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Artificial Intelligence and Data-Driven Innovations in Smart Oral Healthcare and Dental Imaging Systems: A Systematic Literature Review

Abstract
The technologies of artificial intelligence and data-driven have turned out to be instrumental in transforming the smart oral healthcare and dental imaging systems, improving diagnostic accuracy, simplifying workflow, and enabling digital treatment planning. The objective of this systematic literature review was to assess the use, performance and clinical relevance of AI driven innovations for dental imaging and smart oral care systems. The key issues which were examined were cone-beam computed tomography segmentation, automated dental imaging analysis, multimodal image fusion, creation of virtual patient and AI-assisted implant-planning systems. Systematic Search Strategy was performed based on PubMed and other scientific sources according to PRISMA framework. The following criteria were used to include the studies: An original research study, validation research study, comparative research study, systematic review or meta-analysis that have reported on the application of AI in dentistry or oral radiology. The number of studies for the qualitative synthesis was 10. The results showed that deep learning and CNN models performed high segmentation accuracy, faster processing time and better workflow reproducibility and minimised operator dependency. Multimodal integration, such as CBCT, intraoral scanning and facial imaging, further enhanced the creation of comprehensive digital dentistry ecosystems. However, due to the mixed nature of the datasets, explainability, standardization and regulatory issues are yet major hurdles to achieve broad implementation. Overall, the technologies developed with AI have significant promise in the future for supporting intelligent, personalized, and data-driven smart oral health systems.

1. Introduction

Smart oral healthcare is the result of the accelerated shift of traditional dentistry towards digitally empowered, data informed and technology assisted clinical practice. Digital dentistry has become a combination of imaging systems, intraoral scanning, artificial intelligence, automated diagnostic systems, and virtual treatment planning to enhance clinical accuracy and patient-centered care. AI has gained significance as a part of this change as it aids with diagnosis, prediction, treatment planning, and workflow automation in a variety of dental disciplines (Ahmed et al., 2021; Khanagar et al., 2021). Predominantly, previous digital and diagnostic research also suggests that the dental practice becomes more reliant on high-quality imaging, automated interpretation, and computer-assisted decision-making systems (Hung et al., 2020; Kim et al., 2020).

Cone-beam computed tomography has emerged as one of the most significant imaging modalities in contemporary oral health care due to the ability of the modality to give three-dimensional visualization of the teeth, alveolar bone, jaws, airway structures, and maxillofacial structures. CBCT has also been extensively applied in orthodontics, implantology, oral surgery, endodontics and restorative planning due to its ability to provide an anatomical evaluation that is more in-depth than two-dimensional radiographs. Recent research has indicated that artificial intelligence systems based on CBCT in the form of tooth, alveolar bone, and maxillofacial segmentation can be useful in the correct planning of the treatment and reduction of manual diagnostic load (Cui et al., 2022; Iacob et al., 2026). AI-powered CBCT tools have shown their importance as well in automated tooth identification, labelling, and edentulous area localization, which is crucial to digital charting and treatment simulation (do Nascimento Gerhardt et al., 2022).

The key forms of artificial intelligence in dental images are machine learning, deep learning, convolutional neural networks, U-Net (based) architectures, transformer models, and automated segmentation systems. Deep learning has already demonstrated good diagnostic capabilities in dental radiology, such as the identification of apical lesions, a loss of periodontal bone and dental caries (Ekert et al., 2019; Krois et al., 2019; Lee et al., 2018). Despite other successful uses of convolutional neural networks in non-dental medical segmentation, like prostate zonal MRI segmentation, their increased use in dental imaging is indicative of the increasing applicability of AI-based image analysis to health care (Jensen et al., 2019). These are specifically applied in the dentistry field to CBCT segmentation, tooth modelling, anatomical labelling, multimodal fusion, and constructing virtual patients (Fontenele, 2023; Jindanil et al., 2025).

