Open Access Research Journal of
Biology and Pharmacy
Journals home page: https://oarjbp.com/
ISSN: 2782-9979 (Online)

OARJ OPEN ACCESS RESEARCH JOURNALS

(Review Article)

Check for updates

Applications of artificial intelligence in dental implant detection and planning: A narrative review

Shahed Nournia [1] and Soheila Zarean Dolatabadi [2,*]

[1] *Researcher, School of Dentistry, Shahid Beheshti University of Medical Sciences, Tehran, Iran.*
[2] *Researcher, School of Dentistry, Tehran University of Medical Sciences, Tehran, Iran.*

Open Access Research Journal of Biology and Pharmacy, 2026, 17(01), 029-036

Publication history: Received on 02 April 2026; revised on 12 May 2026; accepted on 15 May 2026

Article DOI: https://doi.org/10.53022/oarjbp.2026.17.1.0033

Abstract

In recent decades, Implant dentistry has seen remarkable development across the globe. The field of implantology has revolutionized dentistry significantly, especially in the rehabilitation of single, complete and partial edentulism. Conventionally, practitioners utilize periapical radiographs, panoramic imaging, CBCT scans and periapical radiographs to assess implant locations. CBCT is particularly important as it provides 3D data about density, width, bone height and closeness to vital anatomical structures. This narrative review explores the current applications of AI in dental implant planning and detection, with emphasis on cone-beam computed tomography (CBCT), intraoral scanning, and image-guided system. Machine learning and deep learning enable automated segmentation, virtual planning, and improved surgical precision. Despite strong performance, limitations include data dependency, low transparency, and need for validation. Future work will focus on multimodal systems, real-time guidance, and robotic-assisted implant placement. Overall, AI is making implant dentistry more precise, efficient, and data-driven.

Keywords: Artificial intelligence; Dentistry; Dental Implant; Prognosis; Planning

1. Introduction

Dental implants serve as a reliable treatment option for replacing missing teeth. Their use in the management of complete and partial edentulism is considered an essential approach in modern dentistry. Compared with conventional fixed partial dentures, dental implants offer several advantages, including an overall success rate exceeding 97% over 10 years, a reduced risk of endodontic complications and caries in adjacent teeth, improved preservation of bone at the edentulous site, and decreased sensitivity in the surrounding dentition. (1)

In recent decades, Implant dentistry has seen remarkable development across the globe. The field of implantology has revolutionized dentistry significantly, especially in the rehabilitation of single, complete and partial edentulism. There are numerous studies reporting better quality of life in patients after implant therapy. Detailed planning prior the implant procedure improves the outcomes of the treatment because of the facility of placing in the proper site of the implant and reducing the operative risks.

Conventionally, practitioners utilize periapical radiographs, panoramic imaging, CBCT scans and periapical radiographs to assess implant locations. CBCT is particularly important as it provides 3D data about density, width, bone height and closeness to vital anatomical structures. Since being introduced to dentistry in the terminal years of the twentieth century, CBCT has been established as extensively utilized in maxillofacial surgery, orthodontics, endodontics and implant planning, due to its detailed visualization abilities

* Corresponding author: Soheila Zarean Dolatabadi

Ongoing advancements in imaging sensors, reconstruction algorithms and X-ray tube configuration are anticipated to improve image clarity by minimizing artefacts and noise while also lowering radiation exposure for patients. These advancements may enable practitioners to obtain more precise visuals with improved efficiency and safety. However, manual interpretation of CBCT data demands considerable workload and is influenced by disparities in operator performance.

Artificial intelligence provides a viable solution for these challenges. In general terms, Artificial intelligence denotes digital systems that extract regularities from information sets and apply those structures for forecasting or judgment formation. In dental practice, computational intelligence has turned more valuable for improving diagnostic precision and treatment organization. In implant practice, computational frameworks can examine clinical records, CBCT scans and radiographic images to guide clinicians in selecting appropriate implant orientation, location and dimension. Computational learning techniques generally handle structured and tagged datasets, whereas deep neural frameworks, especially convolution-based networks, are capable of acquiring knowledge from raw visual data and and performing strong image analysis (2-7)

This narrative examination centers particularly on two swiftly advancing applications of machine intelligence in implant therapy: implant planning and implant detection. Artificial intelligence–based implant recognition involves locating or classifying fixtures on two-dimensional X-ray images, whereas implant planning includes AI-guided cone-beam evaluation, structural segmentation, site evaluation, and preoperative guidance (5,6). These uses constitute a key segment of the overall application of machine intelligence in implant field, which additionally involves assisted surgery, result forecasting and restoration design,

A narrative review Is significant since research studies in this domain has increased quickly from 2020 to 2025. Several studies demonstrate promising precision and efficiency results yet techniques and clinical readiness vary greatly. Reviewing current findings can assist researchers and clinicians in identifying areas where AI is valuable and where more confirmation remains needed.

