INSTITUTO UNIVERSITÁRIO EGAS MONIZ

MESTRADO INTEGRADO EM MEDICINA DENTÁRIA

ARTIFICIAL INTELLIGENCE AND ORTHODONTIC: ACHIEVEMENTS, EXPECTATIONS AND CHALLENGES

Trabalho submetido por
Mourad Gargouri
para a obtenção do grau de Mestre em Medicina Dentária

julho de 2024

EGAS MONIZ SCHOOL of HEALTH & SCIENCE | INSTITUTO UNIVERSITÁRIO EGAS MONIZ

INSTITUTO UNIVERSITÁRIO EGAS MONIZ

MESTRADO INTEGRADO EM MEDICINA DENTÁRIA

INTELIGÊNCIA ARTIFICIAL E ORTODONTIA: REALIZAÇÕES, EXPECTATIVAS E DESAFIOS

Trabalho submetido por
Mourad Gargouri
para a obtenção do grau de Mestre em Medicina Dentária

Trabalho orientado por
Prof. Doutor Luís Proença

Trabalho co-orientado por
Prof. Doutor Hélder Nunes da Costa

julho de 2024

ACKNOWLEDGEMENT

I express my gratitude to my supervisor, Professor Doctor Luís Proença, for his time, availability, critique, advice, and most importantly, my deepest thanks for his perseverance and patience.

I am deeply thankful to my co-supervisor Prof. Doctor Hélder Nunes da Costa his support and guidance throughout the registration process, project plan, and the writing of this thesis.

I wish to express my profound appreciation to the Egas Moniz University Institute, to all the professors, staff, and collaborators who accompanied me throughout this academic journey and contributed to my personal and professional development.

DEDICATION

To my beloved family, whose unwavering support and encouragement have been my foundation throughout this journey.

To my dear wife, for her endless patience, understanding, and love, which have been my constant source of strength and motivation.

To my cherished friends, for their steadfast belief in me and their invaluable companionship.

This thesis is a testament to all of you, and I am deeply grateful for your presence in my life.

RESUMO:

A inteligência artificial (IA) está cada vez mais presente na Saúde, especialmente com recurso a abordagens computacionais intensivas. As metodologias de aprendizagem profunda, como Redes Neuronais Convolucionais (RNC), têm-se mostrado valiosas para os profissionais de saúde. Em Medicina Dentária e, em particular na Ortodontia, a integração da IA representa uma mudança de paradigma, revolucionando o diagnóstico, o planeamento do tratamento e o prognóstico.

O objetivo principal deste trabalho é realizar uma revisão abrangente e atualizada da literatura sobre os avanços recentes da IA na Ortodontia. A revisão foca-se nos sucessos alcançados, destacando as aplicações da aprendizagem profunda na análise de imagens, onde a IA se destaca por identificar, com elevada precisão, características em radiografias e exames intraorais. Além disso, é sublinhado o papel da IA como sistema de apoio à decisão clínica, ajudando a formular planos de tratamento individualizados e otimizados.

Neste estudo foram utilizadas as bases de dados PubMed, MEDLINE, Web of Science, Scopus, CENTRAL e Google Scholar, com termos de pesquisa como "inteligência artificial", "rede neuronal artificial", "aprendizagem profunda", "aprendizagem de máquina" e "ortodontia e alinhadores", abrangendo o período de 2019 a 2024.

No trabalho são também abordadas as perspetivas futuras da IA na Ortodontia, antecipando desenvolvimentos e inovações, incluindo a otimização de tratamentos em curso, a integração de novas tecnologias e considerações éticas no uso da IA na saúde oral. Reconhecendo as vantagens da IA, são identificados igualmente desafios como seja a segurança e aceitação pela comunidade médica, com atenção à confidencialidade dos dados dos pacientes e aos mecanismos necessários para o uso responsável da IA.

