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SYSTEMATIC REVIEW

Use of bioinformatic strategies as a predictive tool in implant-supported oral rehabilitation: A scoping review

Rita Silva Bornes, DMD, MSc,[a] Javier Montero, DMD, PhD,[b] André Ricardo Maia Correia, DMD, PhD,[c] and Nuno Ricardo das Neves Rosa, PhD[d]

ABSTRACT

Statement of problem. The use of bioinformatic strategies is growing in dental implant protocols. The current expansion of Omics sciences and artificial intelligence (AI) algorithms in implant dentistry applications have not been documented and analyzed as a predictive tool for the success of dental implants.

Purpose. The purpose of this scoping review was to analyze how artificial intelligence algorithms and Omics technologies are being applied in the field of oral implantology as a predictive tool for dental implant success.

Material and methods. The Preferred Reporting Items for Systematic Reviews and Meta-Analyses extension for Scoping Reviews checklist was followed. A search strategy was created at PubMed and Web of Science to answer the question "How is bioinformatics being applied in the area of oral implantology as a predictive tool for implant success?"

Results. Thirteen articles were included in this review. Only 3 applied bioinformatic models combining AI algorithms and Omics technologies. These studies highlighted 2 key points for the creation of precision medicine: deep population phenotyping and the integration of Omics sciences in clinical protocols. Most of the studies identified applied AI only in the identification and classification of implant systems, quantification of peri-implant bone loss, and 3-dimensional bone analysis, planning implant placement.

Conclusions. The conventional criteria currently used as a technique for the diagnosis and monitoring of dental implants are insufficient and have low accuracy. Models that apply AI algorithms combined with precision methodologies—biomarkers—are extremely useful in the creation of precision medicine, allowing medical dentists to forecast the success of the implant. Tools that integrate the different types of data, including imaging, molecular, risk factor, and implant characteristics, are needed to make a more accurate and personalized prediction of implant success. (J Prosthet Dent 2023;■:■-■)

The growth of population and of increased lifespan has meant that more people are looking for treatments and solutions for lost teeth, resulting in an increased demand for bone regeneration treatments and oral rehabilitation techniques for elderly patients with specific health conditions.[1,2] Patient-related conditions, such as smoking habits, poor oral hygiene, infectious processes, systemic diseases (osteoporosis, diabetes mellitus), and drugs that affect bone metabolism, might influence the progress of bone regeneration and, consequently, the osseointegration of dental implants.[3,4] In addition, factors related to the surgical and prosthetic phase, as well as the inherent characteristics of dental implants, such as wettability, porosity, roughness, may influence the osseointegration process.[5,6]

In the approximately 40 years since the introduction of implants into clinical practice, many complications have been reported, including the loss or fracture of prosthetic dental screws, fracture of the dental implant, and biologic problems such as peri-implant mucositis or peri-implantitis.[7-9] According to Benakatti et al,[7] "dental implants will need maintenance as long as they remain in the patient's oral cavity." Therefore, information about

[a]Guest Lecturer, Universidade Católica Portuguesa, Faculty of Dental Medicine (FMD), Center for Interdisciplinary Research in Health (CIIS), Viseu, Portugal.
[b]Full professor in Prosthodontics, Department of Surgery, Faculty of Medicine, University of Salamanca, Salamanca, Spain.
[c]Assistant Professor, Universidade Católica Portuguesa, Faculty of Dental Medicine (FMD), Center for Interdisciplinary Research in Health (CIIS), Viseu, Portugal.
[d]Assistant Professor, Universidade Católica Portuguesa, Faculty of Dental Medicine (FMD), Center for Interdisciplinary Research in Health (CIIS), Viseu, Portugal.

Clinical Implications

The combination of both AI algorithms and Omics expertise can provide an extremely powerful tool to support the clinician's opinion, not only in terms of identifying implant systems but also in predicting implant success.

the rehabilitation, including the implant system used, fixation method, and abutment used, is needed. Patient history and radiographic examination provide information that allows the clinician to identify the implant system. However, the patient's history is not always accessible, and the identification of the implant system through radiographic examination requires effort and experience.[8-12]

The development of methodologies able to integrate all the factors and predictors is possible with the use of artificial intelligence (AI). These strategies support the prognosis of the implant, predicting eventual clinical conditions such as early bone loss, mucositis, or peri-implantitis.[10,13-15] In addition, when using methods based on advanced neural networks—machine learning—it is possible to foresee the complexity and potential risk involved during the process of oral rehabilitation of the dental implants.[16,17]

The scientific evidence, as well as the assessment tools used in contemporary practice, has been based on clinical, analytical, and radiographic parameters which provide the clinician with limited therapeutic guidelines to deal with the multifactorial complexity of the implant-supported rehabilitation procedures.[18,19] Furthermore, for diagnosing and staging peri-implant disease, such methods can only register the actual tissue destruction rather than current disease activity. Moreover, those conventional strategies do not consider systemic conditions, which may influence the local immunological response, either around a tooth area (periodontitis) or around a dental implant area (peri-implantitis).[18-22]