Dentistry Manual image interpretation and segmentation is usually time consuming, operator dependent and subject to inter-observer variations. These limitations bring about the necessity to use automated tools that can enhance speed, consistency and reproducibility. Tooth and alveolar bone segmentation AI-based systems have shown significant efficiency improvements, with a still clinically acceptable level of accuracy (do Nascimento Gerhardt et al., 2022). Multimodal fusion using AI has also allowed automatic combination of CBCT-generated roots with intraoral scan-generated crowns to assist in more accurate digital tooth-modelling, and tailored treatment planning (Baldini et al., 2025). Likewise, AI-assisted virtual patients creation based on CBCT, MSCT, facial scans, and intraoral scans is indicative of the trend of complete digitalization of oral healthcare processes.

Although there is a rapid increase in the number of AI applications in dentistry, reviews of the literature tend to be general, caries detection, radiographic diagnosis, or a particular specialty in dentistry (Ahmed et al., 2021;Hung et al., 2020; Khanagar et al., 2021). There are also studies that discuss dental issues or imaging issues without necessarily incorporating AI-based CBCT segmentation and smart workflow automation, e.g., dental caries in tobacco users, diagnostic reporting in osteomyelitis, imaging in osteonecrosis with medications, and smart workflow automation to assess the attractiveness of a smile (Doddawad et al., 2022; Goldblatt et al., 2018; Tosun & Kaya, 2020). Thus, a systematic review with a narrow scope is required to review the evidence on AI-based CBCT segmentation, multimodal image fusion, automated virtual patient systems, and implant-planning automation in smart oral healthcare.

The purpose of the systematic review is to assess the artificial intelligence and data-driven innovations of smart oral healthcare and dental imaging systems. In particular, it tries to integrate the research on the subject of AI-based CBCT segmentation, dental imaging automation, multimodal fusion, virtual patient creation, and intelligent digital workflow support. The review also seeks to determine how AI will enhance diagnostic accuracy, decrease the manual workload, improve treatment planning, and enable the evolution of smarter, more integrated and patient-adaptive oral healthcare systems in the future.

2. Methodology

2.1 Review Design

It is a systematic review study aimed at assessing the role of artificial intelligence and data-driven innovations in smart oral healthcare and dental imaging systems. The main areas of the review were AI-based cone-beam computed tomography (CBCT) segmentation, automated dental imaging analysis, multimodal image fusion, virtual patient generation and automated digital workflow in modern dentistry. The review methodological approach was based on the Preferred Reporting Items of Systematic Reviews and Meta-Analyses (PRISMA) framework to provide a clear and systematic approach to the study identification, screening and eligibility and ultimate inclusion. Past AI-focused systematic reviews in the field of dentistry were also used to ensure that the approach to the review followed the accepted standards of conducting the review. The review framework was created based on the PICOS approach which is contained in Table 1.

Table 1. PICOS Framework Used in the Systematic Review

Component	Description
Population	Human dental, oral, and maxillofacial imaging datasets including CBCT, CT, intraoral scans (IOS), digital dental models, and facial scan data
Intervention	Artificial intelligence-based systems including machine learning, deep learning, convolutional neural networks (CNNs), U-Net architectures, transformer models, AI-assisted segmentation tools, and automated workflow systems
Comparator	Manual segmentation, expert clinician assessment, conventional imaging software, and semi-automated digital workflows
Outcomes	Segmentation accuracy, Dice similarity coefficient, precision, recall, sensitivity, surface distance measurements, workflow reproducibility, time efficiency, and clinical applicability
Study Design	Original research articles, validation studies, comparative investigations, systematic reviews, and meta-analyses

2.2 Literature Search Strategy

An extensive literature review was written on PubMed as the main database. Further cross-referencing was done with the studies published in the major journals that covered dental imaging, digital dentistry, artificial intelligence, and maxillofacial radiology. The search strategy was formulated based on three main areas like artificial intelligence, oral healthcare/dentistry, and dental imaging systems.

The search included combinations of keywords and Medical Subject Headings (MeSH) terms such as ("Artificial Intelligence" OR"Machine Learning" OR "Deep Learning") AND ("Dentistry" OR "Oral Healthcare") AND ("Imaging" OR "Radiography") Boolean operators including AND and OR were used to refine the search process and maximize retrieval of relevant studies. The search strategy was developed in alignment with prior systematic reviews investigating AI applications in dentistry and dental radiology.