2. AI Applications in Implant Detection

2.1. Detection and Classification of Dental Implants in Radiographs

Machine intelligence has exhibited notable potential in recognition and categorization of oral fixtures with two-dimensional imaging records, mainly periapical and panoramic X-ray images. Such radiographic approaches are routinely applied in dental clinics because they remain commonly accessible, economically efficient, involve less radiation exposure than volumetric methods (8, 9, 10)

Nevertheless, recognizing implant systems through manual review can be difficult when prior treatment files are unavailable or image resolution is weak. The majority of intelligent platforms created for this aim utilize convolutional learning frameworks, particularly convolution-based networks, prepared with large labeled image repositories to identify variations in fixture form, connection configuration and spiral configuration (10, 11)

Current investigations have documented combined correctness varying between 67% and 98.5%, while many frameworks reaching beyond 90%. Across numerous evaluations, automated systems showed stronger performance compared with oral specialists, while professional outcomes further increased when aided by machine intelligence. Practical uses in newly presenting individuals, assistance for selecting suitable prosthetic components, organization of scientific imaging databases and forensic identification. Relative to hand-operated approaches, automated platforms offer faster assessment, higher uniformity, and less reliance on operator skill (10)

2.2. Limitations and Special Cases

A fundamental drawback present in that most studies relying on validated DIS datasets may not represent real-world DIS identification when dealing with degraded and geometrically distorted dental radiographic images commonly present in routine clinical settings.

A systematic analysis by Wael I. Ibraheem (2024) emphasized significant limitations in artificial intelligence–driven dental implant categorization. The existence of diverse implant varieties generates challenges in precise classification and recognition, particularly when earlier clinical records are unavailable or absent (10)

Two-dimensional dental imaging (2D) including intraoral X-ray images and panoramic radiographs is commonly utilized in regular diagnostic assessment and provides strong spatial clarity for detecting conditions like periodontal bone reduction and dental decay. However, it shows notable limits in detection because of overlapping anatomical features and lack of accurate three-dimensional relationships. Conversely, cone beam computed tomography as a three-dimensional modality provides improved visualization of hard tissues and permits precise depiction of complicated anatomical formations using multiplanar imaging, which markedly improves identification of periapical abnormalities, osseous defects, dental root fractures, and other concealed conditions thatoften overlooked in two-dimensional imaging. Hence, although two-dimensional imaging is beneficial for general evaluation, 3D imaging delivers offer superior diagnostic efficiency in complex cases (12).

3. AI Applications in Implant Planning

3.1. Automated Anatomical Structure Segmentation in CBCT

As stated in the Oral Disease Survey, almost 90% of the individuals worldwide are experiencing various severities of dental disease, with many requiring clinical care (13). Within clinical dental management, diagnostic imaging using various techniques such as cone beam computed tomography, panoramic radiographs and intraoral three-dimensional scans is frequently obtained to assist diagnosis, surgical intervention and treatment planning.

Within the available modalities, CBCT imaging remains the method that delivers full three-dimensional volumetric data of teeth and surrounding alveolar bone. Therefore, separating each tooth along with alveolar bone from CBCT scans to create an accurate three-dimensional model is required in digital dental practice.