Currently, the role of pathogens and their influence on periodontal and peri-implant diseases have been well described,[14,20,21,23,24] and it has been reported that oral dysbiotic status is necessary to trigger these pathologies.[14,20,21,23,24] This understanding has allowed the identification and confirmation of several individual conditions such as risk factors with immunological impact.[23] By considering all these facts, it is possible to create a standard clinical protocol supported by Omics technologies such as proteomics.[23] Omics technologies have emerged as a powerful tool for investigating different molecular mechanisms between health and disease states, for discovering molecules (biomarkers) commonly used in medicine to objectively determine the state of the disease or responses to a therapeutic intervention, and for identifying the targets of new therapies.[23,25]

The Omics methodology is key to the introduction of precision medicine into dentistry, especially in the field of oral rehabilitation, because it can adapt the procedure to follow in light of the patient's biological, social, and lifestyle characteristics.[26] A major goal is to reduce diagnostic mistakes, to develop results, to avoid unnecessary collateral effects, and to clarify why one individual can develop peri-implantitis and others with similar conditions did not.[23,26]

This scoping review aimed to analyze how bioinformatics have been used to predict the success of dental implants and to determine whether studies in which Omics technology have been integrated as a clinical support tool are available.

Table 1. Research methodology on PubMed (MESH)

#1	"Dental Implants"[MeSH Terms]
#2	"Artificial Intelligence"[MeSH Terms]
#3	"Precision Medicine"[MeSH Terms]
#4	"Computational Biology"[MeSH Terms]
#5	"Biomarkers"[MeSH Terms]
Research combination	#1 AND #2; #1 AND #3; #1 AND #4; #1 AND #5
Total number of articles	241 articles

MATERIAL AND METHODS

The methodology described in the Preferred Reporting Items for Systematic reviews and Meta-Analyses extension for Scoping Reviews (PRISMA-ScR) checklist[27] was followed, and the research protocol was registered in the Open Science Framework (OSF) under doi: https://doi.org/10.17605/OSF.IO/XMDHR reviewed and approved by 2 experienced research professionals (A.C., R.B.). The focal question was "how are bioinformatics being used in the field of oral implantology as a predictive tool to ensure implant success?"

A search was carried out on PubMed and on the Web of Science databases with the search strategy in Tables 1-3. In each database, the search was adapted to its characteristics by combining the Boolean operators (AND, OR) with different mesh terms (PubMed) or natural language (Web of Science). All articles used were stored in a bibliographic reference manager library (Zotero), and duplicate articles were removed.

The selection of studies was based on the selection criteria and focus question (Table 4). After excluding duplicate articles, the remaining articles were selected by reading their titles and abstracts. Lastly, the full text of all imported studies was evaluated in detail by 2 reviewers (A.C., R.B.), who individually screened the articles by considering the inclusion and exclusion criteria. Any

Table 2. Research methodology on PubMed (natural language)

(Dental Implants Survival) and (Biomarkers)	
("dental implants"[MeSH Terms] OR ("dental"[All Fields] AND "implants"[All Fields]) OR "dental implants"[All Fields]) AND ("mortality"[MeSH Subheading] OR "mortality"[All Fields] OR "survival"[All Fields] OR "survival"[MeSH Terms] OR "survivability"[All Fields] OR "survivable"[All Fields] OR "survivals"[All Fields] OR "survive"[All Fields] OR "survived"[All Fields] OR "survives"[All Fields] OR "surviving"[All Fields]) AND ("biomarker s"[All Fields] OR "biomarkers"[MeSH Terms] OR "biomarkers"[All Fields] OR "biomarker"[All Fields])	
(dental implants success) AND (biomarkers)	
("dental implants"[MeSH Terms] OR ("dental"[All Fields] AND "implants"[All Fields]) OR "dental implants"[All Fields]) AND ("success"[All Fields] OR "successes"[All Fields] OR "successful"[All Fields]) AND ("biomarker s"[All Fields] OR "biomarkers"[MeSH Terms] OR "biomarkers"[All Fields] OR "biomarker"[All Fields])	
(dental implants) AND (biomarkers)	
("dental implants"[MeSH Terms] OR ("dental"[All Fields] AND "implants"[All Fields]) OR "dental implants"[All Fields]) AND ("biomarker s"[All Fields] OR "biomarkers"[MeSH Terms] OR "biomarkers"[All Fields] OR "biomarker"[All Fields])	
(dental implants) AND (artificial intelligence)	
("dental implants"[MeSH Terms] OR ("dental"[All Fields] AND "implants"[All Fields]) OR "dental implants"[All Fields]) AND ("artificial intelligence"[MeSH Terms] OR ("artificial"[All Fields] AND "intelligence"[All Fields]) OR "artificial intelligence"[All Fields])	
(dental implants) AND (bioinformatics)	
("dental implants"[MeSH Terms] OR ("dental"[All Fields] AND "implants"[All Fields]) OR "dental implants"[All Fields]) AND ("bioinformatical"[All Fields] OR "bioinformatically"[All Fields] OR "computational biology"[MeSH Terms] OR ("computational"[All Fields] AND "biology"[All Fields]) OR "computational biology"[All Fields] OR "bioinformatic"[All Fields] OR "bioinformatics"[All Fields])	
Total number of articles	552 articles