2.3 Eligibility Criteria

The studies that were taken into account had to be written in English and explore the issues of artificial intelligence, machine learning, deep learning, or automated intelligent systems in dentistry or oral healthcare. Qualified studies were those applications that used CBCT, CT, intraoral scanning (IOS), digital dental models, DICOM imaging, STL datasets or other maxillofacial imaging systems. Articles with automated segmentation, tooth detection, anatomical labelling, multimodal image fusion, virtual patient generation, implant-planning guidance, or AI-assisted digital workflows were considered.

The sources were filtered out of the studies that were not related to oral healthcare, that is, they did not involve AI-based methodologies, or they did not have any applications related to imaging. Other editorials, letters, conference abstracts, opinion papers, case reports lacking adequate methodological description were also omitted. The studies, which did not include clinically relevant performance outcomes like segmentation accuracy, Dice similarity coefficient, sensitivity, surface distance measurements, or workflow efficiency, were not included in the studies.

2.4 Study Selection Process

The process of study selection was based on the PRISMA framework which includes identification, screening, eligibility, and final inclusion. All records found by the database search were first of all exported and filtered out duplicates. After the elimination of duplicates, titles and abstracts were filtered in order to determine the studies that are relevant to the topic of AI-enabled smart oral healthcare and dental imaging systems.

The studies that potentially contained the required information were evaluated based on the predetermined inclusion criteria in full-text. Ten studies were ultimately chosen to undergo qualitative synthesis after being fully-text reviewed. These studies consisted of systematic reviews, meta-analyses, comparative validation studies, experimental investigations, and AI-based clinical workflow studies related to CBCT segmentation and digital dentistry applications.

The last included studies were on AI-driven CBCT tooth segmentation, alveolar bone segmentation, automated tooth detection and labelling, virtual patient generation, multimodal image fusion, airway segmentation, and the workflow automation in implant-planning.

2.5 Data Extraction

Structured method of data extraction was employed in order to have uniformity in all the studies that were incorporated. Each article was searched to identify relevant information, such as author details, year of publication, study design, imaging modality, characteristics of datasets, AI methodology, clinical application, comparator methods, performance metrics, and key findings.

Special attention was given to retrieval of the information connected to segmentation accuracy, Dice similarity coefficient, precision, recall, sensitivity, specificity, surface distance measures, processing time, workflow reproducibility, and clinical applicability. Data on the AI architecture type, such as convolutional neural network (CNNs), deep learning systems, U-Net models, and commercial AI-based software systems were also recorded.

2.6 Quality Assessment

The quality of methods of the studies included was evaluated based on the study design, validation strategy, strength of data sets, and transparency of the outcomes. Special focus was on the utilization of reference standards, performance measurement compared to manual expert segmentation, performance metrics reporting, external validation process, and AI workflow reproducibility.

The studies were assessed on various indicators of quality such as size of datasets, multicentre validation, imaging standardization, segmentation accuracy reporting, and comparison with human expertise or physical reference models. Systematic reviews and meta-analyses were also reviewed in terms of clarity of search strategy, transparency of inclusion criteria and methodological rigor in data synthesis.

The methodological quality of validation studies for scale was high, with the multi-centre datasets and the large-scale external validation process with heterogeneous imaging conditions of CBCT. In the same sense, the physical ground truth was used for picking the teeth and using the optical scanning method and iterative closest point surface registration techniques to calculate a high methodological reliability in the validation of segmentation.

2.7 Data Synthesis

The decision to use a qualitative narrative synthesis method over quantitative meta-analysis was due to the large heterogeneity of studies included in the review with respect to the AI architecture, imaging modalities, anatomical targets, dataset composition, and performance measures. The differences among the studies were significant for the applications involving CBCT tooth segmentation, alveolar bone segmentation, upper airway analysis, multimodal fusion systems, virtual patient generation, and automation of implant-planning.

AI-based CBCT segmentation, automated detection and labelling systems, multimodal image fusion, virtual patient creation, and AI-based workflow optimization in digital dentistry were the main areas identified and summarized in the results. This thematic study allowed for the detailed interpretation of the developments, performance results and clinical implications of the AI technologies in and for smart oral health care systems.