Even though automated delineation of dental and alveolar structures has been widely explored in medical image analysis, it remains a practically and technically difficult issue with no clinically usable system. Throughout the previous decade, numerous approaches have been studied to construct manually engineered descriptors, including contour evolution, shape fitting models and graph partitioning, for dental structure segmentation (14-17)

Such low-level descriptors are vulnerable to intricate visual patterns in CBCT dental images, such as minimal contrast between dental structures and adjacent tissue, thereby demanding considerable manual intervention for initialization or correction.In recent years, deep learning methods, particularly those built on convolutional neural networks, have exhibited promising use in many areas owing to their capability to learn meaningful and predictive features from extensive datasets for specific tasks (17-20) . Inspired by the significant achievements of deep learning in visual computing and medical image analysis, a number of studies have explored deep neural networks for segmentation of dental and bony structures (17, 21, 22, 23) Nevertheless, these current approaches remain not yet fully suitable or automated for clinical application due to three principal challenges. First, complete automated segmentation of alveolar and dental workflow that includes locating the dental region of interest, identifying alveolar bone and segmenting individual teeth. Prior research studies are unable to perform all steps in full automation, since they usually focus on isolated tasks like tooth segmentation in a predefined region of interest (17, 24, 25) or alveolar bone extraction (17). Second, managing complex cases commonly present in clinical practice is difficult, including CBCT images showing large structural variations in patients with malocclusion, missing teeth, and metallic interference. Third, earlier studies are generally assessed on limited datasets, usually 10–30 CBCT scans, restricting their performance when generalize across diverse imaging protocols and clinical populations (17).

3.2. Edentulous Area Detection and Bone Dimension Assessment

Evaluation of residual alveolar ridge morphology and CBCT imaging may provide important insights for planning treatment and identifying the best implant position (26). Standard radiographic approaches, such as periapical and panoramic radiographs are restricted in assessing buccolingual width and anatomical form owing to their flat imaging format. Recent improvements in tomographic imaging techniques, particularly CBCT, has gained growing importance (27). Tözüm et al. examined the association between mandibular alveolar ridge form and implant placement complexity in the posterior jaw through CBCT imaging, underscoring the significance of assessing ridge variability for proper implant planning (28) In the same way, Goudarzi et al. carried out an extensive evaluation of posterior mandibular ridge form, organizing it into 14 different types, according to form and attributes, presenting a comprehensive basis for clinical assessment (26). However, despite these findings, no prior investigation has provided a complete comprehensive multidimensional characterization of the mandibular ridge, especially in the posterior edentulous jaw. This lack of information leads to direct implications in patient management.

The absence of a comprehensive and uniform structural classification limits diagnostic accuracy before surgery and complicates planning for implant placement. Without well-defined reference markers for cortical thickness, concavity depth, or ridge width clinicians may overlook hazards such as compromised bone integration, lingual plate breach and inadequate initial stability. Hence, identifying categorizing these anatomical structures through CBCT may enhance surgical decision-making, reduce surgical errors during procedures and guide augmentation planning. An in-depth insight into cortical bone characteristics and posterior mandibular ridge structure, as analyzed by CBCT, is crucial for enhancing implant success and maintaining patient safety. Integrating these parameters into preoperative assessment can guide clinicians in choosing ideal implant angle and placement, identifying augmentation requirements and protecting critical anatomical structures. Earlier research has not fully and comprehensively described the mandibular ridge across all its attributes and classification schemes. Additionally, the precise structure and prevalence of ridge types in dentate areas, especially those suitable for immediate implant placement, are still not adequately investigated (29)

3.3. Virtual Implant Positioning and Treatment Planning

The success of dental implant procedures depend greatly on proper planning before surgery. The use of three-dimensional imaging techniques, like intraoral scanning and cone beam CT has significantly improved clinicians' capacity to assess patient-specific anatomy Furthermore, progress in digital systems for processing imaging information has improved the accuracy and clinical applicability of implant planning These developments enable accurate implementation of virtual strategies into clinical workflow utilizing computer-aided manufacturing and computer-aided design to produce surgical templates for partially and fully assisted implant positioning (30, 31, 32)

As dental technologies rapidly evolve, clinicians often struggle to match the pace of updated digital workflows. Proficiency in these technologies generally demands considerable training and time, and even after that, incorporating them into clinical workflows may remain an extensive process. In addition, differences in clinical expertise and experience may result in inconsistent implant planning, introducing bias that compromise the consistency and reproducibility of outcomes. As a result, artificial intelligence (AI) has been introduced to simplify different steps of pre-surgical planning workflows and reduce clinician burden. Through automation of complex processes, AI can significantly improve time efficiency, enabling clinicians to subsequently focus on assessing, endorsing, or refining implant planning outcomes (32)

