

## REVIEW ARTICLE

# Artificial intelligence and personalized diagnostics in periodontology: A narrative review

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## Abstract

Periodontal diseases pose a significant global health burden, requiring early detection and personalized treatment approaches. Traditional diagnostic approaches in periodontology often rely on a “one size fits all” approach, which may overlook the unique variations in disease progression and response to treatment among individuals. This narrative review explores the role of artificial intelligence (AI) and personalized diagnostics in periodontology, emphasizing the potential for tailored diagnostic strategies to enhance precision medicine in periodontal care. The review begins by elucidating the limitations of conventional diagnostic techniques. Subsequently, it delves into the application of AI models in analyzing diverse data sets, such as clinical records, imaging, and molecular information, and its role in periodontal training. Furthermore, the review also discusses the role of research community and policymakers in integrating personalized diagnostics in periodontal care. Challenges and ethical considerations associated with adopting AI-based personalized diagnostic tools are also explored, emphasizing the need for transparent algorithms, data safety and privacy, ongoing multidisciplinary collaboration, and patient involvement. In conclusion, this narrative review underscores the transformative potential of AI in advancing periodontal diagnostics toward a personalized paradigm, and their integration into clinical practice holds the promise of ushering in a new era of precision medicine for periodontal care.

## KEYWORDS

CNN, deep learning, image analysis, machine learning, prediction

## 1 | INTRODUCTION

Periodontitis is a chronic inflammatory disease of the periodontal structures comprising the gingiva, periodontal ligament, cementum, and alveolar bone and is the sixth-most prevalent health condition globally.<sup>1</sup> Accumulation of biofilm on the tooth surfaces is considered the primary etiological factor for developing gingivitis,<sup>2,3</sup> characterized by red and swollen gingival margins and bleeding on stimulating the gingival sulcus with a probe or during toothbrushing. This phase

is entirely reversible if appropriate intervention is performed through improved oral hygiene and/or professional oral prophylaxis. It then usually progresses to periodontitis, which, if left untreated, eventually leads to tooth loss. Along with caries, periodontitis is one of the most common reasons for dental extractions.<sup>4</sup> Centres for Disease Control and Prevention reports that the prevalence of periodontal disease in American adults is approximately 46% and even higher in elderly people at over 70%. Periodontitis predominantly affects middle-aged<sup>5</sup> and elderly population.<sup>6</sup> The prevalence of periodontitis is high

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in industrialized nations.<sup>7</sup> It is worth mentioning that the proportion of the elderly population in these countries is increasing, which might lead to a further increase in the prevalence of periodontitis.<sup>8</sup>

Periodontology, the study of the supporting structures of teeth and the diseases that affect them, is entering a new era marked by its reliance on data and diagnosis. Two additional factors driving this transformation in periodontology are (i) a deep understanding of the intricate multifactorial etiology of periodontal diseases and (ii) the introduction of a new periodontitis classification in 2017. Firstly, it is well-established that periodontitis is an inflammatory disease mediated by various factors, such as age, smoking, physical activity, obesity, oral hygiene, diabetes, and other systemic diseases.<sup>9,10</sup> Despite advancements in periodontal research in recent decades, the etiology of periodontitis still needs to be understood completely. Secondly, the American Academy of Periodontology and the European Federation of Periodontology proposed a new periodontitis classification during the 2017 World Workshop on the Classification of Periodontal and Peri-Implant Diseases and Conditions.<sup>11</sup> In summary, this new classification moved away from the previous two categories (chronic and aggressive) to a more comprehensive staging and grading system, which brought about several fundamental changes and advancements in the understanding and managing of periodontal diseases. The new system also looks at the severity of the disease, the complexity of managing the condition, and the rate at which the disease progresses. To reflect this complexity, a more extensive set of data points are required to classify adequately, which subsequently should allow a better understanding of a patient's periodontal status and the associated management needs.

On the one hand, in the pursuit of effective periodontal care, the integration of data-driven approaches and advanced diagnostics has become paramount. This usually includes site-based clinical examination for various periodontal parameters (plaque, calculus, bleeding on probing, probing depth, attachment loss, recession, and furcation involvement), a multitude of risk factors that were derived through interviews and/or questionnaires and a large number of image modalities during various stages of treatment to assess the prognosis. Furthermore, despite having increased computing power at a fraction of the cost and advancements in biomarker detection from the oral microbiome, proteome, metabolome, etc., were made, it is not yet possible to integrate them into routine dental diagnosis.