Em conclusão, este trabalho visa fornecer uma perspetiva abrangente sobre o estado atual, as oportunidades futuras e os desafios da integração da IA na Ortodontia, contribuindo para uma compreensão holística desta promissora convergência entre tecnologia e cuidados ortodônticos especializados.

Palavras-Chave: Inteligência artificial, rede neuronal artificial, ortodontia, alinhadores.

ABSTRACT:

Artificial intelligence (AI) is increasingly present in healthcare, especially through the use of intensive computational approaches. Deep learning methodologies, such as Convolutional Neural Networks (CNNs), have proven valuable for healthcare professionals. In Dentistry and particularly in Orthodontics, the integration of AI represents a paradigm shift, revolutionizing diagnosis, treatment planning, and prognosis.

The main objective of this work is to conduct a comprehensive and updated review of the literature on recent advances in AI in Orthodontics. The review focuses on the successes achieved, highlighting the applications of deep learning in image analysis, where AI excels at identifying characteristics in radiographs and intraoral examinations with high precision. Additionally, the role of AI as a clinical decision support system is emphasized, helping to formulate individualized and optimized treatment plans.

In this study, databases such as PubMed, MEDLINE, Web of Science, Scopus, CENTRAL, and Google Scholar were used, with search terms like “artificial intelligence,” “artificial neural network,” “deep learning,” “machine learning,” and “orthodontics and aligners,” covering the period from 2019 to 2024.

The work also addresses future perspectives of AI in Orthodontics, anticipating developments and innovations, including the optimization of ongoing treatments, the integration of new technologies, and ethical considerations in the use of AI in oral health. While recognizing the advantages of AI, challenges such as security and acceptance by the medical community are also identified, with attention to patient data confidentiality and the mechanisms necessary for the responsible use of AI.

In conclusion, this work aims to provide a comprehensive perspective on the current state, future opportunities, and challenges of integrating AI in Orthodontics, contributing to a holistic understanding of this promising convergence between technology and specialized orthodontic care.

Keywords: Artificial intelligence, artificial neural network, orthodontics, aligners.

TABLE OF CONTENTS

LIST OF FIGURES

LIST OF TABLES

LIST OF ACRONYMS

AI	: Artificial intelligence
IOT	: Internet of Things
FDA	: Food and Drug Administration
ML	: Machine Learning
ICC	: Intraclass Correlation Coefficient
CBCT	: Cone Beam Computer Tomography
SD	: Standard Deviation
LRC	: Linear Regression Classifier
RFC	: Random Forest Classifier
CNN	: convolutional neural network
YOLO	: You Only Look Once
CNN	: convolutional neural network
AUC	: Area Under the Curve
SDR	: successful detection rate
DACFL	: Deep Anatomical Context Feature Learning
SCR	: successful classification rate
CAD/CAM	: computer-aided design/computer-aided manufacturing
ANN	: Artificial Neural Network
IDB	: Indirect Bonding
LiDAR	: Light Detection and Ranging
AR	: Augmented Reality
IQR	: Interquartile range
PAR	: Peer Assessment Rating

DACFL	: Deep Anatomical Context Feature Learning
DM	: Dental Monitoring
HIPAA	: Health Insurance Portability and Accountability Act
EU	: Europe Union

I Introduction

The field of orthodontics has evolved significantly over time. Traditional methods, such as braces and manual diagnostic approaches, have demonstrated durability but also faced limitations. In recent decades, the integration of digital imaging and customized appliances has transformed the precision and patient experience in orthodontic treatments. However, challenges persist, necessitating further innovation to address issues like diagnosis accuracy, subjective treatment planning, and patient compliance. The ongoing evolution of orthodontics reflects a continuous quest for cutting-edge solutions, envisioning a future where technology seamlessly addresses these challenges for enhanced efficacy and patient-centric care.

AI has revolutionized medicine, playing a pivotal role in radiology, surgery, and personalized treatment. In orthodontics, the wealth of data, including images and treatment records, holds immense potential for AI-driven insights. The concept of "explainable AI" emerges, emphasizing the need for transparency and understanding in healthcare applications, fostering trust in AI-generated diagnoses and treatment recommendations. This transformative integration of AI in medicine signifies a paradigm shift towards enhanced diagnostic accuracy and personalized patient care.