In computerized implant workflows, has been confirmed as useful for various tasks in preoperative planning. These tasks involve delineation of jaws, maxillary sinus regions, mandibular canal, and prosthetic crowns, together with fusion of CBCT and intraoral scan data in multiple cases (32-34)

AI can eventually produce a treatment plan aligned with individual anatomy using full virtual modeling obtained through CBCT–IOS data anatomical fusion workflows]. AI has shown strong precision in maxillofacial segmentation tasks, achieving accuracies between 92% and 99.7, along with IOS–CBCT registration with a point error of 0.21 mm and 0.22 mm surface-based deviation (32)

AI shows significant capabilities in implant planning workflows, such as analyzing bone density and quality, segmenting anatomical structures automatically, and identification of critical structures like nerves and maxillary sinuses (35). AI-based decision-support tools can propose implant placement by recommending suitable positions, drilling protocols and angulations according to patient-specific bone features, leading to greater accuracy and minimizing operator variation. Moreover, combining AI with virtual and augmented reality has enhanced visualization during surgery and patient interaction, enabling real-time modeling of implant placement cases. Recent research indicates that AI-supported virtual implant planning reaches approximately 93% clinical acceptability, highlighting its feasibility and rising importance in digital implantology in dentistry (32, 35-37)

3.4. Emerging Integrations.

Artificial intelligence (AI) is transforming implant positioning via employing cutting-edge algorithms to interpret information and control procedures, wherein machine learning methods evaluate 3D imaging data, tissue datasets and digital impressions to define optimal implant sites with high precision (38, 39). It handles major tasks like defining bone structures prior to surgery and adjusting drill pathways intraoperatively, producing highly accurate and reliable outcomes. Conventional implant placement based on freehand techniques guided by surgeon expertise and two-dimensional imaging, frequently resulting in complications including nerve injury, implant failure and sinus perforation. This resulted in the emergence of computer-assisted implant surgery (CAIS), initially using static guides derived from CBCT imaging; however, these surgical guides are fixed and can be dislodged during operations. Dynamic guidance systems were subsequently developed to enable live visual monitoring of drilling tools; however, they still need operator adjustment and are impacted by patient motion and adjacent soft tissues. Navigation platforms have evolved into AI-augmented platforms that enhance surgical accuracy, comprising robotic systems that merge AI with mechanical regulation to achieve precise implant placement. These developments, combined with CBCT-based datasets and intraoral scans are moving toward integrated "single-click" processes where execution, guidance and planning become progressively automated. In the future, integrating artificial intelligence with systems Involving augmented reality may further enhance clinical accuracy and visualization across dental implant positioning

AI-based implant navigation systems demonstrate strong performance despite advancements, offering faster workflows, high precision and improved consistency with errors lowered to below 2 degrees and 0.5 mm. However, key limitations persist, such as the "black-box", behavior of AI-based decision-making. (38, 39)

4. Future Directions

Artificial intelligence has transformed from a theoretical idea into a practical tool that is increasingly impacting modern dentistry. In digital implantology, AI and machine learning approaches have demonstrated considerable potential in improving workflow processes particularly through evaluation of CBCT imaging and intraoral scan datasets. These technologies allow more precise anatomical assessment, improved treatment planning, more predictable surgical results.

AI-derived implant systems demonstrate strong performance by improving workflow speed, overall accuracy and consistency with conventional methods. Implant positioning errors have been markedly decreased demonstrating the enhanced reliability of these systems in clinical use. Although these improvements are significant, challenges including the "black-box" AI-based decision processes, demand for extensive validation and reliance on high-quality data still persist.

Future advancements are likely to emphasize on multimodal AI systems that combine individualized clinical data, intraoral scans and CBCT datasets to generate more complete virtual models. Furthermore, real-time surgical guidance, robotic implant placement and augmented reality systems are expected to further enhance surgical accuracy and imaging. Extensive multi-center validation studies will be necessary to ensure the safety, generalizability and accuracy of such innovations across multiple clinical contexts.

5. Conclusion

Artificial intelligence is becoming an increasingly important component of digital implant dentistry. Current evidence suggests that AI-based systems can support implant detection, implant classification, anatomical segmentation, CBCT interpretation, virtual implant positioning, and image-guided surgical planning. By improving the speed, consistency, and accuracy of radiographic assessment and preoperative planning, these technologies may help clinicians reduce operator-dependent variability and improve treatment predictability.