Table 3. Research methodology on Web of Science

(Dental Implants) and (Artificial Intelligence)	
(dental implants) AND (computational biology)	
(dental implants) AND (precision medicine)	
(dental implants) AND (biomarkers)	
(dental implants) AND (bioinformatica)	
(dental implants survival) AND (biomarkers)	
(dental implants success) AND (biomarkers)	
Total number of articles	818 articles

Table 4. Inclusion and exclusion criteria of articles

Exclusion Criteria	Inclusion Criteria
Comparative microbiological technique studies with no relevance for topic	AI strategies, deep learning, and machine learning
Precision of digital printing techniques or traditional dental implant techniques	Tree model decision tools, support vector machine, or convolutional neural network
Precision in printing 3D surgical guidelines	Studies which apply Omics sciences as predictive tool to ensure success of implant
Studies that do not address Omics strategies that contribute to prediction of implant success	
Comparative and experimental studies with different dental investments/materials/design of dental implant surface or rehabilitation components	
Evaluation procedures to assess biofilm adhesion on dental implant	
Mini orthodontic implants or maxillofacial prosthetics	
Studies using animals or nonoral tissues	

differences between them were discussed with a third reviewer (N.R.), who determined the final decision.

The information was gathered from the included articles by 2 independent reviewers (A.C., R.B.), who had developed a methodology to bring together data characterized by the identification of the specific bioinformatic strategy and with regard to the clinical importance and use of that model (Table 5).

RESULTS

A total of 1611 articles were identified on the PubMed and Web of Science databases, and duplicates were removed, leaving 1011 articles. After reading the title and abstract and applying the inclusion and exclusion criteria (Table 4), the total was reduced to 47 articles. After reading the full text, a further 31 were excluded for lack of focus or not answering the focus question, leaving 16 as part of this scoping review (Fig. 1). The Cohen Kappa coefficient defined an achievement level of 84% between investigators.

Figure 1 and Tables 5-7 illustrate the role played by bioinformatics, AI, and Omics as predictive tools in oral implantology during the different phases of oral rehabilitation. Figure 2 shows a word cloud diagram where all the highlighted keywords are differently sized considering their frequency of use in the articles. The words displayed in the largest font were those used most frequently in the 16 articles. The most used words were artificial intelligence, deep learning, machine learning, and convolutional neural networks when combined with other words, including peri-implantitis, dental implant, and biomarkers, showing that studies using bioinformatic models to support clinical decisions in the field of oral implantology are available.

DISCUSSION

During the past 5 years, and especially after 2020, the number of publications on the use of bioinformatic

Table 5. Methodology used in oral implantology: Bioinformatic techniques versus conventional techniques

	Bioinformatic Techniques		Conventional Techniques	
Article Identification	**Omics Strategies**	**AI Strategies**	**Clinical Exam**	**X-ray Exam**
A deep learning approach for dental implant planning in cone-beam computed tomography images[31]	–	X	X	X
A pilot study of a deep learning approach to detect marginal bone loss around implants[32]	–	X	X	X
Artificial intelligence applications in implant dentistry: A systematic review[33]	–	X	–	–
Biosensor and lab-on-a-chip biomarker identifying technologies for oral and periodontal diseases[28]	X	X	X	X
Deep neural networks for dental implant system classification[8]	–	X	–	X
Diagnosing peri-implant disease using the tongue as a 24/7 detector[29]	X	X	X	X
Diagnostic charting of panoramic radiography using deep-learning artificial intelligence system[34]	–	X	X	–
The modern and digital transformation of oral health care: a mini review[35]	–	X	X	X
Efficacy of deep convolutional neural network algorithm for the identification and classification of dental implant systems, using panoramic and periapical radiographs[36]	–	X	–	X
Identification of dental implants using deep learning-pilot study[37]	–	X	–	X
Machine learning-assisted immune profiling stratifies peri-implantitis patients with unique microbial colonization and clinical outcomes[30]	X	X	X	X
Multitask deep learning model for classification of dental implant brand and treatment stage using dental panoramic radiograph images[38]	–	X	–	X
Osseointegration pharmacology: a systematic mapping using artificial intelligence[39]	–	X	–	–
Panoptic segmentation on panoramic radiographs: deep learning-based segmentation of various structures including maxillary sinus and mandibular canal[40]	–	X	–	X
Peri-implant bone loss measurement using a region-based convolutional neural network on dental periapical radiographs[41]	–	X	X	X
Machine learning for identification of dental implant systems based on shape – A descriptive study[7]	–	X	–	–

In addition to conventional techniques used in clinical practice (clinical and radiographic examination), studies in *gray* represent combination of AI tools and Omics.

models to assess implant-supported prostheses has increased. All the studies selected used AI algorithms to help clinicians in planning, diagnosis, and follow-up.

