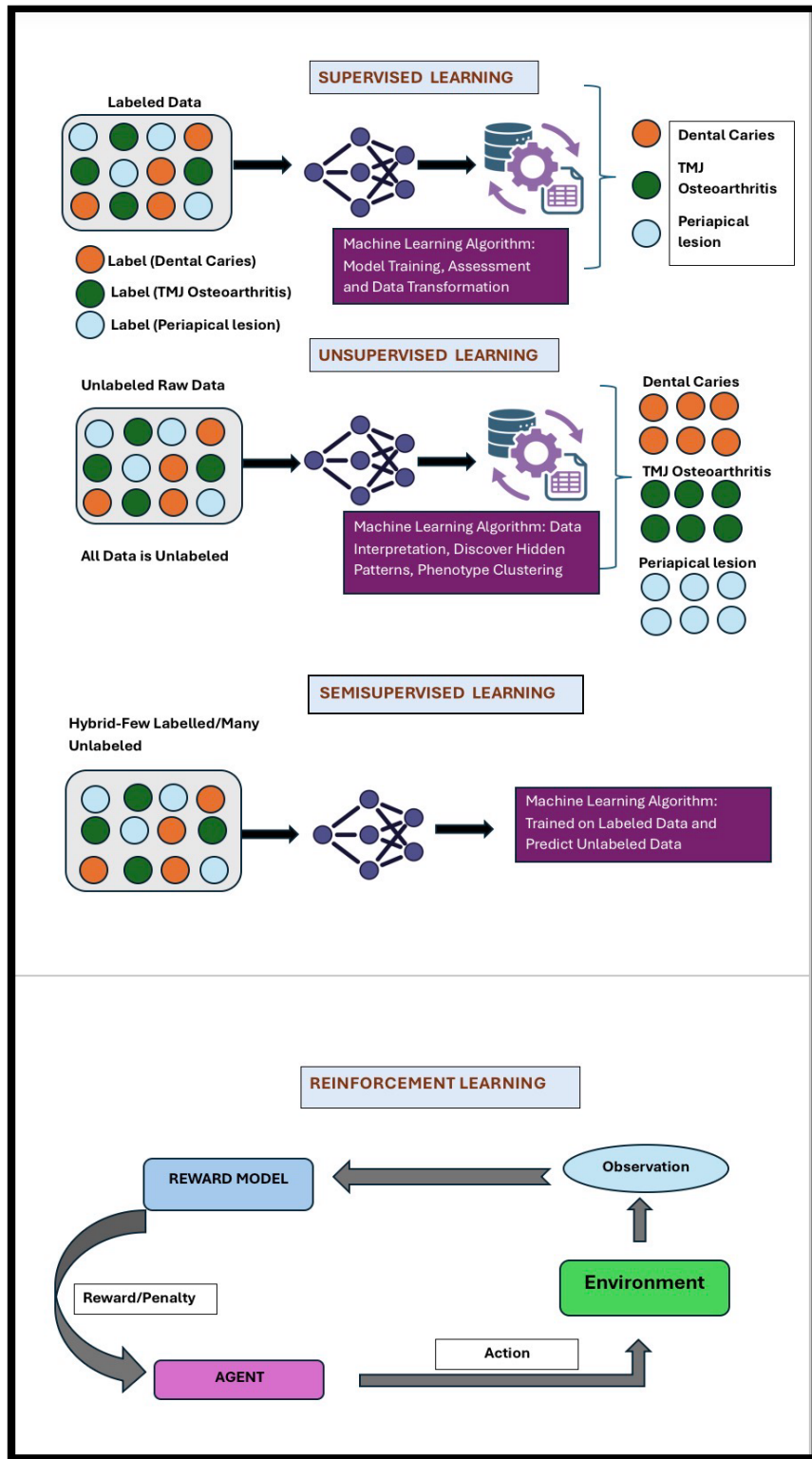


Figure 2. Illustration of Different Machine Learning Models.