Despite these promising developments, AI should currently be regarded as a supportive tool rather than a replacement for clinical judgment. Important limitations remain, including dependence on high-quality and diverse datasets, reduced transparency of decision-making processes, variation among imaging protocols, and the need for broader clinical validation. Future research should focus on multicenter studies, standardized datasets, real-time navigation, multimodal integration of CBCT and intraoral scan data, and the safe incorporation of robotic and augmented reality systems into implant workflows.

Overall, AI has the potential to make dental implant planning and detection more accurate, efficient, and patient-specific. However, its successful clinical implementation will depend on careful validation, ethical use, clinician supervision, and integration into practical digital workflows.

Compliance with ethical standards

Disclosure of conflict of interest

No conflict of interest to be disclosed.

References

[1] Buser D, Sennerby L, De Bruyn H. Modern implant dentistry based on osseointegration: 50 years of progress, current trends and open questions. Periodontol 2000. 2017 Feb;73(1):7-21. Doi: 10.1111/prd.12185. PMID: 28000280.

[2] Kurt Bayrakdar, S., Orhan, K., Bayrakdar, I. S., Bilgir, E., Ezhov, M., Gusarev, M., & Shumilov, E. (2021). A deep learning approach for dental implant planning in cone-beam computed tomography images. BMC medical imaging, 21(1), 86. https://doi.org/10.1186/s12880-021-00618-z

[3] Dashti, M., Londono, J., Ghasemi, S., Tabatabaei, S., Hashemi, S., Baghaei, K., Palma, P. J., & Khurshid, Z. (2025). Evaluation of accuracy of deep learning and conventional neural network algorithms in detection of dental implant type using intraoral radiographic images: A systematic review and meta-analysis. The Journal of Prosthetic Dentistry, 133(1), 137–146. Epub 2024 Jan 4. PMID: 38176985. https://doi.org/10.1016/j.prosdent.2023.11.030

[4] Dashti, M., Amirfarhangi, S., & Soleymanpourshamsi, T. (2026). Letter to the Editor regarding, "Comparing the performance of ChatGPT 4o, DeepSeek R1, and Gemini 2 Pro in answering fixed prosthodontics questions over time" by Shirani. The Journal of Prosthetic Dentistry. https://doi.org/10.1016/j.prosdent.2026.01.027

[5] Pauwels, R., Araki, K., Siewerdsen, J. H., & Thongvigitmanee, S. S. (2015). Technical aspects of dental CBCT: state of the art. Dento maxillo facial radiology, 44(1), 20140224. https://doi.org/10.1259/dmfr.20140224

[6] Dashti, M., Khosraviani, F., Ghadimi, N. et al. Use of artificial intelligence for detection of MB2 canals in maxillary first molars on CBCT: a systematic review and meta-analysis. BMC Oral Health 25, 1860 (2025). https://doi.org/10.1186/s12903-025-07254-x

[7] Dashti M, Londono J, Ghasemi S, et al. Attitudes, knowledge, and perceptions of dentists and dental students toward artificial intelligence: a systematic review. J Taibah Univ Med Sci. 2024;19(2):327–37. https://doi.org/10.1016/j.jtumed.2023.12.010

[8] Sukegawa, S., Yoshii, K., Hara, T., Tanaka, F., Yamashita, K., Kagaya, T., ... & Furuki, Y. (2022). Is attention branch network effective in classifying dental implants from panoramic radiograph images by deep learning?. PLoS One, 17(7), e0269016.

[9] Kong, H. J., Eom, S. H., Yoo, J. Y., & Lee, J. H. (2023). Identification of 130 Dental Implant Types Using Ensemble Deep Learning. The International journal of oral & maxillofacial implants, 38(1), 150–156. https://doi.org/10.11607/jomi.9818

[10] Ibraheem W. I. (2024). Accuracy of Artificial Intelligence Models in Dental Implant Fixture Identification and Classification from Radiographs: A Systematic Review. Diagnostics (Basel, Switzerland), 14(8), 806. https://doi.org/10.3390/diagnostics14080806