Three articles[28-30] discussed bioinformatic models that integrated AI algorithms into established identification and quantification protocols, which are often used in Omics sciences. A total of 13 articles[7,8,31-41] underlined the development of different AI algorithms, for example, machine learning, deep learning, and convolutional neural network to support clinical decision and raising precision and accuracy levels of the rehabilitation process. Of these, 6 studies[8,33,34,36-38] developed AI models for implant type recognition. Most of the articles identified used AI algorithms as a clinical support tool, as opposed to the articles which applied bioinformatic strategies by combining knowledge from AI algorithms with Omics expertise. These findings were expected since the application of strategies based on AI in the field of oral rehabilitation and the importance given to Omics sciences as a complement to a precision diagnosis are very recent.

Comparisons of efficacy were difficult among the different AI models used because of the data input or methods used in the studies reviewed. While each study attempted to standardize the collection of the radiographical images, differences among the studies were identified, including exposure (speed and contrast) and type of radiographic images (2-dimensional [2D] or 3-dimensional [3D]). Furthermore, variations on the radiographic information differed among the reviewed studies where only the implant (with a cover screw or a healing abutment) was visible on the radiograph or the radiograph also showed the prosthetic component. A comparison of studies that used bioinformatics strategies was also difficult since the methodology was completely different among the 3 included studies.

Most articles used 2D images for implant identification; clinicians generally use these to monitor the condition of a dental implant.[8,34,36-38] However, studies that used 3D images were also included. The inclusion of cone beam computed tomography (CBCT) images might aid in the development of AI for the recognition of dental implant types.[33]

Three recently published studies[28-30] in which some bioinformatic approaches were considered were identified. The main goal of these studies was to support the clinical decision in terms of the diagnosis and staging of peri-implant diseases.

Ritzer et al[29] described a diagnosis mechanism for periodontal disease that could be performed by "anyone, anywhere, anytime." This model was characterized by embedding sensors in chewing gum that contained peptide bioresponsive sensors consisting of a protease cleavable linker between a bitter substance and a microparticle. Matrix metalloproteinases in the oral cavity, as upregulated in peri-implant disease, specifically targeted the protease cleavable linker while chewing the gum, thereby generating bitterness for detection by the tongue. This line of research had many advantages: it provided a rapid and accurate diagnosis in that the

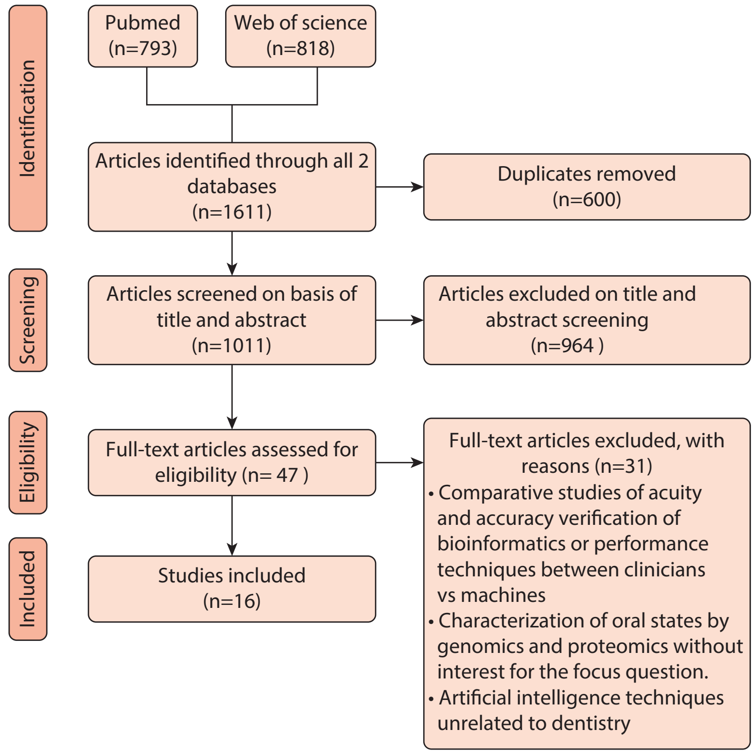

Figure 1. Preferred Reporting Items for Systematic reviews and Meta-Analyses extension for Scoping Reviews (PRISMA-ScR) flow diagram for scoping review process.[21]

Table 6. Description of proposed methodology in studies which combined both bioinformatic techniques: artificial intelligence (AI) and Omics