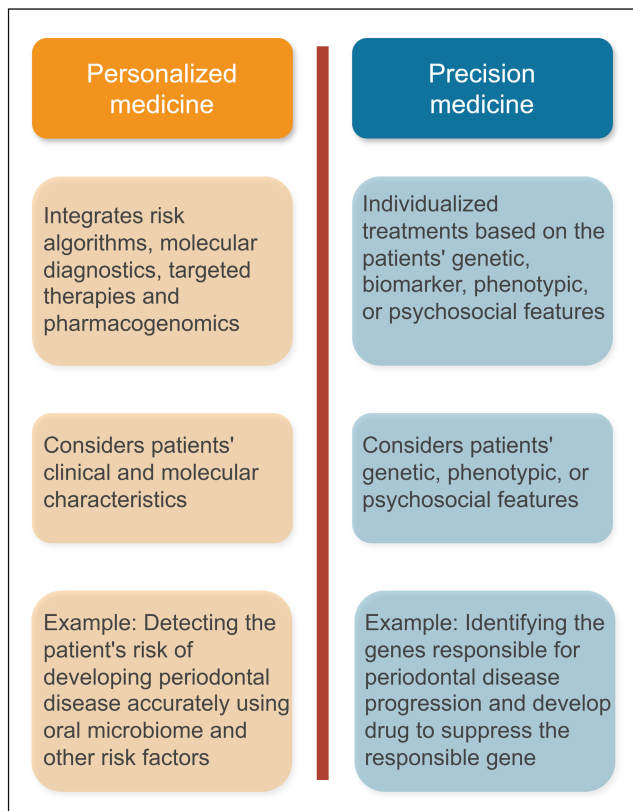
On the other hand, integrating artificial intelligence (AI) into healthcare has revolutionized diagnostic and treatment approaches in many fields,<sup>12</sup> and dentistry is no exception. In recent years, although AI has been used in various scenarios in medicine or dentistry,<sup>13</sup> it has been sparingly used in periodontology.<sup>14</sup> While a recent review article applied the P4 medicine concept to deliver precision periodontal care, there remains a notable gap in the literature regarding personalized periodontal diagnostics.<sup>15</sup> Therefore, this article seeks to delve deeper into the realm of personalized diagnostics within the field of periodontology while shedding light on the potential use of AI in this area. By doing so, we seek to pave the way for future research and application in this domain, ultimately fostering a more evidence-based approach to periodontal care.

## 2 | WHAT IS PERSONALIZED MEDICINE?

Periodontal diagnostics currently employs a risk-based approach of stratification; i.e., based on risk assessments or clinical examinations, we classify patients into different risk or disease strata. Then, we assign similar treatment strategies to all individuals in certain strata ("one size fits all").<sup>16</sup> One pitfall with this approach is that it treats patients in each stratum as a statistical average and does not give importance to individual patient's characteristics or physiological variations. On the other hand, personalized medicine integrates risk algorithms, molecular diagnostics, targeted therapies, and pharmacogenomics (individual's response to drugs) to improve healthcare and link a patient's molecular profile and clinical features.<sup>17-19</sup> In other words, personalized medicine focuses on identifying subgroups of patients within larger populations that are more likely to respond to a particular treatment, for example, nonsurgical periodontal therapy and systemic antibiotics.<sup>20</sup> The term personalized medicine is usually used interchangeably with precision medicine; the latter refers to treatments targeted to the needs of individual patients based on genetic, biomarker, phenotypic, or psychosocial characteristics that distinguish a patient from others with similar clinical presentations.<sup>21</sup> In other words, precision medicine aims to identify specific mutations in a gene, through which treatments could be developed to target specific genetic abnormalities. The differences between personalized and precision medicine are enlisted in [Figure 1](#). Precision medicine is also closely linked to another term, P4 medicine, which aims to use large data sets, including routine and omics data and advanced data analytics, to establish a more predictive, preventive, personalized, and participatory kind of medicine.<sup>22</sup>

## 3 | WHAT IS ARTIFICIAL INTELLIGENCE?

Artificial intelligence is a branch of computer science that focuses on developing intelligent machines or programs capable of performing tasks that typically mimic human intelligence, ideally in a shorter time and with higher accuracy. Machine learning (ML) is a branch of AI, in which statistical models are constructed to classify data or images and to predict the risk or the outcomes through various methods,<sup>23</sup> such as regression, k-nearest neighbors, decision trees (DT), random forest, support vector machines (SVM), etc. In other words, ML focuses on enabling computers to identify patterns and make decisions on data. ML can be broadly classified into supervised and unsupervised learning. Under supervised learning, the mathematical models are constructed using training data with an already available outcome label or classification variable. On the contrary, when the models are not provided with outcome labels to learn from and must independently discern the structures and patterns, it is termed unsupervised learning. In either case, the trained model is validated against an independent data set, where the model's performance is assessed using various metrics, such as sensitivity, specificity, accuracy, balanced accuracy, F1-score (which is the harmonic mean of precision and recall), etc.



**FIGURE 1** Differences between personalized versus precision medicine, with a focus on periodontology.

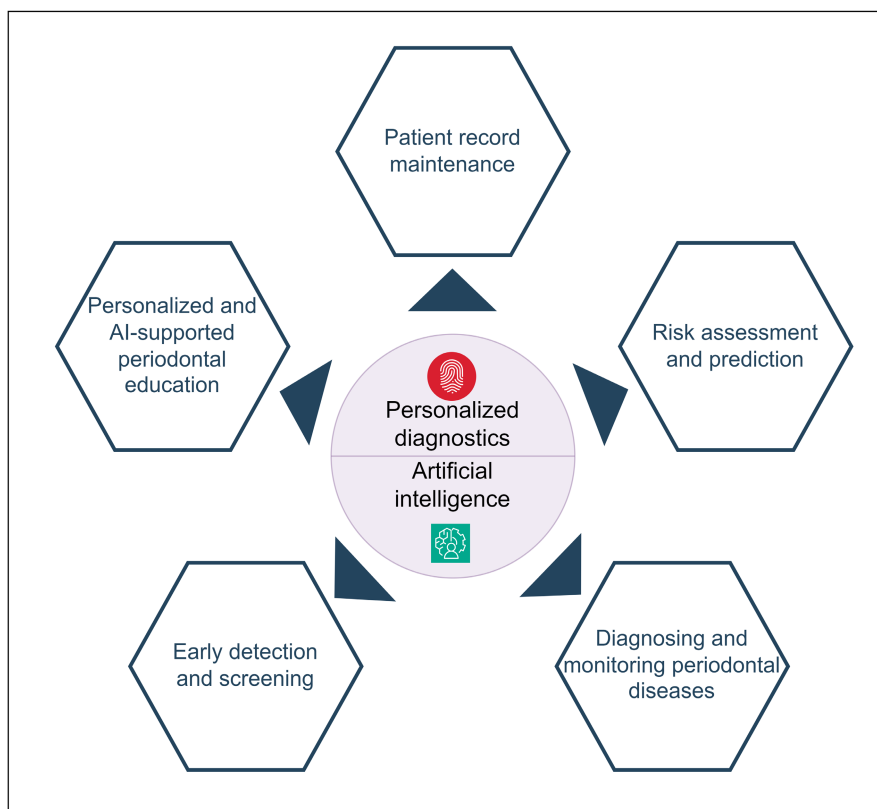
Deep learning (DL) is a sub-branch of ML that employs algorithms inspired by the structure and function of the human brain, known as artificial neural networks (ANN), consisting of interconnected neurons that can process information and learn from the data.<sup>24</sup> Convolutional neural networks (CNN) are a subclass of DL models that are particularly adept at interpreting complex image modalities. They use convolutional layers to process data in small, overlapping chunks, allowing them to recognize local patterns within an image.