The thesis "Artificial Intelligence Achievements, Perspectives, and Challenges" conducts a thorough literature review on the advancements, prospects, and obstacles in the realm of AI across diverse sectors. It explores the integration of AI into various domains, analyzes current perspectives on AI technologies, and addresses implementation challenges. By identifying promising AI advancements, assessing their potential impacts, and proposing strategies to mitigate challenges, the thesis aims to enhance comprehension of the field and provide guidance for future research endeavors.

First, we provide an overview of the achievements in utilizing AI for orthodontic diagnostics and treatment. From exobuccal diagnoses, such as facial asymmetry assessment and smartphone-based facial scanning, to endobuccal diagnostics like treatment needs from endobuccal images, and radiological diagnostics, AI has enabled more precise and efficient diagnosis of orthodontic conditions. Moreover, AI has facilitated personalized treatment planning, arch wire design, teeth extraction decision-making, automated bracket placement, wire bending, mini-implant placement, orthognathic surgery planning, and aligner therapy, transforming the orthodontic treatment paradigm.

Additionally, this work delves into the perspectives surrounding the integration of AI in orthodontics. From leveraging radiology for improved diagnostics to adopting interceptive orthodontics and multifactorial treatment approaches, AI promises to enhance treatment outcomes and patient experiences. The incorporation of microsensors, Internet of Things (IoT) devices, retention strategies, app monitoring systems, and tele-dentistry platforms opens new avenues for remote patient monitoring and care delivery, augmenting orthodontic practice.

However, the adoption of AI in orthodontics is not without its challenges, as explored in this thesis. Data privacy and security, data quality and standardization, and ethical considerations pose significant hurdles. Moreover, clinical validation, integration with clinical workflows, cost considerations, and continuous learning and adaptation require careful attention to ensure efficacy and ethical integrity.

Through this thesis, our goal is to offer a thorough grasp of the accomplishments, perspectives, and challenges associated with the integration of AI in orthodontics. By addressing these considerations, we can navigate the evolving landscape of AI-driven orthodontic care, ultimately improving patient outcomes and advancing the field of orthodontics into the digital era.

II Methodologies

This work reviews AI advancements across sectors, addressing challenges and offering guidance for future research, by utilizing multiple databases for comprehensive coverage including PubMed, MEDLINE, Web of Science, Scopus, CENTRAL, and Google Scholar. Employing a systematic methodology, we initiated our exploration by utilizing keywords/expressions such as "artificial intelligence," "artificial neural network," "deep learning," "machine learning," "orthodontics," and "aligners." Our initial search on PubMed, focusing on "artificial intelligence" and "orthodontics," yielded 126 articles. Expanding the search to include "machine learning" did not alter the count. However, narrowing the publication timeframe to 2019–2024 reduced the count to 64 articles. Similar searches on MEDLINE and CENTRAL yielded comparable results, with 28 articles found on CENTRAL, 24 of which were within the specified timeframe. Exploration on Scopus and Web of Science did not yield relevant results. Nevertheless, an extensive search on Google Scholar using varied keyword combinations produced a substantial number of articles, totaling 18,100. Narrowing the search timeframe to 2019–2024 reduced this count to 16,300. Focusing specifically on the intersection of "artificial intelligence" and "orthodontics" on Google Scholar between 2019 and 2024 returned 15,500 articles, highlighting Google Scholar as the primary source for pertinent literature in this field.

We streamlined our analysis by initially reviewing titles and abstracts, reducing the articles to 277.

After an initial review, we refined our selection by excluding articles that deviated from our research focus, lacked robust results, or exhibited low relevance.

This process yielded a core set of articles categorized into thematic sections: Achievements, further subdivided into Diagnostics (23 articles) and Treatment (30 articles); Perspectives (17 articles); and Challenges (19 articles).