ML also encompasses DL that employs ANN with multiple layers, referred to as deep neural networks, to autonomously discern intricate patterns from extensive data sets^[32–34]. Inspired by the structure and function of the human brain, these networks process information through layers of interconnected nodes, with each node linked to other nodes in the adjacent layers. ANN consists of multiple layers made up of interconnected nodes. Each network consists of an input layer for receiving data, a minimum of one hidden layer for processing and transforming the input, and an output layer that generates the result^[31–34]. The network architecture emulates the nervous system, with nodes representing individual neurons. The nodes in the network receive weighted inputs and propagate activation through subsequent layers, forming complex activation pathways. DL algorithms may automatically identify and extract features from raw data such as in the image analysis of carious teeth or osteoarthritic temporomandibular joints (TMJ) and utilize these features to make predictions or decisions^[10,25,35–37].

DL encompasses three primary architectures. First, convoluted neural networks (CNNs) are specialized for image and visual input. They automatically identify characteristics such as edges, forms, and textures, rendering them particularly effective for tasks like image categorization, object detection, and medical imaging analysis^[29–33]. Second, recurrent neural networks (RNNs) are engineered to handle sequential and time-series data by retaining a memory of previous inputs, making them suitable for sequence prediction, including temporal signals and sequential patterns^[32,35–37]. Long short-term memory (LSTM) networks are an advanced form of RNN that address short term memory limitations and are particularly effective for speech recognition, text processing, and language modeling, where long-term dependencies are important^[36,37]. Additionally, DL approaches have demonstrated significant effectiveness in NLP tasks, including language translation and clinical text mining which are emerging applications in research and dental practice^[25,34,37]. However, DL often requires large amounts of data sets and substantial computational resources for training, making them expensive and time consuming to implement.

Overall, ML and DL techniques can efficiently integrate diverse sources of information such as clinical, imaging, and genetic data, and support ensemble learning strategies that combine multiple models to improve robustness and generalization. As a result, these approaches can provide more precise

diagnostic, prognostic, and predictive capabilities, facilitating personalized treatment strategies and improving decision-making in clinical practice.

3. Applications of Artificial Intelligence in Dentistry

AI has transformed dental research and clinical practice, particularly in image-based diagnostics, treatment planning, and workflow optimization.

DL and CNNs have become essential components of modern dentistry as computational power and large dataset sizes have increased. For instance, input data such as images, texts or voice data, or computer-aided design and manufacturing (CAD/CAM) are incorporated into the neural network, which processes the information and generates an output^[38–41]. The outcomes may include diagnoses, treatment recommendations, or disease predictions. AI can assist dental professionals in analyzing X-rays, Cone Beam Computed Tomography (CBCT) Scans and Magnetic Resonance Imaging (MRI), facilitating the identification, diagnosis, and treatment planning of various dental conditions (**Figure 3**).

In the literature, AI models were trained on the primary dataset and subsequently validated using an independent test dataset to assess their generalizability. The model performance was evaluated using accuracy, sensitivity, and specificity^[41–45].

Researchers have employed AI models to detect periapical diseases and periodontitis^[1,5,40–42,46]. Lin et al. presented a computer-aided diagnostic ML method for diagnosing and assessing bone loss, while other researchers proposed deep algorithm models for categorizing the severity of periapical lesions^[44]. In a study, a combination of pre-trained deep CNN architecture and a self-trained network was used on radiographic images to determine the optimal CNN algorithm. With deep CNN algorithm, the diagnostic accuracy of classifying normal and disease was 73% and for classifying the levels of severity of bone loss was 59% respectively. The study revealed that CNN algorithm was useful in determining the alveolar bone loss in periapical radiographs^[8,45,46]. It is also observed that although the immunological responses and microbial profiles underlying this pattern have not been completely elucidated, AI applications such as multilayer perceptron neural networks may assist researchers in precise identification particularly in aggressive periodontitis by focusing on leukocytes interleukins, and IgG antibodies titers^[41–43].