Article	Pub. year	Proposed Methodology	Clinical Improve
Diagnosing peri-implant disease using the tongue as a 24/7 detector[29]	2017	• Developed diagnostic chewing gums	• Providing rapid read-out within few minutes.
		• “Anyone, anywhere, anytime” diagnostics.	• Saliva diagnostic.
		• Sensors responded to proteins upregulated in peri-implant disease (MMP).	• Accurate diagnosis, even before clinical evidence of disease.
Biosensor and Lab-on-a-chip Biomarker identifying Technologies for Oral and Periodontal Diseases[28]	2020	• Oral biomarkers identification	• Data processed in biosensor and AI algorithms applied to establish personal physiological thresholds and out of personal norm trends.
		• Patient stratification	• Wirelessly transferred output data supports clinical decisions during in-office or tele-dentistry appointments.
		• Bioinformatic analysis using artificial intelligence	
		• Use of biosensors to oral disease identification and risk assessment.	
Machine learning-assisted immune profiling stratifies peri-implantitis patients with unique microbial colonization and clinical outcomes[30]	2021	• Clinical, immunological, and microbiological characterization of patients diagnosed with peri-implantitis undergoing regenerative therapy.	• Relation of immune and microbiological profile for prognosis of peri-implant states and potential risk analysis tool.
		• Used artificial intelligence algorithm - machine learning.	

sensor featured a diagnosis from saliva, which removed the need to collect sulcus fluid in sites accessible only to a professional; expert knowledge in interpretation was not required; and the diagnosis could be used anywhere, in the clinic or at home. Therefore, the data provided demonstrated that the complex kits used at present may be complemented or even replaced by more straightforward and reliable chewing gum diagnosis.[24,29]

Also in 2020,[28] a model was created using advances in light-emitting diode (LED) biotechnology which enabled biosensors and microelectromechanical systems (MEMS) suitable for the oral cavity to identify and quantify molecules such as cortisol, proteins, and bacteria, permitting the uninterrupted monitoring of those molecules in human saliva. Knowledge from such testing gives clinicians the opportunity to prevent patients from developing

Table 7. Description of proposed methodology in studies which only used artificial intelligence tools

Article	Pub. year	Proposed Methodology	Clinical Interest/Clinical Improve
A deep learning approach for dental implant planning in cone-beam computed tomography images[31]	2021	• Measurement of bone thickness and height in different areas of oral cavity in CBCT images by AI and by clinician	• AI results consistent with clinician's measurement in PM/M maxillary and PM mandibular areas
A pilot study of a deep learning approach to detect marginal bone loss around implants[32]	2022	• Convolutional neural networks prepared by training and validating data set by experienced dentists	• CNN detect peri-implant loss bone by using periapical radiographs.
		• Creation of AI algorithm	
Artificial intelligence applications in implant dentistry: A systematic review[33]	2021	By using AI algorithms:	–
		• Recognition of dental implant systems	• AI models recognize implant system
		• Prediction of dental implant success based on risk factors	• Models to predict osseointegration success/ implant success by using different input data
		• Optimization of dental implant design	• AI models to improve design of dental implants
Deep neural networks for dental implant system classification[8]	2020	• Recognition of implant system by using CNN	• Recognition of 11 different implant systems, despite their implant-treatment stage
Diagnostic charting of panoramic radiography using deep-learning artificial intelligence system[34]	2021	• Recognition of 10 dental states in panoramic radiograph, including dental implants	• Allows identification of oral states with no clinician intervention
Efficacy of deep convolutional neural network algorithm for the identification and classification of dental implant systems, using panoramic and periapical radiographs[36]	2020	• Identification and classification of dental implants by deep learning algorithms	• Deep CNN architecture useful for identification and classification of dental implant systems using panoramic and periapical radiographs
Identification of dental implants using a deep learning-pilot study[37]	2020	• Identification of dental implant systems using deep learning method	• Implants identified from panoramic radiographs
Multi-task deep learning model for classification of dental implant brand and treatment stage using dental panoramic radiograph images[38]	2021	• Multitask deep learning use to investigate classifier that categorizes implant brands and treatment stages from dental panoramic radiographs (implant, implant + abutment and implant + crown)	• Classification of implant brands and treatment stages by using CNNs
Osseointegration pharmacology: a systematic mapping using artificial intelligence[39]	2021	• Development of machine learning algorithm to automatically map literature assessing effect of medication on osseointegration	• Identification of effects during diagnosis of dental implants by medication that affect homeostasis, inflammation, cell proliferation, and bone remodeling
Panoptic segmentation on panoramic radiographs: deep learning-based segmentation of various structures including maxillary sinus and mandibular canal[40]	2021	• State-of-the-art deep neural network model designed for panoptic segmentation trained to segment maxillary sinus, maxilla, mandible, mandibular canal, normal teeth, treated teeth, and dental implants on panoramic radiographs	• Automatic machine learning method might assist dental practitioners to treatment plan and diagnose oral and maxillofacial diseases
Peri-implant bone loss measurement using a region-based convolutional neural network on dental periapical radiographs[41]	2021	• Deep CNN detect marginal bone level, top, and apex of implants on dental periapical radiographs	• CNN model can be used to measure radiographic peri-implant bone loss ratio to assess severity of peri-implantitis
The modern and digital transformation of oral health care: a mini review[35]	2021	• Analyses of progress, limitations, challenges, and conceptual theoretical modern approaches in oral health prevention and care, particularly in ensuring quality, efficiency, and strategic dental care in modern era of dentistry	• Digital oral scanner
			• Digital oral health records
			• Application of AR/VR and AI
			• Dynamic navigation system (DNS)
			• Static guided systems
			• Additive manufacturing
			• Tele-dentistry with remote consultation
Machine learning for identification of dental implant systems based on shape – A descriptive study[7]	2021	• Identification of dental implants in panoramic radiographs by using machine learning algorithms	• Machine learning models tested in study proficient enough to identify dental implant systems

