International Journal Dental and Medical Sciences Research
Volume 7, Issue 6, Nov – Dec 2025 pp 37-46 www.ijdmsrjournal.com ISSN: 2582-6018

The Role of Artificial Intelligence in Predicting Dental Implant Success a Systemic Review

Jazem Omer Mohammed Alwossaby1*, Abdullah Ahmed Areqi2
1Orthodontic, Département of Oral and Dental Medicine and Surgery, University of Science and Technology, Sanaa-Yemen
2Département of Pharmacology, Faculty of Pharmacy, University of Science and Technology, Sanaa-Yemen

Date of Submission: 05-11-2025 Date of Acceptance: 15-11-2025

ABSTRACT:
Background: Dental implant design and diagnostics could be much improved by including artificial intelligence (AI) into dentistry. Not intended to replace dental practitioners, artificial intelligence systems provide second-informed opinions based on forecasts and quantitative decisions. Artificial intelligence nowadays has strong and accurate approaches for the diagnosis of dental diseases; nonetheless, little study in this sector highlights the need of more research and development of future prospects. **Purpose**: the aim of this systemic renew to assess artificial intelligence's contribution in dental implant success prediction. **Methodology**: Seventeen studies satisfied all inclusion criteria and were incorporated into the final evaluation. The stringent selection approach reduced the initial 408 records to only 4.2% qualifying research, facilitating a concentrated analysis. **Results**: Findings demonstrate AI's transformative potential across implantology, including diagnostic accuracy (AUC up to 0.954 for automated deep learning models), treatment planning alignment with clinical judgments, and optimization of biomaterials (e.g., 62.5% porosity titanium foam for stress shielding reduction). AI applications—ranging from convolutional neural networks (CNNs) for implant classification to real-time surgical navigation—significantly enhanced precision, with RCTs reporting higher success rates (92% vs. 78%). **Conclusion**: The integration of artificial intelligence (AI) integration into dental implantology improves diagnosis precision, treatment planning, surgical accuracy, and postoperative monitoring. **Limitations**: Larger, different datasets, better model generalizability, and validation in real-world clinical environments are among common issues. To get general acceptance and maximize its influence on dental treatment, artificial intelligence will need addressing these constraints.

Key Words: Artificial Intelligence, Dental Implant, dentistry.implant success.

I. INTRODUCTION:

The integration of artificial intelligence (AI) into dentistry has the potential to greatly improve dental implant planning and diagnosis. AI systems offer second-informed judgements based on forecasts and quantitative decisions, not meant to replace dental practitioners. Nowadays, artificial intelligence has strong and accurate methods for dental disease diagnosis; yet, little study in this field indicates the need of more research and development of future prospects(1).

One example of AI's impact in dental implant planning is its ability to automatically select the best slice for each tooth in an endodontic report, providing valuable insights into the relationship between different root structures(2).

Furthermore, artificial intelligence can help to choose the most easily available area for measurement and study in endodontic reports, therefore enhancing the general correctness and efficiency of dental operations. For example, the artificial intelligence system found via data analysis that the palatal area where the implant would be positioned would be the simplest to reach following the alveolus 2 excision of the next tooth. These developments in artificial intelligence could transform dental implant planning and diagnosis, hence improving patient care and treatment results(3).

A deep convolutional neural network (DCNN) is a type of artificial intelligence that employs a series of nonlinear processing layers for the extraction, transformation, and classification of high-dimensional input sets(4).

A DCNN especially engineered for detection, classification, and segmentation in visual tasks and practical applications has been widely utilised in recent years, with advancements in computational performance and deep learning methodologies(5).

Specifically, Deep Convolutional Neural Networks (DCNN) have been effectively utilized in various medical and dental domains, exhibiting considerable benefits in diagnosis and prognosis, including diabetic retinopathy in retinal fundus images, skin cancer in dermatological photographs, periodontally compromised teeth and dental caries in radiographic images, and oral cystic lesions in cone beam computed tomography(6).

Applications of Artificial Intelligence in Implant Dentistry:

Through enhanced evaluation and therapy planning, artificial intelligence (AI) could transform the discipline of implant dentistry.One-way artificial intelligence can improve this process is by helping dentists proactively handle possible problems and offer more customized treatment regimens, catered to the patient's particular requirements(7).

Furthermore, artificial intelligence can use data analysis and machine learning to raise diagnoses and treatment plans. Even the slightest alterations in dental photos can be found by advanced image analysis algorithms in artificial intelligence, therefore enabling earlier and more accurate diagnosis(8).

Dentists can give more efficient and effective treatment in implant dentistry by using artificial intelligence, therefore improving patient results(9).Moreover, artificial intelligence can save time by automating the diagnosis and treatment planning process, thereby improving efficiency.