#### 4 | SCOPE OF PERSONALIZED DIAGNOSTICS AND AI IN CLINICAL PERIODONTOLOGY

AI has a wide range of applications in the field of dentistry, such as patient record maintenance, risk assessment and prediction, diagnosing and monitoring the diseased state, early detection and screening, as well as in dental education and training (Figure 2).

##### 4.1 | Patient record maintenance

Keeping and maintaining a clinical record is integral in healthcare. Indeed, the United Kingdom's General Medical Council has included clinical record keeping under the first domain in their "Good Medical Practice" guidelines.<sup>25</sup> While these guidelines are primarily meant for physicians, they offer relevant principles for other healthcare



**FIGURE 2** Scope of AI-based personalized diagnostics in the field of periodontology.

professionals, including periodontologists. Incorporating AI tools such as Natural Language Processing (NLP) – a branch of AI that enables machines to understand, interpret, and communicate in a language easily understood by humans – into record-keeping processes streamlines documentation.<sup>26</sup> Besides recording vital information, case records usually contain an enormous amount of unstructured text in the form of notes, which could be practically used in clinical decision-making with the help of NLP is a branch of AI that enables machines to understand, interpret, and communicate in a language easily understood by humans. One such NLP model that is well known today is ChatGPT (OpenAI, San Francisco, USA). A study used NLP to determine the agreement between gingivitis diagnosed using the 2018 criteria (percentage of bleeding on probing, BOP%) versus clinical notes on visual signs of gingival inflammation.<sup>27</sup> Although their NLP model had an excellent performance (98% F1-score), they found that using BOP% alone without considering visual signs might under- or over-estimate the disease. Besides assisting in record maintenance and diagnosing, NLP algorithms can analyze patients' feedback or reviews and provide insights into patients' experiences, which could enhance treatment approaches and ensure patient satisfaction. Furthermore, NLP-driven chatbots could provide patients with accurate and personalized information on their periodontal status using simple language and impart self-care practices to alleviate their condition.<sup>28</sup> By incorporating NLP technologies into routine record maintenance tasks such as periodontal charting, periodontologists can optimize workflow efficiency, reduce administrative burdens, and allow more time for personalized patient interactions and treatment planning. This aligns with the goals of personalized periodontics, empowering dentists to deliver precise, patient-centered care.

## 4.2 | Risk assessment and prediction

Periodontitis is a complex disease associated with various systemic diseases, and several influencing factors were associated with its initiation or progression.<sup>9,10</sup> Many association studies have explored the link between periodontitis and systemic disorders or influencing factors. However, these studies primarily focus on understanding the disease's pathophysiology,<sup>9,29-31</sup> rather than predictive modeling, limiting their direct impact on personalized risk assessment and prediction.<sup>16</sup> Furthermore, tooth loss, the most common sequelae of untreated periodontitis, underscores the need for effective prediction models. While tooth loss is the outcome of interest from patients' perspectives, it is seldom reflected in these studies.<sup>32</sup>

Predicting periodontitis and tooth loss at an earlier stage could empower patients to take proactive preventive measures, thereby tackling the physical, mental, and financial implications caused by it. The new periodontal disease classification already considers a couple of risk factors, such as smoking and diabetes. There are also various periodontal disease risk assessment systems or risk calculators in place that use mathematical algorithms and leverage risk factors

and clinical parameters to predict the patient's risk of periodontal disease progression.<sup>33,34</sup>