AI, artificial intelligence; AR, augmented reality; CBCT, cone beam computed tomography; CNN, convolutional neural networks; MMP, matrix metalloproteinases; M, molar; PM, premolar; VR, virtual reality.

different pathological conditions and enables early identification of mucositis or peri-implantitis. It also allows clinicians to control the different stages of a prediagnosed pathology, preventing progression.[28]

Recently, in addition to the importance given to the accuracy of the diagnosis achieved by using the strategies Ritzer et al[29] and Steigman et al,[28] emphasis has also been given to the stratification of patients in determining the risk profile of patients and creating a consistent risk system. Wang et al[30] used a robust outliner-resistant machine learning algorithm for immune deconvolution and concluded that the peri-implant immune microenvironment shaped the microbial composition and the regeneration course. Immune signatures have shown the untapped potential in improving the risk-grading for peri-implantitis, as well as the influence of medication during osseointegration. Many patients seeking implant-supported restorations are elderly, polymedicated, or with

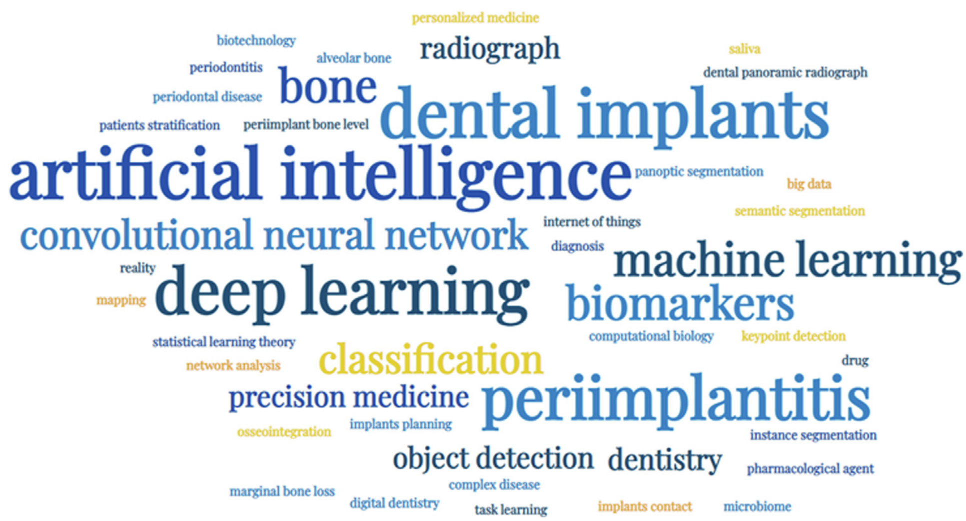

Figure 2. Representative word cloud of keywords taken from 16 articles, part of different areas of expertise being developed, as well as example of most used bioinformatic technologies so far.

comorbidities. Even though all these situations are considered during the planning period, the effect of medication during the surgical procedures is generally unclear. To precisely read and map all the process of bone integration, a machine learning algorithm has been designed to identify the influence of medications during the process, which might affect the metabolic activities involved.[39]

Alauddin et al[35] underlined the importance of scanning in dentistry, referring to limitations, challenges, and theoretical approaches for the prevention and diagnosis of oral diseases. They also mentioned that this progress has been influenced by informatic models such as augmented reality (AR) and virtual reality (VR), the internet, communication technologies, digital oral health records, digital scanners, and AI. These authors concluded that scanning might aid in AI development and in updating the systems of AI, VR, and AR and pointed out the importance of these models in dentistry to facilitate data collection and the development of different AI algorithms such as deep learning, machine learning, and neural networks.[35] Those strategies should reduce unnecessary contact between clinician and patient and shorten the duration of the treatment, which will make it more cost-effective.[35]

Importance has been given to planning oral rehabilitation, which depends on the clinician's experience and knowledge. AI systems have been used to support diagnosis and planning, and measurements from 3D images are recommended to identify anatomic variations. AI systems have been described that detect vital structures and diagnose injuries, improving implant placement and ensuring optimal oral rehabilitation.[31,40] Revilla-León et al[33] stated that cone beam computer tomography (CBCT) images could help in the development of AI models and in facilitating the recognition of dental implant systems. Using 3D images optimizes the measurement of teeth and edentulous ridges, allowing accurate planning and implant placement.[11,12,24,31,38-41] Once all the data are automatically gathered and organized in a database and then combined with the risk factors, these technologies can improve treatment precision.