2.8 Outcome Measures

Segmentation accuracy, Dice similarity coefficient, sensitivity, specificity, precision, recall, average surface distance, Hausdorff distance, root mean square deviation, and workflow time efficiency were the main outcomes that were evaluated in this review. Secondary outcomes were reproducibility of AI-assisted digital workflows, reduction in manual operator dependency, clinical applicability and integration potential in smart oral healthcare ecosystem.

A particular focus was placed on investigations that either showed clinically relevant precision increase, automated workflow acceleration, virtual patient reconstruction, and/or intelligent support in treatment-planning. Multiple studies were included that showed that AI-enabled systems significantly cut processing time without compromising clinically acceptable segmentation accuracy and reproducibility. As found segmentation results that matched those of skilled radiologists, but were much more efficient.

3. Results

3.1 Study Selection

A total of 549 records were obtained through database search and manual reference check using the PRISMA methodology. From these, 300 records were collected from Web of Science, PubMed and ScienceDirect databases and 249 records were collected from the reference lists of collected papers. There were 414 records after removing duplicate records. In the screening process of titles and abstracts, 284 records were eliminated as they did not directly pertain to artificial intelligence or smart oral healthcare or dental imaging systems. Then 130 records were subjected to full-text evaluation of their eligibility. At this point, 120 records were filtered out because they were not relevant, conference abstracts, non-healthcare studies, language-restricted papers or overlapping studies. Finally, 10 studies were included in the final qualitative synthesis. The study selection process was based on PRISMA framework, which involved identification, screening, eligibility assessment and finally inclusion of studies pertaining to the applications of AI in smart oral healthcare and dental imaging systems. The selection process is described in detail in Figure 1.

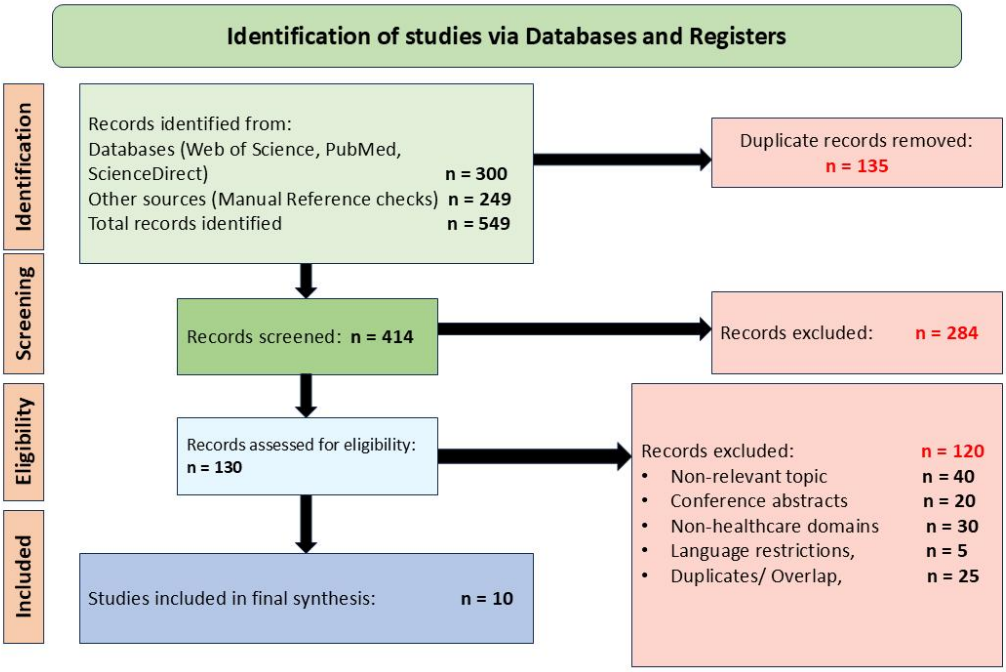

Figure 1. PRISMA Flow Diagram Showing Identification, Screening, Eligibility, and Inclusion of Studies

3.2 Characteristics of Included Studies

Finally, 10 studies from 2021 to 2026 were reviewed. The literature included systematic reviews, meta-analyses, validation studies, comparative studies and experimental studies of AI. The studies as a whole touched on the use of AI for CBCT segmentation, automation of dental imaging, multimodal image fusion, virtual patient generation, and support of implant-planning workflow. The studies included in the review covered diverse arenas of clinical application with

CBCT segmentation, implant planning, multimodal fusion and virtual patient systems, as well as differing imaging modality, study design and AI methodology. Table 2 describes the characteristics of included studies in detail.