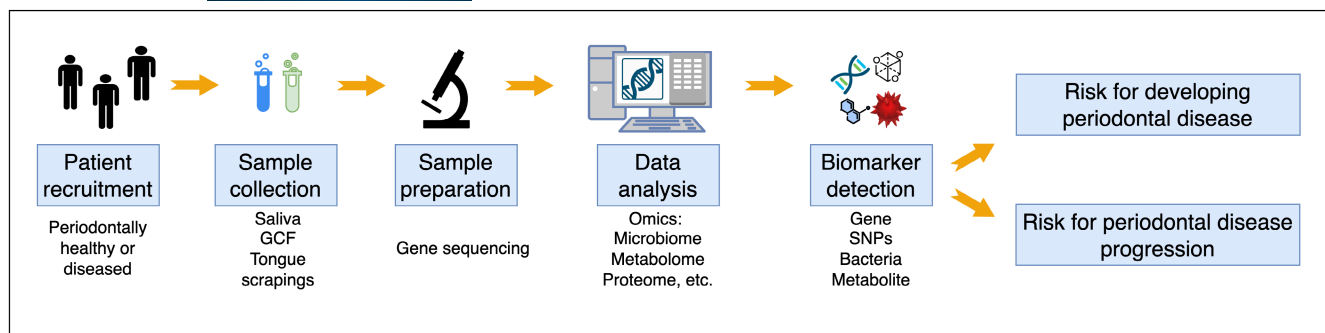
Recently, a retrospective study evaluated the prediction of periodontitis progression using ANN. The authors used parameters such as patient's age, sex, smoking status, plaque, BOP, probing depth, and clinical attachment loss and graded the patients based on the 2017 periodontitis classification. The model had an accuracy, sensitivity, and specificity of 84.2%, 85.7%, and 80.0%, respectively.<sup>35</sup> A couple of other studies developed similar ANN models to assess the periodontitis risk, with some models performing even better.<sup>36,37</sup> Notably, all these studies included risk factors apart from smoking and diabetes as stated in the new periodontal disease classification, but none of them tried to integrate the genetic profile of the patient or the composition of oral microbiome, metabolome, or proteome for periodontal risk assessment. Studies have shown that assessing these multi-omics could detect more interacting biomarkers that could influence the pathogenesis,<sup>38</sup> which could help in deducing molecular pathways, enhancing predictive capabilities and personalized risk assessment in periodontics.<sup>39-44</sup>

## 4.3 | AI in diagnosing and monitoring periodontal diseases

Advanced diagnostics and screening techniques must be widely followed to keep periodontal health in check, mainly involving a comprehensive periodontal examination. Complimenting clinical examination, various image modalities are performed to help dentists with diagnosing periodontal diseases and to monitor the prognosis of periodontal treatment. While the utilization of AI in periodontology remains relatively limited, few studies have explored its potential in various diagnostic tasks, such as assessment of panoramic radiographs or periapical radiographs to detect periodontal bone loss (PBL), to stage and grade periodontitis, and to identify dental implant types.

Radiography is often used as a noninvasive adjunct to clinical periodontal examination to determine the presence and extent of bone loss. To describe the severity of the disease at presentation, PBL is used in conjunction with probing depths or clinical attachment loss and previous history of tooth loss due to periodontitis.<sup>11</sup> Few studies explored the role of AI in detecting and/or quantifying PBL, mainly using CNN, and often showing these models to perform similar to or superior to human examiners.<sup>45-52</sup> Some studies also employed radiographs to classify patients into different stages of periodontitis based on the PBL severity, again yielding superior<sup>48,53,54</sup> or similar performance compared to dental professionals.<sup>46</sup>

In addition to radiographs, intra-oral photographs are widely used to document patients' health status, for example, to record gingivitis or gingival recession. Few studies used automated CNN models to detect and classify oral photographs into healthy and gingivitis and had varying degrees of accuracy.<sup>55,56</sup> Some studies also used CNN to detect dental plaque from the clinical photographs in primary<sup>57</sup> and in permanent dentition.<sup>58</sup>



**FIGURE 3** Common workflow employed in biomarker discovery using omics technologies from oral specimens such as saliva, tongue scrapings, or gingival crevicular fluid.

Apart from detecting periodontal diseases, CNN was also employed to detect and distinguish dental implants on radiographs.<sup>59,60</sup> With the increase in dental implant use, there is a rise in the prevalence of implant-related complications such as peri-implantitis.<sup>61–63</sup> Knowing the implant type is relevant to addressing a range of these complications. DL was used to identify and classify dental implant types in a large-scale multicenter study involving 5 dental college hospitals and 10 private dental clinics.<sup>64</sup> In this study, apart from being accurate in classifying the dental implant types, the DL model required significantly less time (4.5 min) than the general dentists (91.3 ± 38.3 min) and dental implantologists (75.6 ± 31.0 min) for classifying all 25 dental implant systems assessed. The use of ML applications extends beyond implant classification. For instance, another study utilized ML techniques for immune profiling of peri-implantitis patients and found that the microenvironment surrounding the implants shapes the microbial composition, thereby influencing the course of regeneration. By leveraging the microbial data from peri-implant sites, they clustered the patients with similar immunologic profiles, leading to personalized risk stratification of progressive peri-implantitis in response to regenerative therapy.<sup>19</sup>

These AI-driven tools enhance treatment outcomes and patient satisfaction by providing accurate diagnoses and targeted treatments to individual patient needs, aligning with personalized periodontics principles.