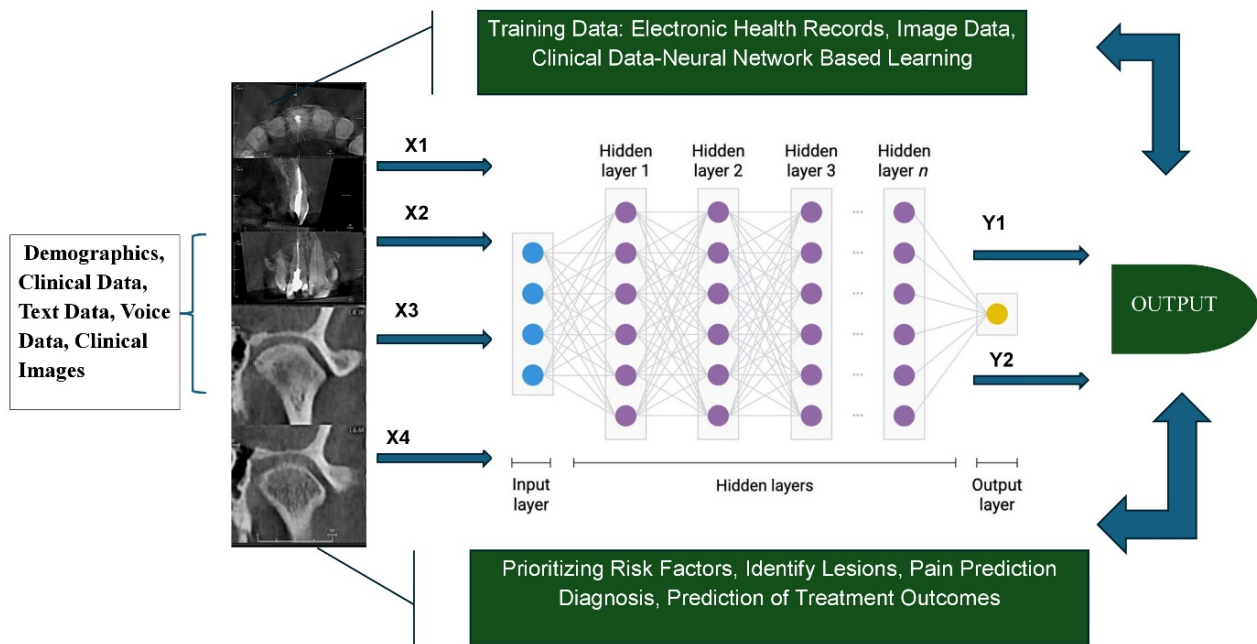


Figure 3. Schematic Illustration of the Machine Learning and Dental Applications.

Studies have also shown AI models' accuracy in understanding complex root canal anatomy and root fractures^[6,36,37,44,45]. Fukuda et al. used a CNN-based deep learning model for detection of vertical root fractures on panoramic radiographs^[47]. The CNN-based model for detection of vertical root fracture was built using DetectNet with DIGITS. The model demonstrated a precision of 0.93 concluding as promising tool to detect vertical root fracture^[47].

Similarly, Saghir et al. revealed that ANN can serve as a supplemental tool for identifying the apical foramen on radiographs, hence improving the accuracy of working length determination^[48], while in another study ANN outperformed endodontist by wide margin in determination of the working length^[41]. Another recent study found that DL models could reach a cross-validation accuracy of over 91% in classifying and predicting the difficulty of endodontic treatment using periapical radiographs^[48–51] demonstrating that ANN can function as a decision-making system in challenging clinical situations.

When predicting the mobility of teeth and durability of composite resin restorations a multilayer perceptron neural network showed satisfactory performance^[40,51,52]. In one study, CNNs method was used to predict the debonding probability of CAD/CAM composite resin crowns^[39,52] achieving 98.5% accuracy on test images derived from 3D stereolithography models of patient specific dental dies^[8,52,53]. AI models along

with CAD/CAM have demonstrated promise in areas such as dental charting, tooth shade selection, automated restoration design, mapping the preparation finishing line, manufacturing casting optimization, predicting facial changes in patients wearing removable prostheses, and designing removable partial dentures^[53].

With the advancements in neural networks, AI is increasingly being utilized in prosthetic dentistry laboratories to autonomously design dental restorations that optimize fit, function and aesthetics^[8,53,54]. AI is also useful in fabricating various RPD designs and components. Recently, AI models and CNN have been used to classify dental arches and assist in the fabrication of RPDs. A high diagnostic accuracy of 99.5% and 97% was observed for maxillary and mandibular arches respectively^[55]. Additionally, AI models have been applied to analyze 3-D representations of the teeth and jaws for orthodontic treatment planning and simulations demonstrating higher concordance in assessing treatment requirements using orthodontic data set^[54].