All things considered, including artificial intelligence into implant dentistry could improve dental treatment efficacy, accuracy, and efficiency, thereby benefiting patients as well as clinicians(10).

Using artificial intelligence (AI) in implant placement and restoration offers enormous and revolutionary possible advantages. In several facets of implant dentistry including implant type detection, implant success prediction, and implant design optimization AI models have shown considerable promise(11).

Combining artificial intelligence models with finite element analysis computations helps to maximize implant design so improving acceptance of prosthodontic therapy and functionality. By including ontological criteria and patient risk variables, artificial intelligence models may also forecast implant success, so lowering the risk of problems and raising general success rates of dental implant operations(12).

This work aims to assess artificial intelligence's contribution in dental implant success prediction. The question of this study was that haw can AI models be used to determine dental implant success.

II. METHODOLOGY:

Data Sources and Searches:

Artificial intelligence's contribution in dental implant success prediction were assessed in this systematic review using PRISMA methods. Without regard for date or language, thorough searches were conducted in PubMed, EBSCO and Science Direct. The subsequent search Words and technique employed in this systematic Review were: (("Artificial Intelligence" OR "Machine Learning" OR "DeepLearning" OR "Neural Networks, Computer "OR "Support Vector Machine" OR "Random Forest".

Also, we used these terms, ("Dental Implants" OR "Dental Implantation" OR "Dental Implant-Abutment Design" OR "Dental Implant Failure" OR "Dental Prosthesis, Implant-Supported". The terms and keywords were modified for each database as required.

This systematic study reported based on the Preferred Reporting Items for Systematic Reviews and Meta-analyses (PRISMA) guidelines (13).

Data Extraction and Quality Assessment:

As the PRISMA flowchart (figure 1) below describes, data extraction is an essential phase in the process of the systematic review. This phase consisted in methodically collecting and organizing information from several studies covered in the review. This method consisted in four phases, with the main actions taken in each one:

Identification phase: 408 total studies came from three databases: PubMed, ScienceDirect, EBSCO. Examining the technique used for alphabetical title sorting, 48 were omitted from replication or duplication .

Screening phase: Pre-defined eligibility criteria guided evaluation of the remaining 360 articles. The title rejected 124 papers; 40 based on the abstract; 80 articles were excluded since they were theoretically identical. And the last articles numbered 116. **Eligibility phase:** Following a thorough and exact analysis of the whole texts, it was decided that 99 articles in all failed the set eligibility requirements and were thus labelled as unfit.

Inclusion phase: The final analysis comprised 17 studies in all. Following a careful review of titles, abstracts, and complete texts, The inclusion process guaranteed that only research fulfilling the

relevance, quality, and methodological criteria would be taken under consideration.
The quality of the included studies was assessed on the Newcastle-Ottawa Scale (NOS) in terms of research group selection, group comparability, and exposure or result of interest(14). The NOS comprises nine objects. Every item was allocated. a star if the under-examination study satisfied the requirements related to the item. good evidence (9-6 stars), Fair evidence (3–5 stars), and poor evidence (≤ 4 stars) were then three separate groups the studies fell into.

Table 1: Newcastle-Ottawa Scale (NOS) for Quality Assessment of the included studies

			NOS Score				
No	**Authors / year**	**Study design**	**Selection**	**Comparability**	**Outcomes**	**Total**	**Quality Score**
1	Sukanta K. et al., 2024(15)	Comparativestudy	****	**	***	9*	Good
2	Hussein Farroukh,et,al, 2025 Lebanon (16)	Numerical study using (FEA)	***	**	**	7*	Good
3	i-Hyun Park et al., 2023(17)	Retrospective study	**	**	***	7*	Good
4	Sukanta K. Satapath y et al., 2024, (15)	Randomize d Controlled Trial (RCT)	****	**	***	9*	Good
5	(WidmannGet,al) 2009(18)	Randomized Controlled Trials (RCTs)	****	**	***	9*	Good
6	R. S. Senthil Rajan et al., 2024(19)	Randomize d Controlled Trial (RCT)	****	**	***	9*	Good
7	Jae- Hong Lee etal, 2024(20)	Randomize d Controlled Trial (RCT)	****	**	***	9*	Good
8	Zheng G,et,al 2008 (21)	Randomized Controlled Trials (RCTs)	****	**	***	9*	Good
9	Lee et al., 2020(22)	Diagnostic Accuracy Study	**	*	**	5*	Fair
10	(Petrykiv et al.) 2008 (23)	Experimental Study	**	*	**	5*	Fair
11	Mangano, et al., (2023)(24)	/Case Series (case control)	**	**	**	6*	Good
12	Farroukh et al.,. (2024)(25)	clinical prediction	****	**	***	9*	Good
13	Jae-Hong Lee et al, 2020,(26)	Diagnostic test Study	***	**	**	7*	Good
14	Mangano F ,et al, 2004(27)	Case series	****	**	***	9*	Good
15	Takahashi et al., 2020(28)	Cross Sectional study (Pilot study)	*	**	**	5*	Fair
16	Georgios os et al., 2016(29)	Cross- section study	*	**	**	5*	Fair
17	Norberto -Lopez et al., 2024(30)	Clinical trial	****	**	***	9*	Good