#### 4.4 | Early detection and screening

Periodontal diseases are to-date diagnosed clinically by probing the gingival sulcus of the teeth to detect periodontal pockets. Two problems arise due to this method: (1) periodontal probing is technique sensitive and is prone to errors due to the examiner's skills, limiting its accuracy; and (2) by the time the pockets are detected, the periodontal disease has already established and progressed to the extent that the condition is irreversible. Therefore, earlier detection of periodontal diseases is essential. In the medical field, peripheral blood is frequently drawn to assess a wide range of biomarkers in the serum, albeit it is invasive and may deter patient compliance due

to associated pain and discomfort. Dentists have an advantage by having access to other noninvasive mediums, such as saliva, gingival crevicular fluid (GCF), and tongue scrapings. Among these, saliva is well-researched due to its ease of collection and acknowledged as a mirror of the body's systemic state.<sup>65</sup>

Using the already mentioned omics technologies has led to the detection of a wide range of biomarkers in metabolome, microbiome, proteome, etc., which broadened our knowledge and understanding of the pathophysiology of periodontal diseases (Figure 3). The resulting big data set lends itself to being analyzed using AI; nevertheless, this approach has been less utilized in the field of periodontology. A recent review on AI-assisted salivary biomarker discovery has summarized that only three studies did AI-assisted biomarker discovery for periodontal diseases.<sup>66</sup> In essence, two of those used ML to detect biomarkers from metabolome or microbiome.<sup>67,68</sup> Another study compared the oral microbiome composition in patients with periodontal disease with or without rheumatoid arthritis using ML.<sup>69</sup> However, the review also concludes that AI-driven early detection methods offer promise in personalized periodontal care by integrating multi-omics data sets and semi-supervised learning.<sup>66,70</sup> Once the pathophysiology of periodontal disease is fully understood, using the wide array of biomarkers discussed above, specific self-testing kits could be developed to detect the patient's risk of developing or progressing periodontal disease more precisely.

Common self-testing kits known to laymen are pregnancy testing kits and blood glucose level testing kits. However, the recent COVID-19 pandemic made self-testing a reality in many homes.<sup>71</sup> Unlike COVID-19 testing kits, periodontal disease testing kits could be designed for multiple noninvasive specimens such as saliva, tongue scrapings, or GCF (collecting GCF at home would be challenging, though). Although there are a few chairside diagnostic kits aimed at periodontal diseases, such as Perioscan, Periogard, Periocheck, etc., they are designed to assess specific biomarkers, which makes them less accurate compared to a testing kit designed for a broad spectrum of biomarkers.

Another method involving self-testing is image assessment on smartphones, which have become an essential part of our lives. Modern smartphones can capture high-resolution pictures that could rival yesteryear professional camera's performance. A recent

study evaluated the effectiveness of AI-assisted self-monitoring by patients using images of their mouths taken post-periodontal treatment. The patients received digital reminders on smartphones, which resulted in better compliance, improved oral self-care behavior, reduced plaque accumulation, and improved periodontal outcomes after 1- and 3-month follow-ups.<sup>72</sup> Furthermore, a couple of clinical trials (NCT04326413 and NCT05685355) were registered to assess periodontal health using self-recorded intraoral photographs.<sup>73,74</sup> AI-based apps could automatically detect signs of gingivitis or poor oral hygiene on these images, subsequently notifying the patient about steps to be followed that could improve their periodontal health. It might also be possible to link such apps with the patient's general dentist and/or physician to alert them of the concerned patient's periodontal status requiring medical attention.

Through early detection, it is also possible to target prevention at earlier stages by motivating the patients to improve their oral hygiene, which is the cornerstone for preventing periodontal diseases. Although it can be argued that the biofilm load is not directly proportional to the periodontal disease severity,<sup>75</sup> it is well-established that improved oral hygiene can prevent the development of periodontal disease.<sup>76-78</sup> Patients should be made aware of various oral hygiene tools, such as powered toothbrushes with built-in AI tools that track patients' fields and the duration of toothbrushing. These tools guide patients toward smart brushing, which could enable them to maintain better oral hygiene and prevent the onset of periodontal diseases. Furthermore, such devices are also known to be more compliant.

In conclusion, integrating AI-driven early detection tools in periodontology is a pivotal step toward personalized periodontal care. These innovations have the potential to transform personalized care from a concept to a practical reality, empowering patients and dental professionals.

## 5 | PERSONALIZED AND AI-SUPPORTED PERIODONTAL EDUCATION

Training periodontology oftentimes relies on standardized models, regularly mounted in phantom heads, to allow probing and scaling. Repeating examinations on a set of such training models would elicit memorization of the standardized model rather than a real learning experience and is, admittedly, far away from clinical reality.<sup>79</sup> Instead or additionally, dental students could be trained using dynamically varying periodontal models, for example, through haptic-based augmented reality (AR) or virtual reality (VR) training simulators. AR and VR are AI-based technologies that alter or enhance the perception of the real world. In AR, the digital information (e.g., a radiograph or a CBCT image) is overlaid on the operator's view through external display devices. Conversely, VR immerses the operators in a totally digital environment via a headset covering the field of vision, creating a sense of presence in a virtual world.

There are AR/VR-based training simulators to learn various diagnostic and treatment methodologies in the field of dentistry, ranging

from rubber dam insertion, (access) cavity preparation, and placement of implants<sup>80-83</sup>; these were found to be improving students' experience and learning outcomes.<sup>84-88</sup> However, when it comes to periodontology, few haptic-based dental simulators exist, and their applications in training are limited.<sup>89</sup> For example, PerioSim, a VR-based periodontal training simulator, allows training of tactile sensation via haptic feedback for multiple structures such as teeth, gingival, and calculi, with students employing virtual periodontal instruments (probe, explorer, or scaler).<sup>90</sup> Although it was possible to detect the periodontal pockets with this simulator, it was not possible to measure the pocket depth or detect any furcation involvements. Another haptic-based simulator was developed to train caries removal and pocket probing skills. It was observed that on consecutive training, students achieved pocket probing forces between 0.4 and 0.5 N.<sup>91</sup> Recently, a VR-based simulator prototype with haptic feedback, Haptodont, has been developed with the possibility to measure pocket depths. While testing this prototype with a control group, both groups produced a probing depth error between 0.3 and 0.6 mm, and an average probing force of less than 0.5 N.<sup>92</sup> However, with the current technology, such AR/VR simulators could be expanded in their scope of use to have different clinical scenarios for each student and at each time point. This might ensure that there is no memorization effect and improve the learning efficiency.<sup>79</sup> Furthermore, it is possible to include haptic feedback mechanisms<sup>93,94</sup> for the user to adjust their probing forces, which is a critical factor in periodontal examination.<sup>95,96</sup>