In cases of dental extraction, an ANN model achieved 98% accuracy in predicting facial swelling following extraction of impacted third molars^[55]. Additionally, ML models have been explored for their ability to detect cysts, tumors and lymph node metastases. The ML model reported excellent accuracy of 91–98% in distinguishing between dental cysts,

tumors and abscess lesions^[56–58]. The algorithm reported 94% accuracy in distinguishing odontogenic lesions using manually engineered features from CBCT images^[56–59]. AI also demonstrates potential in predicting recurrences of oral squamous cell carcinoma with studies reporting accuracy between 70 to 90% for recurrence and survival prediction. However, the models are still developing and need more data and validation for widespread clinical integration^[57–59].

In dental implantology, ML model achieved 99% accuracy in predicting dental implant success rates by analyzing patient data implant features and surgical information^[60]. ML models specifically support modern technologies in predicting the mechanical performance of implant systems. It predicts longevity of dental implants, significantly reducing the computational time required to optimize designs by analyzing complex variable relationships, yielding results nearly as good as traditional methods for stress prediction at the implant bone interface^[1,5,60,61]. It is also well known that the implant placement accuracy is key to long term implant survival. Implant placement often considers the spatial anatomical structures of the jaw such as nerves blood vessels. Concurrently implant surgery is also affected by factors such as limited visibility in the operating area confined surgical space and interference from saliva and tongue. Therefore, implant surgery is complex and predominantly relies on the technical experience and expertise of surgeons indicating that the learning curve for dental implant surgeons is comparatively long^[5,8,60]. However, the success rate of AI in predicting implant success or osseointegration has been found to vary between 62%–80%^[55,60–62].

In recent years, surgical robots have gained gradual acceptance in dental clinics and among patients as research has advanced. In 2017, the Yomi oral implant surgical robot system received FDA approval and became the world's first commercial system of its kind globally^[62–64]. It provides a visual interface and guidance for surgical instruments, assisting clinicians in precise implant placement. Modern surgical robots have addressed human limitations such as visual impairment, fatigue, and arm tremors through precise positioning and computer-controlled motion of surgical instruments and craniofacial parts, thereby achieving precise implant placement. Today many robotic systems perform semi-automated surgical procedures with increasing efficiency under the supervision of skilled surgeons. Procedures such as biopsies and TMJ surgeries exemplify image-guided cranial interventions that

have demonstrated clinical success^[63,64].

Moreover, AI-driven NLP including chatbots as well as virtual and augmented reality technologies can assist patients in scheduling appointments, addressing inquiries and enhancing their understanding of oral health. Dental professionals can use visualizations from the image analysis software to communicate and recommend treatments to patients, enhancing understanding and encouraging timely interventions. Reviewing their own dental images helps patients develop a greater awareness of their oral health and pursue timely treatment when necessary^[65,66]. Furthermore, integration of AI models with dental and other additional health data, for instance, cardiovascular, neurological and behavioral factors can enable a more comprehensive approach for managing dental disorders and other comorbidities.

4. Applications of Artificial Intelligence in the Diagnosis and Treatment of Temporomandibular Disorders

The Diagnostic Criteria for Temporomandibular Disorders (DC/TMD) is currently widely recognized and used by both clinicians and researchers^[11,67]. The framework comprises Axis I and Axis II, which provide diagnostic standards for differentiating TMD subtypes and assessing jaw functions as well as behavioral and psychological factors. Nonetheless, imaging techniques such as CBCT and MRI are utilized to provide detailed assessment of the TMJ and adjacent structures in some cases^[11,13].

AI algorithms can aid health care professionals in classification of orofacial pain, diagnosis of TMD, treatment planning and prediction of treatment response^[10,19,20]. By utilizing ML and DL algorithms, pain diagnosis can be classified based on risk stratification, clinical presentations, and standardized frameworks. This approach enhances the differentiation between nociceptive and neuropathic pain phenotypes, ultimately improving diagnostic accuracy^[68]. AI technology also contributes to a deeper understanding of the pain mechanisms through the integration of virtual reality simulation and neuroimaging data (functional and structural). Growing evidence suggests that combining ML with TMD related neuroimaging data can identify structural and functional alterations within

pain-related networks, thereby enhancing clinicians' decision-making capabilities^[10,20].