Study selection:

The chosen studies had a comprehensive procedure intended to find, screen, and include the ones satisfying particular eligibility requirements. To compile a large volume of material, first a thorough search method was used across several databases.

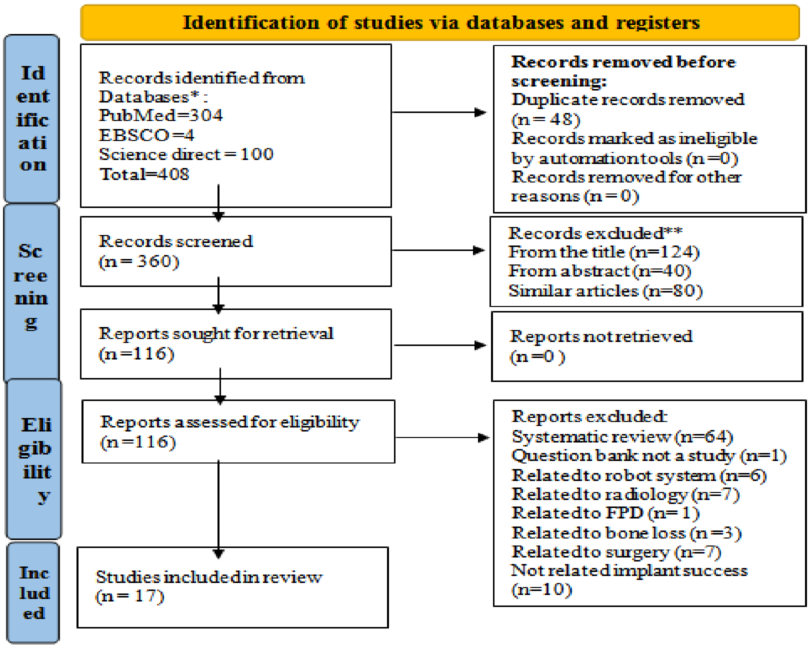

Figure 1: PRISMA flow diagram for new systematic reviews which included searches of databases

Once the studies were found, data was compiled and entered into Microsoft Excel to streamline the title and abstract screening process and weed out unnecessary studies including repeated publications.

A full text evaluation of the remaining papers followed this approach to evaluate their eligibility depending on pre-defined criteria including the study design, time period, interventions, and outcomes. The study included several published papers that satisfied the qualifying criteria; hence data was compiled from these sources.

Following PRISMA criteria, the choosing process was recorded in a flow diagram illustrating identification, screening and inclusion stages together with reasons for exclusion at each point.

III. DATA SYNTHESIS AND ANALYSIS

Criteria and assessments of artificial intelligence's contribution in dental implant success prediction helped data to be arranged into an evidence table. A summary of study characteristics, findings, and variances in the sections on the discussion and results was generated. The large differences among the chosen publications made meta-analysis impossible.In this systemic review, many of studies used Excel, the Statistical Package for the Social Sciences (SPSS), and other program tools in data analysis approaches.

IV. RESULTS:

Seventeen studies satisfied all inclusion criteria and were incorporated into the final evaluation. The stringent selection approach reduced the initial 408 records to only 4.2% qualifying research, facilitating a concentrated analysis. To enhance clarity,

Starting 408 entries found from three databases, 360 studies underwent title/abstract screening following 48 duplicate records' removal. From these, 244 records were excluded124 based on title irrelevance, 40 following abstract review, and 80 as comparable article sleaving 116 full-text reports for eligibility assessment. 99 papers were disqualified from full-text screening: 64 were systematic reviews, 1 was a question bank, 6 focused on robot systems, 7 on radiography, 1 on fixed partial dentures (FPD), 3 on bone loss, 7 on surgery, and 10 were irrelevant to implant success.

Our results show the great progress and possibilities artificial intelligence (AI) offers in improving several facets of dental diagnostics and implantology. With great accuracy and recall for implants and endodontic treatments.