Table 2. Characteristics of Included Studies

Author(s)	Study Type	Imaging Modality	AI Application	Main Outcome
(Ahmed et al., 2021)	Systematic Review	Multiple dental imaging systems	General AI applications in dentistry	AI improved diagnosis, treatment planning, and clinical decision-making
(Reymus et al., 2026)	Comparative Validation Study	CBCT	AI-driven tooth segmentation	Clinically acceptable segmentation trueness and reproducibility
(Cui et al., 2022)	Experimental AI Study	CBCT	Tooth and alveolar bone segmentation	High segmentation accuracy with 500× faster workflow
(Iacob et al., 2026)	Systematic Review	CBCT	Maxillofacial structure segmentation	High Dice similarity coefficients in AI segmentation
(Sobouti et al., 2026)	Systematic Review and Meta-analysis	CBCT/CT	Upper airway segmentation	AI achieved high precision and recall performance
(Schiavon et al., 2025)	Comparative Study	Digital implant planning datasets	AI-assisted implant planning	Significant reduction in workflow preparation time
(Baldini et al., 2025)	Validation Study	CBCT + IOS	Automated tooth modelling	AI fusion demonstrated high efficiency and consistency
(Jindanil et al., 2025)	Experimental Study	MSCT/CBCT + facial scans	Virtual patient creation	AI improved registration speed and reproducibility
(Wang et al., 2021)	Deep Learning Study	CBCT	Multiclass orthodontic segmentation	Accurate segmentation with major reduction in processing time
(Gerhardt et al., 2022)	AI Validation Study	CBCT	Automated tooth detection and labelling	High detection accuracy with rapid AI processing

The main research fields identified in the studies comprised of automated tooth segmentation, automated alveolar bone segmentation, multiclass CBCT segmentation, virtual patient modelling, AI-assisted implant planning, and multimodal image fusion (CBCT and intraoral scanning systems). The majority of the studies used deep learning methods that are based on convolutional neural networks and automated segmentation frameworks.

3.3 Distribution of Research Themes

In the included studies, it was found that studies on segmentation, intelligent workflow automation in digital dentistry using CBCT data dominated. The majority of investigations focused on automated segmentation of teeth, alveolar bone, airway structures and anatomical regions of the maxillofacial area. Other research highlighted the benefits of multimodal fusion combining CBCT and intraoral scanning systems, the creation of virtual patients, and the use of AI for implant planning.

CBCT was found to be the most common imaging modality in all literature included because of its role in orthodontics, implantology, oral surgery and digital planning. The most commonly employed AI techniques in the selected studies were deep learning techniques, specifically CNNs and segmentation based architectures.

3.4 AI-Based CBCT Segmentation Outcomes

Many of the studies incorporated showed high performance of the AI models in the segmentation of CBCT. Multiple quantitative performance measures associated with smart oral healthcare systems were reported in the included studies related to segmentation accuracy, processing time, reproducibly, and workflow optimization with the support of AI. The key outcomes of the major performances are presented in Table 3.

Table 3. Performance Outcomes of AI-Based Dental Imaging Systems

Study	AI Task	Key Performance Metrics	Major Findings
(Cushway et al., 2022)	Tooth and alveolar bone segmentation	Dice score: 94.1% (tooth), 94.5% (bone)	Comparable to expert radiologists with significantly faster processing
(Wang et al., 2021)	Multiclass CBCT segmentation	Dice score: 0.934 (jaw), 0.945 (teeth)	AI reduced segmentation time from hours to seconds
(Gerhardt et al., 2022)	Tooth detection and labelling	Accuracy: 99.7% (dentate), 99% (partial edentulous)	AI completed detection within 1.5 seconds
(Baldini et al., 2025)	CBCT-IOS fusion	High reproducibility and consistency	AI fusion was approximately 32× faster than manual workflow
(Schiavon et al., 2025)	Implant planning assistance	Workflow preparation time	AI reduced preparation time from 3.84 to 1.88 minutes