Extending these applications to diagnostic imaging, several studies have utilized DL algorithms and image data to assess TMJ morphology alterations and diagnose degenerative joint diseases using CBCT images and found heterogeneous sensitivities and specificities^[10,19,20,69–72]. Multiple studies have employed clinical symptoms and diagnostic findings to predict TMD subtypes with ANN demonstrating vari-

able diagnostic accuracy^[71–74]. NLP-based models have also shown promising performance in differentiating TMD conditions^[75,76]. **Table 1** summarizes studies that used AI to support clinicians in diagnosing TMD using diverse data sources including diagnostic images, health records and biomarkers which may enhance diagnostic precision. However, the accuracy of TMD prediction model varies considerably due to disorder complex spectrum and contingent on dataset size and the algorithms employed during model development.

Table 1. Summary of Major Artificial Intelligence Studies on TMD.

Studies	Study Objective	Methods	Performance Metrics and Inference
Bas et al. ^[70]	This study evaluated the use of Artificial Neural Network (ANN) for diagnosing TMJ internal derangement.	Clinical symptoms and diagnosis of TMJ internal derangement in 161 patients were used to train a neural network. Subsequently, symptoms and diagnoses of 58 new patients were used to verify ANN's ability to diagnose disc displacements.	The study reported heterogeneous sensitivity and specificity for detecting displacements using ANN. In detecting unilateral anterior displacement with reduction, the sensitivity and specificity of ANN were 80% and 95%, unilateral anterior displacement without reduction, the sensitivity and specificity were 69% and 91%, bilateral anterior displacement without reduction, the sensitivity and specificity were 37% and 100%, respectively, bilateral anterior displacement with reduction, the sensitivity and specificity were 100% and 89%, respectively.
Bianchi et al. ^[73]	This study evaluated the diagnosis of TMJ osteoarthritis (TMJOA) using quantitative bone imaging (CBCT) biomarkers combined with four machine learning models: logistic regression, random forest, light GBM and XGBoost	The clinical, biological and high resolution CBCT markers from 52 TMJ OA patients and controls were analyzed.	XGBoost + LightGBM model achieves an accuracy of 0.823, AUC 0.870, and F1-score 0.823 to diagnose the TMJ OA status.
de Dumast et al. ^[72]	This study employed a deep neural network (Shape Variation Analyzer, SVA) and web-based system (data storage, computation and integration, DSCI) to assess shape changes in TMJOA.	The training data set consists of 259 condyles from controls and patients diagnosed with TMJ OA. For image analysis 34 condyles from 17 patients and for integrative statistical model analysis 17 age- sex-matched control subjects were tested. The imaging dataset consisted of three-dimensional (3D) surface meshes of mandibular condyles constructed from cone beam computed tomography (CBCT) scans.	The study demonstrates a comprehensive phenotypic characterization of TMJ disease across clinical, imaging and biological levels combining advanced shape analysis with neural-network based classification of TMJ OA. The DSCI and tested the neural network, indicated 5 stages of structural degenerative changes in condylar morphology in the TMJ with 91% close agreement between the clinician consensus and the SVA deep neural network.
Kim et al. ^[76]	This study developed automated methods for detecting the mandibular condyle and TMJ OA using CNNs and faster region-based CNN (R-CNNs).	Panoramic images are collected retrospectively, and 1,000 images are classified into three categories normal, abnormal, and unreadable.	An R-CNN model and a Visual Geometry Group-16 (VGG16) model are used for learning and condyle discrimination. The TMJ OA classification algorithm achieved a sensitivity of 0.54, specificity of 0.94 and accuracy of 0.84 demonstrating that CNNs can effectively classify panoramic images.
Radke et al. ^[71]	This study used ANN to detect normal TMJ and non-reducing displaced disk from frontal chewing data.	The study subjects were 68, normal joints 29, unilateral non-reducing displaced discs 18, and bilateral non-reducing disc displacement were 21. Right sided gum chewing and left sided chewing were recorded.	The study reported heterogeneous sensitivity and specificity for detecting displacements using ANN. The ANN successfully identified the presence and type of non-reducing disk displacement from frontal-plane recordings of patients seeking treatment.
Reda et al. ^[19]	This study presented an AI based system for supporting non-expert dentists in the early recognition of TMD.	This study involves implementation of core cognitive computing services, the web interface and preliminary testing.	The study provides preliminary proof of concept supporting the feasibility of implementing an AI-based system in early identification of TMD.