Muresanu et al.'s study shows how well AI automates the diagnosis of dental problems on panoramic radiographs. On external validation, the model's performance dropped, nevertheless, which emphasizes the requirement of better generalizability.

Al-Asali et al. focused on 3D bone segmentation and implant position prediction on

CBCT scans using U-Net models. With dice scores of 0.93 and low volume mistakes, their method was highly accurate in segmenting missing tooth areas and projecting implant placements. The study emphasizes how artificial intelligence might automate and improve dental implant planning, therefore lowering manual labor and raising accuracy.

On the other hand, Lee et al. explore the feasibility of using deep learning (DL) to assess bone quality from panoramic radiographs, comparing results with CBCT values and a surgeon's tactile sense. this study emphasizes DL's possible use as a supplemental method for evaluation of bone quality. But the low dataset size and the subjective character of bone quality classification demand more study to confirm and improve the model for therapeutic usage.

The Rajan et al. randomized controlled trial Provides stunning evidence for AI's capacity to predict dental implant success using preoperative CBCT pictures. Apart from less challenges and interventions, the AI-assisted group demonstrated a 92% success rate—far higher than the 78% in the traditional assessment group. With its 87% accuracy in output prediction, . These findings support adding artificial intelligence into implant dentistry to improve planning accuracy and reduce postoperative risks.

Recent advancements in implant dentistry show how increasingly artificial intelligence (AI) and advanced biomaterials are being used to improve clinical results and precision. Although more clinical validation is required, Lee et al. (2020) showed that an automated deep convolutional neural network (DCNN) outperformed dental practitioners in categorising dental implant systems (AUC 0.954), hence lowering diagnostic variability. While cautioning against greater porosities (>70%), due mechanical hazards, Farroukh et al. (2024) found 62.5% porosity as ideal for titanium foam implants, balancing rigidity (13.82 GPa) with stress shielding decrease.

Deep learning (AUC > 0.975) and clustering (AUC > 0.947) were found by Park et al. (2023) to properly classify implant dimensions, implying combination approaches could increase dependability. Though ethical and financial obstacles still exist, Saeed et al. (2023) underlined the part robotics and artificial intelligence play in maximising implant insertion and diagnostics.

This research taken together highlight the potential of artificial intelligence as a decision-support tool, the biomechanical benefits of porous implants, and the need of multidisciplinary cooperation to guarantee clinically viable and ethical sound technological integration in implant dentistry.

Table (2) studies on The Role of Artificial Intelligence in Predicting Dental Implant Success

No	Authors / year/country/ reference	Purpose of Study	Type of study/samplesize	Summary of Results
1	Sukanta K. Satapathy et al., 2024 India (15)	To investigate the utility of AI-assisted treatment planning for dental implant placement by comparing AI- generatedplans with traditionalclinical plans	Comparative study 20 patients	AI-generated treatment plans closely align with clinical plans, indicating potential for accurate and efficient implant placement.
2	Hussein Farroukh,et,al, 2025 Lebanon (16)	To numerically determine the optimal porosity of titanium foam implants for dentalapplications, minimizing stressshielding while balancingstiffness and energy absorption.	Numerical study using FiniteElement Analysis(FEA	Porosity of 62.5% is optimal for dental implants due to its balanceof stiffness, energyabsorption, and reduced risk of stress shielding.
3	i-Hyun Park et al., 2023 South Korea (17)	Analysis) for automatically classifyingdental implants by diameter and length using periapicalradiographs.	Retrospective, AI-based analysis using deep learning Clustering	Both DL and Clustering models showedreliable performance with high accuracy, sensitivity, specificity, and AUC- ROC.
4	Sukanta K. Satapath y et al., 2024,India(15)	Toinvestigate the utility of AI-assisted treatment planning by comparing AI-generated plans with traditionalclinical plans.	Randomize d Controlled Trial (RCT)	AI-generated plansclosely align with clinical plans interms of accuracy andefficiency; minimaldeviations in positioning, angulation, and depth.
5	(WidmannGet,al) 2009 Hoboken, New Jersey (18)	To develop and evaluate a laboratory training technique for navigatedoral implantsurgery using a surgical navigation system and dental dumm	Randomized Controlled Trials (RCTs)	The technique successfully simulates navigated implant surgery, evaluating critical aspects like anatomical safety andprecision.