Future directions in implant dentistry could combine different types of data (imaging, molecular, risk factors, and implant characteristics) to make a more accurate and clinically useful prediction of the outcome of implant-supported prostheses. Despite the relevance of identifying different implant systems and in precisely planning the oral rehabilitation procedures, creating a database which gathers all the pertinent information related to a patient's medical records (medication, pathologies, periodontal chart, and dental chart) is essential. Such a record can store data about surgical phases, prosthetic and follow-up appointments, and a wider range of biomedical information such as microbiology, proteomics, genomics, and metabolomics. Therefore, the clinician can access an early diagnosis to predict and plan the safest and most appropriate strategy to adopt and follow.[10,15,22,25]

CONCLUSIONS

Based on the findings of this scoping review, the following conclusions were drawn:

1. Both strategies analyzed (AI algorithms and Omics sciences) could be combined to create bioinformatic tools which could be integrated into clinical protocols.
2. This fusion allowed a clinical precision approach because it reduces misdiagnosis and, eventually, allows the prediction of possible outcomes.

REFERENCES

1. Papapanou PN, Sanz M, Buduneli N, Dietrich T, Feres M, Fine DH, et al. Periodontitis: Consensus report of workgroup 2 of the 2017 world workshop on the classification of periodontal and peri-implant diseases and conditions: classification and case definitions for periodontitis. *J Clin Periodontol*. 2018;45:162–170.
2. Knight ET, Murray Thomson W. A public health perspective on personalized periodontics. *Periodontol*. 2000 2018;78:195–200.
3. Albrektsson T, Donos N. Working Group 1. Implant survival and complications. The Third EAO consensus conference 2012. *Clin Oral Implants Res*. 2012;23:63–65.
4. Zitzmann NU, Schärer P, Marinello CP. Factors influencing the success of GBR: Smoking, timing of implant placement, implant location, bone quality and provisional restoration. *J Clin Periodontol*. 1999;26:673–682.
5. Calciolari E, Mardas N, Dereka X, Anagnostopoulos AK, Tsangaris GT, Donos N. The effect of experimental osteoporosis on bone regeneration: part 2, proteomics results. *Clin Oral Implants Res*. 2017;28:135–145.
6. Puleo D. Understanding and controlling the bone−implant interface. *Biomaterials*. 1999;20:2311–2321.
7. Benakatti V, Nayakar R, Anandhalli M. Machine learning for identification of dental implant systems based on shape − a descriptive study. *J Indian Prosthodont Soc*. 2021;21:405–418.
8. Sukegawa S, Yoshii K, Hara T, et al. Deep neural networks for dental implant system classification. *Biomolecules*. 2020;10:984–997.
9. Sadid-Zadeh R, Kutkut A, Kim H. Prosthetic failure in implant dentistry. *Dent Clin North Am*. 2015;59:195–214.
10. Alassy H, Parachuru P, Wolff L. Peri-Implantitis diagnosis and prognosis using biomarkers in Peri-Implant crevicular fluid: a narrative review. *Diagnostics*. 2019;9:214.
11. Sahiwal IG, Woody RD, Benson BW, Guillen GE. Macro design morphology of endoseous dental implants. *J Prosthet Dent*. 2002;87:543–551.
12. Michelinakis G, Sharrock A, Barclay CW. Identification of dental implants through the use of Implant Recognition Software (IRS). *Int Dent J*. 2006;56:203–208.
13. Zarco M, Vess T, Ginsburg G. The oral microbiome in health and disease and the potential impact on personalized dental medicine: the oral microbiome. *Oral Dis*. 2012;18:109–120.
14. Costalonga M, Herzberg MC. The oral microbiome and the immunobiology of periodontal disease and caries. *Immunol Lett*. 2014;162:22–38.
15. Carinci F, Romanos GE, Scapoli L. Molecular tools for preventing and improving diagnosis of peri-implant diseases. *Periodontol 2000*. 2019;81:41–47.
16. Dawson A, Chen S, Buser D, Cordaro L, Martin W, Belser U. *The SAC Classification in Implant Dentistry*. 1st ed. Berlin, Germany: Quintessence Publishing: Books; 2009:50–120.
17. Nobre AM, Salvado F, Nogueira P, Rocha E, Ilg P, Maló P. A Peri-Implant disease risk score for patients with dental implants: validation and the influence of the interval between maintenance appointments. *J Clin Med*. 2019;8:252–264.
18. Lahteenmaki H, Umeizudike KA, Heikkinen AM, et al. aMMP-8 Point-of-Care/Chairside oral fluid technology as a rapid, non-invasive tool for periodontitis and Peri-Implantitis screening in a medical care setting. *Diagnostics*. 2020;10:562–574.
19. Kinane DF, Stathopoulou PG, Papapanou PN. Periodontal diseases. *Nat Rev Dis Primers*. 2017;3:1–14.
20. Buduneli N. *Pathogenesis and Treatment of Periodontitis*. 1st ed. London: IntechOpen; 2012; InTech; 2012:33–54.