Using AR/VR-based technologies in periodontal education goes beyond training students in general periodontal procedures; it enables personalized learning experiences. This involves tailoring educational content and simulations to match individual student needs, learning styles, and skill levels. Furthermore, they also serve as a bridge to personalized periodontics by allowing students to interact with dynamically varying periodontal scenarios. This prepares them to understand and adapt to individual patients' unique conditions and challenges in clinical practice, thereby directly contributing to improved clinical preparedness in personalized periodontics.

## 6 | IMPACT ON PERIODONTAL RESEARCH

In the context of personalized periodontics, the integration of AI technologies plays a pivotal role in advancing personalized diagnostics within mainstream periodontal healthcare. This requires a coordinated effort from various stakeholders, such as researchers, clinicians, policymakers, industry partners, and patients. As part of the research community, we could take some steps to advance personalized diagnostics.

Firstly, the dentist must be informed about their patient's systemic health parameters associated with periodontal diseases, such as blood glucose levels, serum inflammatory markers, etc. As previously discussed, the management of periodontal diseases needs a multi-disciplinary approach for which the linking of high-quality data from various sources is essential.<sup>97</sup> AI facilitates the analysis

of large-scale, multi-dimensional data sets encompassing systemic health parameters, aiding in identifying common risk factors and predictive modeling for periodontal diseases before their onset, which could help impart valuable information to the dentist in applying personalized periodontics in their practice.

Secondly, we could foster collaborative research between different disciplines to bring diverse expertise to address complex challenges and develop personalized diagnostic technologies. Although AI algorithms can uncover hidden correlations and insights from diverse data sets, multiple teams collaborating brings the question of data sharing. Standardized protocols and frameworks for data collection and sharing between institutes should be established. This should also address data privacy and ethical concerns and offer streamlined solutions. Once the data-sharing agreements are in place, researchers should also try to perform comparative studies against existing methods using AI-driven analyses to validate personalized diagnostics' effectiveness and clinical utility.

Thirdly, we should keep patients informed about the technological advancements AI brings to our discipline and their potential impact on well-being. AI technologies can empower patients by providing a more immersive diagnostic and prognostic experience and personalized treatment recommendations, thereby enhancing patient engagement and supporting the informed decision-making process. This could be helpful in advocating policy changes.

Finally, we should also work with regulatory agencies, industry partners, and healthcare providers to establish guidelines and obtain approvals for implementing personalized technologies. We should also gather real-world evidence from health insurance providers and industry partners to evaluate and monitor the long-term performance of personalized diagnostics in real-world scenarios. This real-world data feedback loop enables continuous improvement, refinement, and validation of personalized diagnostics tools, ensuring their effectiveness and relevance in clinical practice.

## 7 | DATA-DRIVEN PUBLIC HEALTH PERSPECTIVE

Translating AI-driven personalized periodontal diagnostic approaches from bench to chairside is theoretically possible. However, with potentially infinite combinations of stratifications and resulting interventions, the question of how this approach to healthcare can be standardized is raised.

Firstly, it is possible through understanding the molecular and microbiological basis of the disease, as described before.<sup>98</sup> Prospective population-based studies focussing on periodontal health parameters can provide valuable insights into disease progression and treatment response among different population cohorts. In this direction, such studies in some industrialized nations collected information on various clinical and biological parameters.<sup>99</sup> Based on this information, re-stratifying the population cohorts based on similar biological pathways or microbial and metabolic signatures could unlock new

diagnostic and therapeutic strategies.<sup>18,100</sup> Besides this, several factors influence the application of personalized diagnostics on a population level. One such factor is the availability of population-level big data using automated data collection in day-to-day routine life. With the help of wearable devices, fitness trackers, smartphones, powered toothbrushes, and other Internet of Things devices, we could continuously collect data on various health parameters such as body weight, body mass index, physical activity, heart rate, blood oxygen levels, oral hygiene status, and other vital signs, offering a real-time picture of an individual's health. With large population-level data collected over time, a better understanding of the disease, which, in turn, results in better health for individuals and populations, is likely achievable.<sup>98</sup> Advancements in powered toothbrushes, potentially integrating intra-oral scanners and AI-driven analytics, could enable continuous monitoring of periodontal health indicators such as plaque accumulation, gingival status, or even initial caries lesions, which offers real-time detection, motivating patients toward action.