6	R. S. Senthil Rajan et al., 2024 India (19)	To evaluate the role of AI in predicting the success of dental implants using preoperative CBCT images bycomparing AI-assisted assessments with traditional methods.	Randomize d Controlled Trial (RCT)	AI-assisted group showed higher implant success rates, lowercomplicatio n rates, and fewer postoperativ intervention s compared to the traditional group.
7	Jae-Hong Lee etal., 2024 South Korea (20)	To evaluate the clinical applicability of deeplearning for assessing bone quality using panoramic radiographs compared with asurgeon's tactile sense and CBCT values.	Randomize d Controlled Trial (RCT)	DL using PA imagescorrelated significantly with CBCT and the surgeon's tactilesense inclassifying bone quality for implant sites.
8	Zheng G,et,al2008 British (21)	To implement and assess the effectiveness of an integrated computer- aidedsystem for dental implantology, focusing on both preoperative planning and intra-operativenavigation	Randomized Controlled Trials (RCTs)	The integrated system showed enhanced accuracy in planning and navigating dental implant surgery using a phantom model.
9	Lee et al., 2020 South Korea (22)	To evaluate Comparison between Automated Deep Learning and Dental Professionals in Classification of Dental Implant Systems from Dental Imaging	Diagnostic Accuracy Study	Automated DCNN outperformed most dental professionals (board-certified periodontitis, periodontology residents, non-specialized residents) in classifying dental implant systems (DISs) from radiographs. DCNN showed
10	(Petrykiv et al.) 2008 British (23)	Identify implant "phenotypes" and predict individual implant mean bone levels (IIMBL) using clinical and radiographical data.	Experimental Study	wo implant phenotypes identified: one susceptible to peri-implantitis (5.2mm IIMBL) and another resistant to it. PCA identified significant variables: number of teeth, plaque score, implant surface, periodontitis severity,age and diabetes
11	Mangano, et al., (2023) (24)	To asses Artificial intelligence and augmented reality for guided implant surgery planning	Proof of Concept/Technical Report/Case Series (case control)	Presented a novel protocol using AI and AR for 3D planning of dental implants. Protocol included: 1) 3D data acquisition, 2) AI-driven CBCT segmentation, 3) AR surgical planning, 4) CAD surgical guide design, and 5) surgery. Demonstrated feasibility for simple guided implant surgery cases.
12	**Farroukh et al.,. (2024)** (25)	To evaluate Numerical investigation of the optimal porosity of titanium foam for dental implants	clinical prediction	Investigated the optimal porosity of titanium foam for dental implants using numerical simulations. Identified porosity ranges that optimize mechanical properties and bone ingrowth.
13	**Jae-Hong Lee et al., 2020, South Korea** (26)	to evaluate deep convolutional neural network (DCNN) for the classification of dental implant systems (DISs) and the accuracy of the performance was compared against that of dental professionals using dental radiographic images	Diagnostic test Study	High: AUC of 0.954 Forautomated DCNN, outperform dental profession .
14	**Mangano F ,et al, 2004 Moscow, Russia** (27)	The aim of this work is to present a new protocol for implant surgical planning which involves the combined use of artificial intelligence (A) and mixedreality.	Case series	The YOLOv8 model effectively detected dental conditions like implants and endodontic treatments, but struggled with periapical lesions and bone loss.
15	**Takahashi et al., 2020 Japan** (28)	to build an automated system leveraging a deep learning- based object detectiontechnique (YOLOv3) to recognize implant systems.	Cross Sectional study (Pilot study)	the deep learning model successful y identifies dental implants frompanoramic radiograph
16	**Georgios Papantonopoul os et al., 2016 Greece** (29)	To cluster implants and identify implant "phenotypes " and predictors of individual implant mean bone levels (IIMBL).	Cross- section al study 72patients with 237 implants	Three clustersidentified: - Cluster 1:96% peri-implanted, mean IIMBL5.2 mm. - Clusters 2 & 3: 5% and 7% affected, mean IIMBL1.6 mm. - RMSE: 0.133 (ES), 0.149 (SVMs).
17	**Norberto Quispe-Lopez et al., 2024 Spain** (30)	To evaluate bonechanges around equiseta	Clinical trial	The lowest marginal bone loss (MBL) wasobserved inabutment height (β = -0.43), followed by crestal position (β = 0.34), and keratinized mucosa width (β = - 0.22); MBL depended on abutment height (β = - 0.37) and patient's age (β = -0.36)

V. DISCUSSION:

Many of the most recent studies in our systematic review which span diagnosis accuracy, treatment planning, and biomaterial design investigate the function of artificial intelligence (AI) in predicting and optimising dental implant success. Especially several studies showed how artificial intelligence might improve implantological accuracy.

Satapathy et al. (2024) and Lee et al. (2024) observed that AI-generated treatment plans closely matched clinical assessments, with low changes in implant location and angulation, thereby indicating AI's dependability in preoperative planning. With good diagnostic accuracy (AUC = 0.954), automated deep learning models (DCNNs) also outperformed dental practitioners in categorising dental implant systems (DISs) from radiographic images (Lee et al., 2020). These results highlight how artificial intelligence may lower human error and standardise diagnosis procedures, especially in complicated cases needing great accuracy.