(Sobouti et al., 2026)	Upper airway segmentation	Precision, Dice score, IoU >90%	AI demonstrated highly accurate airway segmentation
(Reymus et al., 2026)	CBCT tooth segmentation validation	Surface deviation and segmentation trueness	AI achieved clinically acceptable segmentation reliability

Multiple studies contained in the list showed that the AI models performed well in the CBCT segmentation. The quantitative performance measures included in the studies show that AI-assisted systems for segmentation provided high accuracy with significant reduction in manual processing time and operator dependency. The fully automatic segmentation systems achieved comparable performance with experienced radiologists and high reproducibility under varying imaging conditions and patient datasets for smart oral healthcare systems. Table 3 provides an overview of the key performance results.

Generalizability of AI models in heterogeneous CBCT settings was shown to be strong in large-scale multicentre segmentation studies. Multiclass segmentation techniques also facilitated proper outlineing of dental and skeletal structures during orthodontic processes. Moreover, AI-based labelling systems were found to be very fast in processing speed and a high score on both dentate and partially edentulous cases.

3.5 AI in Multimodal Fusion and Virtual Patient Creation

There was an increase in research on multimodal integration with CBCT, IOS, facial scanning and digital patient modelling. Fusion systems were shown to achieve significant registration efficiency, reproducibility, and workflow standardization with the help of AI.

A system of automated tooth modelling incorporating CBCT-based roots and IOS-based crowns demonstrated clinically acceptable levels of alignment accuracy at the expense of greatly reducing processing time relative to manual methods of fusion. Likewise, AI-based virtual patient systems with CBCT, facial scans, and intraoral scanning data have provided very reproducible registration accuracy and have been shown to prepare digital workflow much faster. These results show that artificial intelligence is playing an ever-increasing role in the creation of a modern digital dentistry ecosystem that uses three-dimensional imaging, facial recognition, and virtual treatment simulation.

3.6 AI-Assisted Implant Planning and Workflow Automation

Research studies on AI-guided planning of implants showed significant efficiency in the workflow and clinical reproducibility. AI-enabled systems minimized the level of human assistance that was needed when preparing digital datasets and in planning the treatment. Clinically acceptably accurate, automated implant-planning workflows were found to save a significant amount of time during the preparation. Proficiency in clinical decision-making in the field of implantology and restorative dentistry was also enhanced by AI systems that enhanced consistency in anatomical analysis and the simulation of digital treatments and further facilitated more efficient clinical decision-making.

3.7 Evidence from Systematic Reviews and Meta-Analyses

The systematic reviews and meta-analyses included revealed that AI has been used in various fields of dentistry, such as oral radiology, orthodontics, implantology, restorative dentistry, and periodontics, and the applications have been growing. The results showed that AI-driven systems boosted the accuracy of diagnoses, segmentation efficiency, workflow standardisation, and clinical decision support consistently.

Meta-analytic results also revealed high precision, Dice similarity coefficient, recall, and intersection-over-union (IoU) values for airway segmentation and maxillofacial structure analysis with AI support. In most of the studies optimal results of segmentation were obtained with significant decrease of the operator dependency and processing time.

3.8 Overall Synthesis of Results

Overall, in the 10 final studies, the AI systems showed great promise in enhancing smart oral healthcare and dental imaging systems. AI has played a significant role in advancing the field of smart oral care in a number of key areas: enhancing automation, diagnostic accuracy, clinical reproducibility, and seamless integration of digital workflows in various dental specialties. The main advantages found in the included studies are presented in Table 4.

Table 4. Major Advantages of AI in Smart Oral Healthcare Systems

Domain	AI Contribution	Clinical Significance	Reference
CBCT Segmentation	Automated tooth and bone delineation	Improved diagnostic precision and reduced manual workload	(do Nascimento Gerhardt et al., 2022)
Orthodontics	Multiclass anatomical segmentation	Enhanced treatment planning and digital workflow efficiency	(Kukreja & Kukreja, 2025; Meskó et al., 2018)
Implantology	AI-assisted implant planning	Faster and more reproducible surgical preparation	(Dashti et al., 2024; Tuzoff et al., 2019)
Virtual Patient Systems	Multimodal image fusion and registration	Improved digital treatment simulation	(Jindanil et al., 2025; Tyndall, 2024)