Secondly, large-scale surveys incorporating periodontal health assessments, supported by smart devices and further integrated with geospatial data, provide patterns or regional variation insights into periodontal disease trends. Linking survey data with geospatial health records might enhance the depth of information collected and allow the researchers to correlate survey responses with health outcomes or medical history.<sup>101</sup>

Thirdly, tackling misinformation and improving public knowledge on an interventional level involves targeted efforts from a public health perspective. Targeted public health campaigns focussing on periodontal health education are essential for combating misinformation and promoting health literacy among the population. Collaborations between dental associations, public health agencies, big tech, and social media companies can develop AI-driven tools to disseminate accurate periodontal health information and tackle the spread of misconceptions online. Implementing algorithms to detect and flag posts and comments with misinformation can have a significant impact, as demonstrated during the recent COVID-19 pandemic.<sup>102</sup>

Finally, payers, ranging from patients to health insurance providers to government initiatives, have limited resources<sup>103</sup> and may be interested in leveraging personalized diagnostics to engage in risk-based contracting with healthcare providers. This includes giving incentives to providers for delivering preventive periodontal care that aligns with personalized approaches,<sup>104</sup> leading to positive periodontal outcomes. It is worth mentioning that (dental) health insurance is one of the most significant factors in deciding access to healthcare. Lack of insurance coverage is associated with poor access to healthcare, poorer clinical outcomes, and overall health.<sup>105</sup> The situation is particularly grim in developing countries where health expenditures can be catastrophic for individuals and their families at worst. Countries should work toward relieving healthcare resources by leveraging innovative digital technologies and adapting to dynamic health trends.<sup>106</sup> Through personalized diagnostics, shifting the emphasis from reaction-based treatment to prevention is possible, which may be cost-effective long-term.

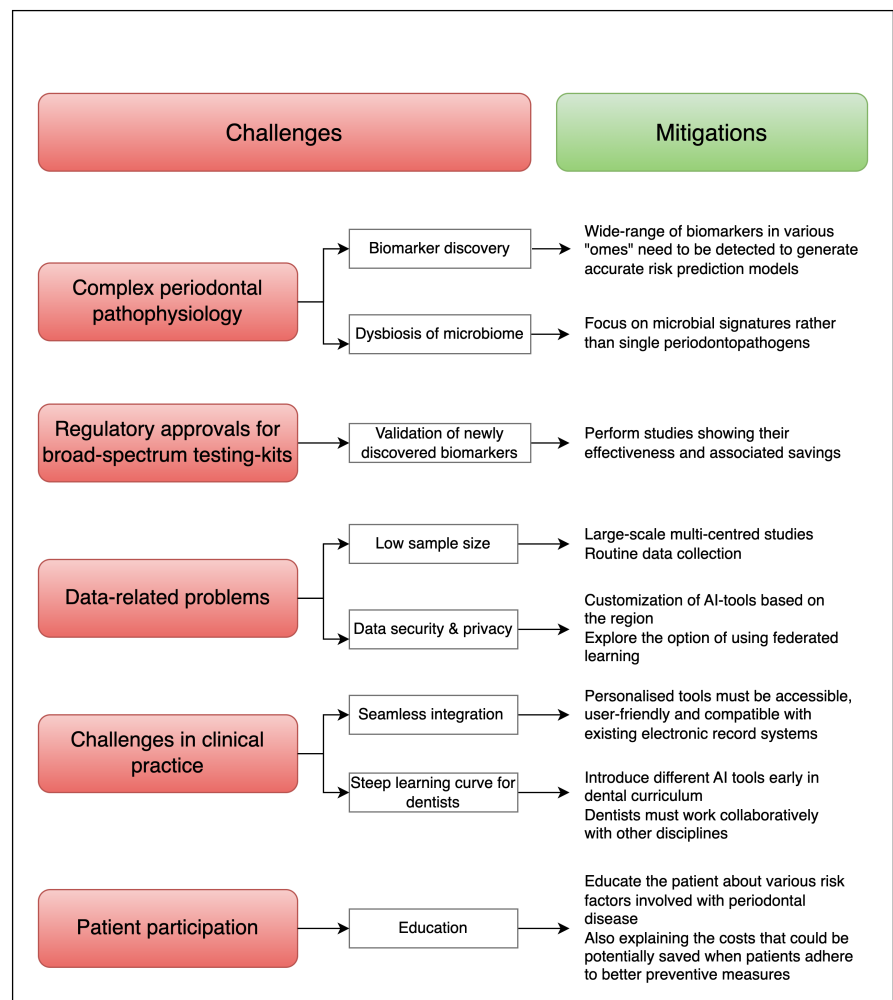
## 8 | CHALLENGES

Although periodontal diseases share a multifactorial etiology, it is essential to acknowledge that personalized diagnostics in periodontology is still in its primitive stages.<sup>107</sup> The list of most important challenges in integrating personalized diagnostics in clinical practice and their mitigations are enumerated in Figure 4.

Before they could become conventional, it requires an enormous effort in biomarker discovery and their validation to an extent that we are confident about the pathophysiology of periodontal diseases. Another challenge is that the periodontal diseases are caused by dysbiosis in the oral microbiome, rather than a single periodontopathogen. Furthermore, the magnitude of dysbiosis and the manifestation of periodontitis differs from patient to patient. Therefore, it is important to focus on the metabolic or microbial signatures that are prevalent during the shift from healthy to periodontally diseased state, rather than individual metabolites or bacteria.<sup>20</sup> This also makes it difficult to manufacture simple testing kits. Also, manufacturing a multitude of new testing kits or materials will be expensive, and challenging to acquire regulatory approvals. Therefore, studies showcasing the effectiveness of these testing kits and the resulting savings in healthcare expenditure are essential to convince the industry partners to invest in this. Furthermore, as AI-based

personalized diagnostics gain traction in periodontology, it is imperative to consider the regulatory and bioethics landscape governing their implementation. Recent guidelines from the World Health Organization<sup>108</sup> and the U.S. Food and Drug Administration<sup>109</sup> provide valuable frameworks and considerations for the ethical development and deployment of AI technologies in healthcare. These guidelines emphasize transparency, accountability, privacy protection, and fairness in AI systems, aligning with the principles of ethical AI use.