Our results are consistent with the results In narrative review on artificial intelligence in periodontology and implantology, Khan et al. discovered that AI improved implant treatment planning, type of implant identification, design enhancement, and prognosis of implant treatment results.(31).

In a systematic review, Macrì et al. assessed the current material on the use of artificial intelligence in dental implant treatment schemes. Dentists are more and more interested in using artificial intelligence for implant rehabilitations. According to the data at hand, artificial intelligence (AI) implant planning improved predictability and accuracy over more traditional approaches. AI aids in implant planning, automated bone recognition, surrounding structural analysis including teeth, maxillary sinus, and neural structure, AI has certain restrictions since it requires conventional training and its procedures lack regularity(32).

To evaluate implant dentistry artificial intelligence utilisation, Revilla-León et al. carried out another rigorous study. They attained a precision of 93.8 to 98% with the AI replicas created using radiographs (panoramic and periapical) to identify the type of implant. Designed using several input data, the models ranging from 62.4 to 80.5% predict the success of osseointegration. Artificial intelligence models maximise implant designs agreed with their relevance in improving the design of implants. At the intersection between implant and bone, the pressures seem to drop 36.6% unlike finite element models(10).

Moraschini et al. established the systematic evidence accessible to identify uses and accuracy of artificial intelligence in dental implants, therefore doing a scoping study. Two most often used artificial intelligence applications were the identification of several systems in implants and surgical planning of implants. With a mean of 88.7%, AI models performed really well; prediction models for marginal bone loss displayed an accuracy up to a mean of 93%(33).

Our results showed, Moraschini et al. mapped the systematic evidence accessible to identify uses and accuracy of artificial intelligence in dental implants, therefore doing a scoping study. Two most often used AI applications were the identification of various systems in implants and surgical planning of implants. With a mean of 88.7%, AI models performed really well; prediction models for marginal bone loss displayed an accuracy up to a mean of 93%(24).

But as Saeed et al. (2023) point out, these developments call for strict ethical and legal systems to handle data privacy, algorithmic bias, and cost restrictions. The variation in study designs between numerical simulations and randomised controlled trials (RCTs) emphasizes the need of consistent measurements to assess therapeutic efficacy of artificial intelligence(11).

Studies include Papantonopoulos et al. (2016) and Petrykiv et al. (2008) used artificial intelligence to find implant "phenotypes" and peri-implantitis predictors, therefore exposing clusters of high- and low-risk patients. For instance, important predictors of bone loss (IIMBL) were factors including plaque score, diabetes, and degree of periodontitis.(23).

This result in line with study conducted by Elgarba et al. 8 also conducted a review with an eye towards applying artificial intelligence to preoperative dental implant treatment strategies. They also assessed the degree of automation of the presurgical implant treatment plans' software employed clinically. They discovered that virtual patients are created in part by time saving, accurate, compatible division of anatomical markers discovered with artificial intelligence. The devices now in use for implant placement virtually displayed differing degrees of automation(34).

VI. FUTURE FOCUS AND RESEARCH AVENUES:

AI-Driven Personalized Medicine:Personalized medicine's promise for dental implantology will define AI going forward.

By means of a broad spectrum of patient data analysis, artificial intelligence algorithms can generate customized therapy recommendations that take individualized anatomy, medical history, and lifestyle aspects into account. AI-driven personalized treatment plans will result in improved long-term outcomes(35).

Real-Time AI Assistance in Complex Cases**:** As artificial intelligence develops, its function in real-time surgical aid will becoming more important in complex situations. AI can offer real-time changes during surgery in complex circumstances such patients with damaged bone structure or many missing teeth, thereby enabling doctors to negotiate challenging anatomical aspects with more ease(35).

AI in Minimally Invasive Procedures**:** Advancement of minimally invasive implant techniques is also likely to depend much on AI. AI can help lower the invasiveness of implant operations by offering very accurate diagnostic insights and real-time guidance, thereby promoting faster recovery periods and less complication(35).

VII. LIMITATIONS AND CHALLENGES IN IMPLEMENTING AI IN DENTAL IMPLANTOLOGY

Successful clinical adoption of artificial intelligence (AI) into dental implantology depends on addressing important ethical and regulatory issues related to this field. The lack of consistent regulatory systems controlling artificial intelligence applications in dentistry raises questions regarding the safety, efficacy, and consistency of AI-driven diagnosis and treatment planning instruments(36). Moreover, ethical issues related to patient data protection, informed permission, and adherence to laws including the General Data Protection Regulation (GDPR) have to be closely addressed to guaranteeresponsible use of AI technology and preserve patient confidence.