[11] Al-Wahadni, A., Barakat, M. S., Abu Afifeh, K., & Khader, Y. (2018). Dentists' Most Common Practices when Selecting an Implant System. Journal of prosthodontics : official journal of the American College of Prosthodontists, 27(3), 250–259. https://doi.org/10.1111/jopr.12691

[12] Yoo, Y. S., Kim, D., Yang, S., Kang, S. R., Kim, J. E., Huh, K. H., Lee, S. S., Heo, M. S., & Yi, W. J. (2023). Comparison of 2D, 2.5D, and 3D segmentation networks for maxillary sinuses and lesions in CBCT images. BMC oral health, 23(1), 866. https://doi.org/10.1186/s12903-023-03607-6

[13] Jin, L. J., Lamster, I. B., Greenspan, J. S., Pitts, N. B., Scully, C., & Warnakulasuriya, S. (2016). Global burden of oral diseases: emerging concepts, management and interplay with systemic health. Oral diseases, 22(7), 609-619.

[14] Gan, Y., Xia, Z., Xiong, J., Zhao, Q., Hu, Y., & Zhang, J. (2015). Toward accurate tooth segmentation from computed tomography images using a hybrid level set model. Medical physics, 42(1), 14-27.

[15] Gan, Y., Xia, Z., Xiong, J., Li, G., & Zhao, Q. (2017). Tooth and alveolar bone segmentation from dental computed tomography images. IEEE journal of biomedical and health informatics, 22(1), 196-204.

[16] Keyhaninejad, S., Zoroofi, R., Setarehdan, S. & Shirani, G. Automated segmentation of teeth in multi-slice CT images. International Conference on Vis. Inf. Eng. (2006).

[17] Cui, Z., Fang, Y., Mei, L., Zhang, B., Yu, B., Liu, J., Jiang, C., Sun, Y., Ma, L., Huang, J., Liu, Y., Zhao, Y., Lian, C., Ding, Z., Zhu, M., & Shen, D. (2022). A fully automatic AI system for tooth and alveolar bone segmentation from cone-beam CT images. Nature communications, 13(1), 2096. https://doi.org/10.1038/s41467-022-29637-2

[18] Deng, J. et al. Imagenet: a large-scale hierarchical image database. In 2009 IEEE Conference on Computer Vision and Pattern Recognition, 248–255 (IEEE, 2009).

[19] Krizhevsky, A., Sutskever, I., & Hinton, G. E. (2017). ImageNet classification with deep convolutional neural networks. Communications of the ACM, 60(6), 84-90.

[20] Shen, D., Wu, G., & Suk, H. I. (2017). Deep learning in medical image analysis. Annual review of biomedical engineering, 19, 221-248.

[21] Cui, Z., Li, C., & Wang, W. (2019). ToothNet: Automatic tooth instance segmentation and identification from cone beam CT images. Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition, 6368–6377.

[22] Chung, M., et al. (2020). Pose-aware instance segmentation framework from cone beam CT images for tooth segmentation. Computers in Biology and Medicine, 120, 103720.

[23] Jang, T. J., Kim, K. C., Cho, H. C., & Seo, J. K. (2022). A Fully Automated Method for 3D Individual Tooth Identification and Segmentation in Dental CBCT. IEEE transactions on pattern analysis and machine intelligence, 44(10), 6562–6568. https://doi.org/10.1109/TPAMI.2021.3086072

[24] Wu, X., et al. (2020). Center-sensitive and boundary-aware tooth instance segmentation and classification from cone-beam CT. In 2020 IEEE 17th International Symposium on Biomedical Imaging (ISBI) (pp. 939–942). IEEE.

[25] Yang, Y., et al. (2021). Accurate and automatic tooth image segmentation model with deep convolutional neural networks and level set method. Neurocomputing, 419, 108–125.