Smart Workflow Automation	Automated detection and labelling	Reduced operator dependency and workflow time	(Fontenele, 2023; Yang et al., 2020)
Oral Diagnostics	AI-supported clinical decision systems	Improved diagnostic consistency and accuracy	(Rajkomar et al., 2019; Song et al., 2023)
Airway and Maxillofacial Analysis	Automated segmentation of airway and facial structures	Improved anatomical analysis and treatment support	(On et al., 2025; Tosun & Kaya, 2020)
Digital Dentistry Ecosystems	Integration of CBCT, IOS, facial scans, and AI systems	Development of comprehensive smart oral healthcare platforms	(Naoe et al., 2020; Oliveira-Santos et al., 2023)

The results also suggest that AI driven dental imaging is moving beyond just the diagnostic tools to the era of smart dentistry with segmentation, multimodal fusion, virtual patient construction, implant planning, and automated clinical workflow management. Overall, the studies included in this review show that AI applications in oral health are emerging as a key element of today's data-driven oral healthcare systems.

4. Discussion

The results of this systematic review indicate the major role of AI in smart oral healthcare and dental imaging systems. AI powered systems have enhanced the accuracy of diagnoses, streamlined clinical processes, minimized human error, and enabled personalized treatment planning. The computer models based on deep learning and convolutional neural networks have achieved excellent results in the segmentation of CBCT, automated tooth detection, analysis of maxillofacial structures, and automation of dental workflows (Litjens et al., 2017; Rajkomar et al., 2019). AI-powered systems also help in enhancing operational efficiency by decreasing the time spent on segmentation, implant planning, and image interpretation (Reymus et al., 2026; Schiavon et al., 2025). All of these advances contribute to the ever-increasing use of smart technologies in contemporary digital dentistry and patient-centred oral health care (Schwendicke et al., 2020).

Compared to conventional dental imaging processes, AI-powered dental imaging systems provide a greater degree of efficiency, repeatability, and standardization. Conventional workflows require manual segmentation and operator knowledge, and may bring subjectivity and variability, as well as scaling up processing time (Jindanil et al., 2023). On the other hand, AI-driven systems are able to rapidly segment and detect anatomical parts with clinically acceptable accuracy (Sobouti et al., 2026; Wang et al., 2021). Additionally, deep learning models give better consistency in the analysis of panoramic radiograph, tooth numbering, identification of a lesion and anatomical localization (Tuzoff et al., 2019; Vinayahalingam et al., 2019). Automated systems thus minimize the operators' intervention and help ensure more uniform diagnostic results. Moreover, AI for implantology and CBCT analysis aids in digital treatment planning and workflow reproducibility in challenging clinical scenarios (Jacobs et al., 2018).

AI has shown to have wide application in clinical practice in several fields of dentistry. AI-powered CBCT segmentation in orthodontics is used to accurately segment the teeth and skeletal structures, aiding in anatomical analysis, treatment planning, and digital simulation (Dot et al., 2024; Khan & Ahad, 2021; Turosz et al., 2023). AI-assisted implant planning and automated digital dataset creation streamline clinician workflow and ensure procedural consistency, which is vital for implantology.AI-supported implant planning and automated digital dataset preparation can make a significant difference by reducing the workload for clinicians and ensuring procedural consistency. Examples of the oral surgery applications are automated detection of cysts, tumors, impacted teeth and mandibular nerve structures in panoramic and CBCT images (Vinayahalingam et al., 2019; Yang et al., 2020). Multimodal fusion and virtual patient systems are also powered by AI, allowing the integration of CBCT, facial scans, and intraoral scanning to create a personalized treatment simulation and digital workflow optimization. Remote diagnostics and image interpretation can also be improved through AI and improve the accessibility and efficiency of oral health care delivery, which is becoming more and more available with the new tele-dentistry systems and smart health care frameworks (Meskó et al., 2018; Topol, 2019).