The necessity of specific professional training to enable the efficient implementation of artificial intelligence in clinical practice presents even another important obstacle. To properly interpret AI-generated recommendations and include them into evidence-based decision-making, dental practitioners need thorough knowledge on artificial intelligence system capabilities(36).

To close the knowledge gap and maximize the clinical use of artificial intelligence in implantology, organized training programs together with multidisciplinary cooperation between dental practitioners, AI developers, and regulatory authorities will be crucial. Realizing the full possibilities of artificial intelligence while preserving high standards of patient care and ethical behavior depends on tackling these difficulties.

VIII. CONCLUSION:

The integration of artificial intelligence (AI) integration into dental implantology improves diagnosis precision, treatment planning, surgical accuracy, and postoperative monitoring. Notwithstanding current difficulties including ethical conundrums, regulatory uncertainty, and the necessity for clinician training.

REFERENCES:

[1]. Carrillo-Perez F, Pecho OE, Morales JC, Paravina RD, Della Bona A, Ghinea R, et al. Applications of artificial intelligence in dentistry: A comprehensive review. J Esthet Restor Dent. 2022;34(1):259–80.

[2]. Mladenovic R, Kalevski K, Davidovic B, Jankovic S, Todorovic VS, Vasovic M. The role of artificial intelligence in the accurate diagnosis and treatment planning of non-syndromic supernumerary teeth: a case report in a six-year-old boy. Children. 2023;10(5):839.

[3]. Alqutaibi AY, Algabri RS, Alamri AS, Alhazmi LS, Almadani SM, Alturkistani AM, et al. Advancements of artificial intelligence algorithms in predicting dental implant prognosis from radiographic images: A systematic review. J Prosthet Dent. 2024;

[4]. Gulshan V, Peng L, Coram M, Stumpe MC, Wu D, Narayanaswamy A, et al. Development and validation of a deep learning algorithm for detection of diabetic retinopathy in retinal fundus photographs. jama. 2016;316(22):2402–10.

[5]. LeCun Y, Bengio Y, Hinton G. Deep learning. nature 521, 436–444 (2015). Sci Rep. 2023;13:15925.

[6]. Lee J-H, Kim D-H, Jeong S-N, Choi S-H. Detection and diagnosis of dental caries using a deep learning-based convolutional neural network algorithm. J Dent. 2018;77:106–11.

[7]. Ahmed R. The Role of Artificial Intelligence in Modern Dentistry: Transforming Diagnosis and Treatment Planning. Dentistry. 2025;1:100001.

[8]. Ossowska A, Kusiak A, Świetlik D. Artificial intelligence in dentistry—Narrative review. Int J Environ Res Public Health. 2022;19(6):3449.

[9]. Monterubbianesi R, Tosco V, Vitiello F, Orilisi G, Fraccastoro F, Putignano A, et al. Augmented, virtual and mixed reality in dentistry: a narrative review on the existing platforms and future challenges. Appl Sci. 2022;12(2):877.

[10]. Revilla-León M, Gómez-Polo M, Vyas S, Barmak BA, Galluci GO, Att W, et al. Artificial intelligence applications in implant dentistry: A systematic review. J Prosthet Dent. 2023;129(2):293–300.

[11]. Alshadidi AAF, Alshahrani AA, Aldosari LIN, Chaturvedi S, Saini RS, Hassan SA Bin, et al. Investigation on the application of artificial intelligence in prosthodontics. Appl Sci. 2023;13(8):5004.

[12]. Hassani H, Amiri Andi P, Ghodsi A, Norouzi K, Komendantova N, Unger S. Shaping the future of smart dentistry: From Artificial Intelligence (AI) to Intelligence Augmentation (IA). IoT. 2021;2(3):510–23.

[13]. Moher D, Liberati A, Tetzlaff J, Altman DG, Group P. Preferred reporting items for systematic reviews and meta-analyses: the PRISMA statement. Int J Surg. 2010;8(5):336–41.

[14]. Areqi, Abdullah Ahmed, et al. "Evaluation of the in vivo subacute toxicity of Otolith as a novel traditional hypoglycemic agent." Indian Journal of Traditional Knowledge (IJTK) 24.6 (2025): 536-542..

[15]. Satapathy SK, Kunam A, Rashme R, Sudarsanam PP, Gupta A, Kumar HSK. AI-Assisted Treatment Planning for Dental Implant Placement: Clinical vs AI-Generated Plans. J Pharm Bioallied Sci. 2024;16(Suppl 1):S939.