Table 1. *Cont.*

Studies	Study Objective	Methods	Performance Metrics and Inference
Talaat et al. [74]	This study develops and tests the performance of AI models for the diagnosis of TMJ osteoarthritis from CBCT images.	A total of 2,737 CBCT images from 943 patients were used for the training and validation of AI models. Later two evaluators performed a DC/TMD based assessment to generate a separate model-testing of 350 images in which confirmed diagnosis was considered as reference.	The Cohen's kappa showed statistically significant differences in the agreement between the AI and the radiologist with the golden reference for the diagnosis of all signs collectively ($p = 0.0079$) and for subcortical cysts ($p = 0.0214$). AI diagnosis possesses a statistically higher agreement with golden reference compared to the radiologist. AI is expected to eliminate the subjectivity associated with human interpretation and expedite the diagnostic process of TMJOA.

Note: Data from assorted studies [19,71–74,76].

Growing evidence suggests that AI models can enhance pain recognition and enable automatic extraction of patient pain related information from clinical data set [70,72–76]. In particular, NLP techniques can automatically detect a patient's pain status from clinical notes. The important limitation of these tools is that they can determine the presence or absence of a pain or intensity of pain not other pain characteristics possibly because pain is inherently subjective, meaning it is a personal feeling unique to each individual and significant variability exists in how people perceive, interpret, and react to painful stimuli due to complex biological, psychological, and social factors like genetics past experiences, mood, and culture. This area requires further exploration in a more complex environment coupled with a comparison with a standard reference to enable the practical application of these models [77].

In regard to treatment planning, informing patients about their condition, associated risk factors, coping mechanisms, preventive strategies and potential treatment outcomes are the primary goal of patient education [10,20,77]. This approach supports informed decision making, promotes adherence to treatment, and ultimately contributes to improved clinical outcomes. Advances in NLP have further expanded new possibilities to enhance patient provider communications. NLP enhances effective communication across languages resulting in improved comprehension and engagement. Using advanced AI algorithms can offer insights and recommendations for treatment alternatives through analyses of extensive data set. This facilitates the generation of evidence-based suggestions tailored for particular patients. Through the patient's chronic painful TMD history, socioeconomic demographic data, and associated investigations, AI may deliver personalized recommendations that correspond to each patient's unique circumstances and needs [75,78]. AI algorithms can assist patients and clinicians in symptom monitoring,

reminding them of medication adjustments and identifying potential drug interactions, thereby improving adherence [76–78].

Existing research has highlighted the importance of clustering the patient subgroup and analyzing their responses to interventions. The SL methods were employed to interpret these clusters. For instance, Miettinen et al. utilized a data-driven approach in a cohort of 320 patients with persistent pain to identify the most contributing factors associated with various pain phenotypes [79]. The data set employed in this study included predictors categorized into seven distinct groups: pain phenotype-related factors, demographic factors, pain etiology, morbid lifestyle factors, psychological variables, and treatment-related factors. The analysis identified sleep disturbances, fear of pain, self-rated, poor health and systolic blood pressure as the most contributing factors associated with pain phenotypes [78–80]. While the proposed algorithm demonstrated limited performance in terms of non-pain phenotypes variables and the data set contained a considerable degree of noise. Similarly, AI algorithms have shown positive effects on pain management, notably in alleviating pain levels and diminishing dependence on other interventions [10,77,78]. However, previous research has exclusively assessed general pain level instead of the pain on specific site. Moreover, several studies are criticized for their small sample size and self-reported subjective data. These limitations underscore the need for further research to determine the long-term adherence to therapy and enduring benefits of those interventions.

5. Clinical Implications and Limitations of AI

Current evidence suggests that AI models are intended to support dental professionals rather than substituting them.

Dental professionals must ensure that AI-driven applications provide clinically relevant insights aligned with best practice guidelines^[80] while AI specialists develop robust algorithms to guarantee system accuracy and reliability. When creating and using AI systems, it is crucial to assess potential drawbacks and implement regulations to prevent adverse outcomes^[81,82]. Patients should have a comprehensive understanding of the utilization of their data, the rationale behind AI recommendations and limitations of the technology. Adherence to the standardized protocols for data collection, such as the Health Insurance Portability and Accountability Act (HIPAA), is important to protect patient information from misuse^[81]. Furthermore, robust data protection measures, including encryption and secure storage must be employed to safeguard patient information^[2,23,25]. Therefore, standardization of AI tools is needed with adequate regulations ensuring that AI systems are safe, effective and ethical.