21. Sahingur SE, Cohen RE. Analysis of host responses and risk for disease progression. *Periodontol*. 2004;34:57–83.
22. Gul SS, Abdulkareem AA, Sha AM, Rawlinson A. Diagnostic accuracy of oral fluids biomarker profile to determine the current and future status of periodontal and Peri-Implant diseases. *Diagnostics*. 2020;10:838.
23. Rakic M, Pejcic N, Perunovic N, Vojvodic D. A Roadmap towards Precision Periodontics. *Medicina (Kaunas)*. 2021;57:233–251.
24. Srivastava N, Nayak PA, Rana S. Point of care- A novel approach to periodontal diagnosis-A review. *J Clin Diagn Res*. 2017;11:1–6.
25. Tonetti MS, Greenwell H, Kornman KS. Staging and grading of periodontitis: Framework and proposal of a new classification and case definition. *J Periodontol*. 2018;89:159–172.
26. Belibasakis GN, Bostanci N, Marsh PD, Zaura E. Applications of the oral microbiome in personalized dentistry. *Arch Oral Biol*. 2019;104:7–12.
27. Tricco AC, Lillie E, Zarin W, et al. PRISMA Extension for Scoping Reviews (PRISMA-ScR): checklist and explanation. *Annals of Internal Medicine*. 2018;169:467–473.
28. Steigmann L, Maekawa S, Sima C, Travan S, Wang CW, Giannobile WV. Biosensor and Lab-on-a-chip Biomarker-identifying technologies for oral and periodontal diseases. *Front Pharmacol*. 2020;11:1–18.
29. Ritzer J, Luehmann T, Rode C, et al. Diagnosing peri-implant disease using the tongue as a 24/7 detector. *Nat Commun*. 2017;8:264–281.
30. Wang CW, Hao Y, Di Gianfilippo R, et al. Machine learning-assisted immune profiling stratifies peri-implantitis patients with unique microbial colonization and clinical outcomes. *Theranostics*. 2021;11:6703–6716.
31. Bayrakdar SK, Orhan K, Bayrakdar IS, et al. A deep learning approach for dental implant planning in cone-beam computed tomography images. *BMC Med Imaging*. 2021;21:86–101.
32. Liu M, Wang S, Chen H, Liu Y. A pilot study of a deep learning approach to detect marginal bone loss around implants. *BMC Oral Health*. 2022;22:11.
33. Revilla-León M, Gómez-Polo M, Vyas S, et al. Artificial intelligence applications in implant dentistry: a systematic review. *J Prosthet Dent*. 15 June 2021. https://doi.org/10.1016/j.prosdent.2021.05.008 [Epub ahead of print.].
34. Basaran M, Celik O, Bayrakdar IS, et al. Diagnostic charting of panoramic radiography using deep-learning artificial intelligence system. *Oral Radiol*. 2022;38:363–369.
35. Alauddin MS, Baharuddin AS, Ghazali MIM. The modern and digital transformation of oral health care: a mini review. *Healthcare (Basel)*. 2021;9:118.
36. Lee JH, Jeong SN. Efficacy of deep convolutional neural network algorithm for the identification and classification of dental implant systems, using panoramic and periapical radiographs A pilot study. *Medicine*. 2020;99:26–38.
37. Takahashi T, Nozaki K, Gonda T, Mameno T, Wada M, Ikebe K. Identification of dental implants using deep learning—pilot study. *Int J Implant Dent*. 2020;6:53–63.
38. Sukegawa S, Yoshii K, Hara T, et al. Multi-Task deep learning model for classification of dental implant brand and treatment stage using dental panoramic radiograph images. *Biomolecules*. 2021;11:815–833.
39. Mahri M, Shen N, Berrizbeitia F, et al. Osseointegration pharmacology: a systematic mapping using artificial intelligence. *Acta Biomater*. 2021;119:284–302.
40. Cha JY, Yoon HI, Yeo IS, Huh KH, Han JS. Panoptic segmentation on panoramic radiographs: deep Learning-Based segmentation of various structures including maxillary sinus and mandibular canal. *J Clin Med*. 2021;10:2577.
41. Cha JY, Yoon HI, Yeo IS, Huh KH, Han JS. Peri-Implant bone loss measurement using a Region-Based convolutional neural network on dental periapical radiographs. *J Clin Med*. 2021;10:1009.

Corresponding author:
Dr Rita Silva Bornes
Rua Mártir São Sebastião, n 115
3730-069 Vale de Cambra
PORTUGAL
Email: rbornes@ucp.pt

CRediT authorship contribution statement

Rita Silva Bornes: Conceptualization, Methodology, Validation, Visualization, Writing − original draft, preparation, Writing − review & editing, Project administration. **Javier Montero:** Conceptualization, Methodology, Validation, Visualization, Writing − original draft, preparation, Writing − review & editing, Project administration, Supervision. **André Ricardo Maia Correia:** Conceptualization, Methodology, Validation, Visualization, Writing − original draft, preparation, Writing − review & editing, Project administration, Supervision, Funding acquisition. **Nuno Ricardo das Neves Rosa:** Conceptualization, Methodology, Validation, Visualization, Writing − original draft, preparation, Writing − review & editing, Project administration, Supervision, Funding acquisition.

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