[16]. Joshi N, Patil S, Dhatrak P. Design and development of porous titanium alloy dental implant: A review. In: AIP Conference Proceedings. AIP Publishing; 2025.

[17]. Park J-H, Moon HS, Jung H-I, Hwang J, Choi Y-H, Kim J-E. Deep learning and clustering approaches for dental implant size classification based on periapical radiographs. Sci Rep. 2023;13(1):16856.

[18]. Widmann G, Stoffner R, Keiler M, Zangerl A, Widmann R, Puelacher W, et al. A laboratory training and evaluation technique for computer-aided oral implant surgery. Int J Med Robot Comput Assist Surg. 2009;5(3):276–83.

[19]. Rajan RSS, Kumar HSK, Sekhar A, Nadakkavukaran D, Feroz SMA, Gangadharappa P. Evaluating the role of AI in predicting the success of dental implants based on preoperative CBCT images: A randomized controlled trial. J Pharm Bioallied Sci. 2024;16(Suppl 1):S889–91.

[20]. Lee J-H, Yun J-H, Kim Y-T. Deep learning to assess bone quality from panoramic radiographs: The feasibility of clinical application through comparison with an implant surgeon and cone-beam computed tomography. J Periodontal Implant Sci. 2024;54(5):349.

[21]. Zheng G, Gu L, Wu Z, Huang Y, Kang L. The implementation of an integrated computer-aided system for dental implantology. In: 2008 30th Annual International Conference of the IEEE Engineering in Medicine and Biology Society. IEEE; 2008. p. 58–61.

[22]. Lee J-H, Kim Y-T, Lee J-B, Jeong S-N. A performance comparison between automated deep learning and dental professionals in classification of dental implant systems from dental imaging: a multi-center study. Diagnostics. 2020;10(11):910.

[23]. Papantonopoulos G, Gogos C, Housos E, Bountis T, Loos BG. Prediction of individual implant bone levels and the existence of implant "phenotypes." Clin Oral Implants Res. 2017;28(7):823–32.

[24]. Mangano FG, Admakin O, Lerner H, Mangano C. Artificial intelligence and augmented reality for guided implant surgery planning: a proof of concept. J Dent. 2023;133:104485.

[25]. Farroukh H, Kaddah F, Wehbe T. Numerical investigation of the optimal porosity of titanium foam for dental implants. Heliyon. 2024;10(6).

[26]. Areqi, Abdullah Ahmed, Doa'a Anwar Ibrahim, and Mohamed Salama. "Postulated anti-diabetic effect of fish ear stone (Otolith) in experimental animals." Journal of Chemical and Pharmaceutical Research 7.9 (2015): 518-525.27. Mangano FG, Yang KR, Lerner H, Admakin O, Mangano C. Artificial intelligence and mixed reality for dental implant planning: A technical note. Clin Implant Dent Relat Res. 2024;26(5):942–53.

[27]. 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;6:1–6.

[28]. Bountis T, Loos BG. Prediction of individual implant bone levels and the existence of implant "phenotypes." 2016;

[29]. Quispe-López N, Guadilla Y, Gómez-Polo C, López-Valverde N, Flores-Fraile J, Montero J. The influence of implant depth, abutment height and mucosal phenotype on peri‑implant bone levels: A 2-year clinical trial. J Dent. 2024;148:105264.

[30]. Khan SF, Siddique A, Khan AM, Shetty B, Fazal I. Artificial intelligence in periodontology and implantology—A narrative review. J Med Artif Intell. 2024;7.

[31]. Macrì M, D'Albis V, D'Albis G, Forte M, Capodiferro S, Favia G, et al. The role and applications of Artificial Intelligence in Dental Implant Planning: a systematic review. Bioengineering. 2024;11(8):778.

[32]. Moraschini V, de Almeida DCF, Louro RS, de Oliveira Silva AM, Neto MPC, Dos Santos GO, et al. Accuracy of artificial intelligence in implant dentistry: A scoping review with systematic evidence mapping. J Prosthet Dent. 2024;

[33]. Elgarba BM, Fontenele RC, Tarce M, Jacobs R. Artificial intelligence serving pre-surgical digital implant planning: A scoping review. J Dent. 2024;143:104862.

[34]. Ali MA. The Role of Artificial Intelligence in Modern Dentistry: Applications, Challenges, and Future Directions. Futur Dent Res. 2024;2(2):39–49.

[35]. Ong JCL, Chang SY-H, William W, Butte AJ, Shah NH, Chew LST, et al. Ethical and regulatory challenges of large language models in medicine. Lancet Digit Heal. 2024;6(6):e428–32.