Though the findings are encouraging, some technical issues would have to be addressed to enable the use of AI in smart oral healthcare to become widespread. The heterogeneity of the datasets and the absence of external validation of the datasets across imaging systems and patients are one of the significant limitations. The quality of the CBCT, imaging protocols, and anatomical complexity could have an impact on the generalizability of AI and model robustness (Hung et al., 2020). The presence of metal artefacts, noise and incomplete anatomical structures are still important obstacles in the accurate segmentation and automatic analysis. Moreover, AI systems require high percentage of manual labour in terms of annotation and high-quality labelled data during model training, which complicates and increases the burden of development (Zhou et al., 2018). There is also no standardization of reporting AI performance, evaluation measures and segmentation protocols and it is hard to directly compare studies. Although new AI models are always being developed, the clinical use of AI to provide reliable translation remains to be multi centre validated, benchmarked transparently and incorporated into the existing clinical practices (Khanagar et al., 2021).

With the increasing presence of AI in oral healthcare, it is essential to tackle ethical and regulatory challenges related to patient privacy, transparency, and clinical responsibility. AI systems are usually based on the large data pools of images and online patient records, which leaves the question of data security and privacy. Explainability is also pertinent because a lot of deep learning models can be regarded as a black box and are not easily explainable (Schwendicke et al., 2020). If the results are not explainable, it can lead to diminished trust by clinicians and potentially make it more difficult to establish medico-legal responsibility if a diagnostic error or if an inappropriate treatment plan is made. AI systems used in dentistry are also in an early stage of regulation, especially in terms of the validation of clinical results, transparency of algorithms, and software approval criteria. As a result, the future of AI in oral health hinges on the careful integration of technology with patient care, maintaining safety standards, and promoting ethical practices, while also ensuring clear clinical oversight.

The future of smart oral health care is likely to see the emergence of technologies such as explainable artificial intelligence, federated learning, real-time diagnostic systems, robotic technology, and digital twin technology. Explainable AI frameworks could enhance the trust and transparency of clinicians, for instance, through interpretable diagnostic results and decision-making processes. The federated learning methods might also offer an opportunity to learn AI models in a decentralized and privacy-preserving way allowing to decentralize learning among institutions with no direct data sharing. Real-time AI-assisted CBCT and intraoral imaging diagnostics would benefit in both speeding up and enhancing clinical decision making in the clinical workflow. Moreover, robotic systems and cognitive architectures might be used to assist in delivering automated clinical support, and intelligent treatment support in the dental spaces of the future (González-Santamarta et al., 2020). The future of AI in oral health promises personalized healthcare ecosystems, where AI-based tools and systems personalize treatment plans, diagnostics, and preventive care to an individual patient, ultimately improving the quality and efficacy of oral health care.The future of AI in oral health could see the development of personalized healthcare systems where AI tools and systems can customize treatment plans, diagnostics, and preventive care for individual patients, improving the effectiveness and quality of oral health care.

5. Conclusion

As the growth of AI and data-driven innovations progresses steadily, the environment of intelligent oral health and dental imaging is shifting towards a major transformation, improving the accuracy of diagnostics, efficiency of work, and treatment planning opportunities. This systematic review demonstrates that the AI-based technologies and, in particular, deep learning and convolutional neural network models have demonstrated their effectiveness in the segmentation of CBCT, automated tooth identification, multimodal image fusion, generation of virtual patient and automated implant planning. These technologies greatly cut down on manual work, operator variability and enable for standardized and reproducible clinical workflow. The reviewed studies indicate also that AI-based tools may assist with anatomical interpretation of the orthodontic analysis, implantology, oral surgery, and even in simulating the digital treatment and deliver faster and more precise outcomes. The ongoing development of the complete digital dentistry ecosystems are also reflected in the integration of CBCT imaging, intraoral scanning, and facial registration technologies. However, issues like dataset heterogeneity, metal artifacts, lack of standardization, explainability, and regulatory issues still restrict the widespread clinical implementation of these advances. The future of intelligent systems in oral health care is bright, as the development of the area of explainable artificial intelligence, federated learning, and robotic dentistry, as well as real-time diagnostics with AI support, are bound to further cement the place of intelligent systems. Conclusively, AI has become a significant component of the contemporary digital dentistry and has a lot of potential in the future of personalized, efficient, and data-driven smart oral healthcare systems.

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46.