[26] Goudarzi, F., Anbiaee, N., & Shakeri, M. T. (2024). Comprehensive view of the posterior mandibular ridge morphology. International journal of oral and maxillofacial surgery, 53(2), 170–177. https://doi.org/10.1016/j.ijom.2023.03.012

[27] Chen, L. C., Lundgren, T., Hallström, H., & Cherel, F. (2008). Comparison of different methods of assessing alveolar ridge dimensions prior to dental implant placement. Journal of periodontology, 79(3), 401–405. https://doi.org/10.1902/jop.2008.070021

[28] Tözüm, M. D., Ataman-Duruel, E. T., Duruel, O., Nares, S., & Tözüm, T. F. (2022). Association between ridge morphology and complexity of implant placement planning in the posterior mandible. The Journal of prosthetic dentistry, 128(3), 361–367. https://doi.org/10.1016/j.prosdent.2020.07.034

[29] Yildirim, O., Eberlikose, H., & Gulen, O. (2025). Morphological and cortical bone assessment of the edentulous posterior mandible using CBCT Implications for implant planning and mandibular cortical index evaluation. BMC oral health, 25(1), 1893. https://doi.org/10.1186/s12903-025-06951-x

[30] Shujaat, S., Bornstein, M. M., Price, J. B., & Jacobs, R. (2021). Integration of imaging modalities in digital dental workflows – possibilities, limitations, and potential future developments. Dento maxillo facial radiology, 50(7), 20210268. https://doi.org/10.1259/dmfr.20210268

[31] Jacobs, R., Salmon, B., Codari, M., Hassan, B., & Bornstein, M. M. (2018). Cone beam computed tomography in implant dentistry: recommendations for clinical use. BMC oral health, 18(1), 88. https://doi.org/10.1186/s12903-018-0523-5

[32] B. M.Elgarba, R. C.Fontenele, E. A.Dawood, P.Lahoud, J.Meeus, and R.Jacobs, "Clinical Feasibility of AI-Driven Automated Virtual Dental Implant Placement: A Cross-Sectional Comparative Study," Clinical Implant Dentistry and Related Research27, no. 6 (2025): e70111, https://doi.org/10.1111/cid.70111

[33] Fontenele, R. C., Gerhardt, M. D. N., Picoli, F. F., Van Gerven, A., Nomidis, S., Willems, H., Freitas, D. Q., & Jacobs, R. (2023). Convolutional neural network-based automated maxillary alveolar bone segmentation on cone-beam computed tomography images. Clinical oral implants research, 34(6), 565–574. https://doi.org/10.1111/clr.14063

[34] Verhelst, P. J., Smolders, A., Beznik, T., Meewis, J., Vandemeulebroucke, A., Shaheen, E., Van Gerven, A., Willems, H., Politis, C., & Jacobs, R. (2021). Layered deep learning for automatic mandibular segmentation in cone-beam computed tomography. Journal of dentistry, 114, 103786. https://doi.org/10.1016/j.jdent.2021.103786

[35] Elgarba, B. M., Fontenele, R. C., Tarce, M., & Jacobs, R. (2024). Artificial intelligence serving pre-surgical digital implant planning: A scoping review. Journal of dentistry, 143, 104862. https://doi.org/10.1016/j.jdent.2024.104862

[36] Dashti M, Ghaedsharaf S, Ghasemi S, Zare N, Constantin EF, Fahimipour A, et al. Evaluation of deep learning and convolutional neural network algorithms for mandibular fracture detection using radiographic images: A systematic review and meta-analysis. Imaging Sci Dent. 2024;54(3):232–9. https://doi.org/10.5624/isd.20240038

[37] Dashti, M., Azimi, T., Khosraviani, F., Azimian, S., Bahanan, L., Zahmatkesh, H., Ashi, H., & Khurshid, Z. (2025). Systematic Review and Meta-Analysis on the Accuracy of Artificial Intelligence Algorithms in Individuals Gender Detection Using Orthopantomograms. International Dental Journal, 75(3), 2157–2168. https://doi.org/10.1016/j.identj.2024.12.018

[38] Macrì, M., D'Albis, V., D'Albis, G., Forte, M., Capodiferro, S., Favia, G., Alrashadah, A. O., García, V. D., & Festa, F. (2024). The Role and Applications of Artificial Intelligence in Dental Implant Planning: A Systematic Review. Bioengineering (Basel, Switzerland), 11(8), 778. https://doi.org/10.3390/bioengineering11080778

[39] Menon, S. S., Jacob, S. A., Eldho Paul, A., Kurumathur Vasudevan, A., Balakrishnan, B., Rajan Peter, M., & Suresh, R. (2026). Use of Artificial Intelligence in Dental Implant Navigation Systems: A Scoping Review. Cureus, 18(1), e100776. https://doi.org/10.7759/cureus.100776