Expanding on these concepts robust data governance, interoperability and scalability are critical considerations in the deployment of AI models, particularly in healthcare. Data governance refers to the policies, or security that ensure the ethical use of data throughout its life cycle while interoperability refers to the ability of different systems, platforms and organizations to exchange information and use data seamlessly^[83,84]. Scalability is another important consideration in implementation of AI models. It means handling complexes, increasing volume of data while maintaining accuracy and compliance^[84,85]. The implementation of AI models in small clinical settings or individual practices is uncomplicated, but limited data can affect model robustness and generalizability. While large multi-center hospitals can generate volumes of heterogeneous data from sources such as electronic health records, imaging systems and laboratory databases^[83–85]. Systems deployed in larger settings must efficiently analyze high dimensional data; nevertheless, this poses significant technical and infrastructure challenges, necessitating further advancement in AI models.

Beyond this, computational complexity is a significant concern in ML models because it influences^[86] the computational resources, time, and scalability needed for model training and inference. It is mostly determined by the size of the dataset, the number of features, and the methodology utilized. As data dimensionality increases, techniques like support vector machines and decision trees may become com-

putationally costly^[86–88]. Deep learning models typically have increased computational complexity due to their multi-layered neural networks and huge number of parameters, which necessitate significant computer power and memory during training. The key strategies for reducing AI complexity included model compression and optimization (pruning), architectural efficiency (using techniques like parameter efficient fine tuning), data quality optimization, inference time scaling and hardware acceleration^[87,88]. These strategies must be carefully considered to balance model accuracy, efficiency, and scalability in real-world applications.

Moreover, previous studies have demonstrated that AI models often struggle to perform in diverse populations due to biases in training data^[88–90]. Most AI related studies are single center studies with small, homogeneous populations, limiting generalizability to broader healthcare settings. Algorithms trained on homogeneous datasets often fail to generalize across varied groups, resulting in underrepresentation and inaccuracy in minority settings where data are often inadequate or inconsistent^[89,90]. Although AI can simplify clinical operations in controlled contexts, its implementation in real-world settings typically upsets established workflows and increases healthcare personnel workloads, especially when adequate infrastructure and specialized training are lacking.

To address these problems, AI tools must have strong evaluation frameworks, diversified datasets, and human-centered design processes that ensure tools not only meet clinical efficacy criteria but also align with the complexity of real-world healthcare systems^[26,89,90]. Education on AI for healthcare professionals is also critical as it enables clinicians to recognize and correct algorithmic biases while effectively integrating AI technologies into existing clinical workflows. Tailored training programs that combine technical knowledge of AI systems with practical, context-specific tactics can help clinicians address interoperability challenges, build trust in AI technologies, and facilitate their effective incorporation into clinical environments. Collectively these solutions are important for promoting effective AI adoption across a variety of healthcare settings.

6. Conclusions

AI holds transformative potential in diagnosis and management of dental conditions and TMD by enhancing diagnos-

tic accuracy, enabling personalized treatment and automating data analysis. Incorporating patient-specific factors such as demographics, lifestyle or social history, dental and medical history, behavioral and genetic assessment can further optimize diagnostic precision and enable personalized therapies by evaluating clinical, radiographic, and behavioral data. Despite limitations concerning data protection and clinical validation, continued research with larger datasets is essential to fully realize the benefits of ML and DL for improving patient outcomes.

Author Contributions

Conceptualization, M.S. and L.Y.; writing—original draft preparation, M.S.; writing—review and editing, M.S. and L.Y. Both authors have read and agreed to the published version of the manuscript.

Funding

Not applicable.

Institutional Review Board Statement

Not applicable.

Informed Consent Statement

Not applicable.

Data Availability Statement

The data used in this study are available from the corresponding author upon reasonable request.

Acknowledgments

The authors are grateful to Ritu Sahu, BDS for her input in this work regarding the literature search on clinical aspects of dentistry.

Conflicts of Interest

The authors declare no conflict of interest.

AI Use Statement

During the preparation of the manuscript, the authors used ChatGPT for paraphrasing a few sentences. After using the tool, the authors reviewed and edited the content and took full responsibility for the content of the published article.

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