Personalized diagnostics should seamlessly integrate into the clinical workflow by ensuring the tools and technologies are accessible, user-friendly, and compatible with the electronic health record systems already in place. Also, dental professionals might face a steep learning curve in adopting personalized diagnostics, which might be mitigated by providing additional training beyond what is imparted in dental schools. Policymakers should also implement structural changes in the undergraduate and postgraduate dental curriculum to train graduating dentists to use the technologies discussed above practically.<sup>110</sup> Furthermore, to have the highest impact, dentists must work collaboratively with multiple disciplines involving general physicians, immunologists, cardiovascular specialists, and endocrinologists, which might face some logistic challenges and a lack of cooperation from some colleagues.



**FIGURE 4** Most common challenges faced in integrating personalized periodontal diagnostics in clinical practice and mitigating steps that could be taken to tackle the challenges.

While integrating AI-based personalized diagnostics into clinical practice, one should be aware of the errors caused by the noises and artifacts in any training data that might lead to missing a diagnosis or wrongly diagnosing a case. In such cases, dentists might encounter a new wave of medico-legal cases.<sup>111</sup> Therefore, medico-legal laws need to be amended to include clauses regarding AI use to protect the integrity of dental professionals while not harming patients' health or well-being. Conversely, it could also be argued that AI tools might be beneficial to patients and dentists in medico-legal cases as well.<sup>111</sup> By documenting vast amounts of patient data and analyzing clinical procedures using *scene graphs* – an approach that maps out the steps and interactions during medical procedures – AI can help establish a clearer understanding of the circumstances surrounding medical incidents, potentially aiding in legal proceedings.<sup>112</sup> However, it is crucial to develop robust guidelines and standards for using AI in such contexts to ensure ethical and responsible utilization of these technologies.

Developing AI algorithms generally demands a large amount of high-quality training data. Currently, most dental AI research is conducted on a small scale within academic settings. Such single-centered AI is very likely affected by a lack of generalizability, as demonstrated in diagnosing apical lesions on dental radiographs.<sup>113</sup> Reasons for this are diverse and related to nonrepresentative data in terms of data recording (image quality, machines, resolution, etc.), environment (health care system, care status, treatment procedures, etc.) and population (age, socio-economic status, regional immunities, etc.), among others. Missing generalizability can lead to unfair healthcare decisions and negatively affect the health of individuals. The fairness of ML algorithms predicting the likelihood of terminating preventive dental care was recently evaluated, pointing out worse predictive performance for ethnic minorities, younger individuals, and those with low income.

To tackle these problems, multi-center studies should be conducted to enrich the diversity of underlying data, and benchmarking should be established to assess the fairness and generalizability of AI. Notably, multi-center studies and data pooling come with their own challenges, such as data accessibility, interoperability, and data protection. The latter could be addressed with appropriate data-sharing agreements or via federated learning<sup>114</sup> without compromising data security and privacy. For the latter, effective communication and cooperation between different centers remain a requirement, and technical knowledge is needed across centers for successful implementation. While accessibility could be addressed using data lakes and cloud solutions, interoperability needs international standards on terminology, database structures, and treatment procedures.

Finally, as discussed above, successfully diagnosing and treating periodontal diseases is not a one-man show. For example, treating locally using scaling and root planning and neglecting high blood glucose levels, systemic inflammatory markers, or oral hygiene would not achieve anticipated results.<sup>29,31</sup> Therefore, patients should be motivated about their essential role in maintaining oral health. This requires educating the patient about various risk factors involved

with their disease and suggesting changes in diet, physical activity, and lifestyle in general, which might require more effort from the patient to comply in the long run. One major factor that could captivate patients' interest is the costs associated with periodontal treatments and the money they would save by proactively improving their oral hygiene and overall well-being. Better periodontal outcomes could be achieved with equal involvement from the patient's side. Likewise, knowing patients' perceptions and attitudes toward personalized (and AI-based) dentistry is also important. Although it was considered that AI-based communication lacks personality and patients preferred clinician-based decisions, the trends are now changing, and more patients today seem to accept the AI-based approach.<sup>115,116</sup>

## 9 | CONCLUSION

In conclusion, the integration of personalized diagnostics in periodontology has the potential to revolutionize the field by offering more accurate and efficient diagnoses, personalized treatment plans, and better patient outcomes. As we move toward a more data-driven approach to oral healthcare, we must continue to explore the possibilities of AI in this field and work toward implementing its innovative solutions in clinical practice.

### AUTHOR CONTRIBUTIONS

All listed authors have contributed substantially to the manuscript and agreed to the final submitted version.

### ACKNOWLEDGMENT

Open Access funding enabled and organized by Projekt DEAL.

### CONFLICT OF INTEREST STATEMENT

One of our authors, Falk Schwendicke, is a co-founder of dentalXrai Ltd., an AI-based dental start-up for medical image analytics. This company, however, did not influence the presentation of the ideas in this review. There are no conflicts of interest related to this review.

### DATA AVAILABILITY STATEMENT

No new data were generated for this review. Therefore, data sharing is not applicable.

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**How to cite this article:** Pitchika V, Büttner M, Schwendicke F. Artificial intelligence and personalized diagnostics in periodontology: A narrative review. *Periodontology 2000*. 2024;95:220-231. doi:[10.1111/prd.12586](https://doi.org/10.1111/prd.12586)