Following a meticulous review of these articles, we selected the most pertinent and impactful studies. We eliminated duplicate articles that employed similar methodologies and yielded comparable statistical results. This meticulous selection process resulted in a final set of 15 articles focused on diagnostics, 15 on treatment, nine on perspectives, and 10 on challenges. Notably, three of these articles addressed concepts relevant to multiple themes, demonstrating the interconnectedness within the field.

This systematic approach allowed us to efficiently organize the literature according to its thematic focus, facilitating a more in-depth exploration of key areas within the intersection of artificial intelligence and orthodontics.

III Development

1 Artificial intelligence and orthodontics: Achievements

AI has revolutionized orthodontics, driving advancements in diagnosis and treatment. This section explores AI's achievements in exobuccal, endobuccal, and radiological diagnostics, as well as treatment modalities. From automated facial analysis to personalized treatment planning and automated procedures such as bracket placement and wire bending, AI has transformed orthodontic care, enhancing precision and efficiency for improved patient outcomes.

1.1 Exobuccal diagnostics

AI has impacted exobuccal diagnoses in orthodontics, offering innovative solutions and advancements in various aspects such as automated facial analysis or treatment need.

1.1.1 Automated detection of facial midline and assessment of asymmetry

Orthodontic treatment decisions hinge on evaluating skeletal asymmetry and analyzing soft tissue. While three-dimensional (3D) photographs offer objectivity, two-dimensional (2D) frontal facial photographs are still used, albeit with varying midline determination methods. Machine Learning (ML)could standardize asymmetry assessments, reducing variations.

A novel approach by Yurdakurban et al. (2021) leveraging ML algorithms has been developed for cases necessitating asymmetry assessment, such as those associated with facial paralysis. This method strives to standardize and quantify asymmetry assessment and determination of midline within orthodontic practice. The research entailed analyzing frontal facial photographs obtained during routine diagnostic evaluations of patients visiting the department of orthodontics.

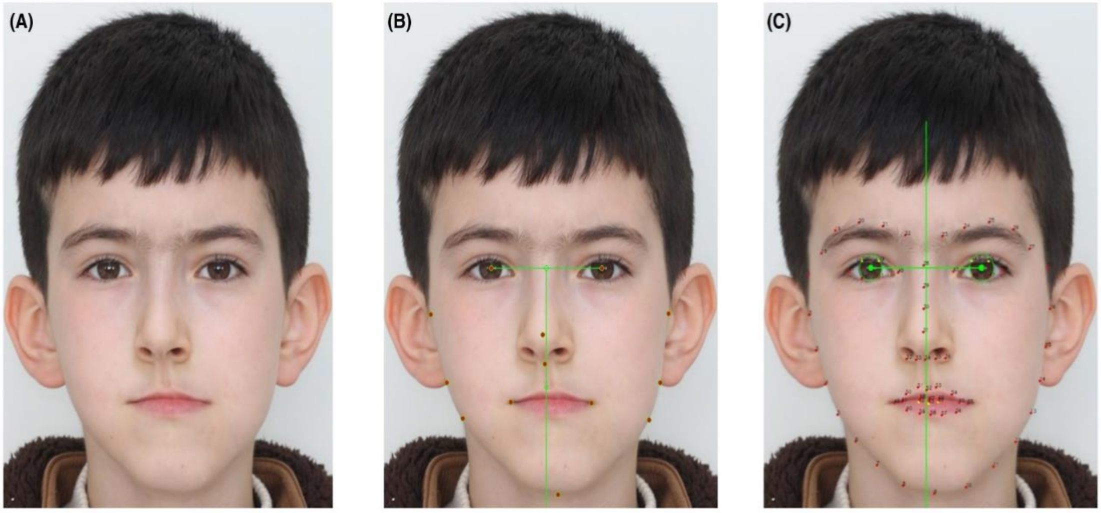
Two researchers individually positioned predetermined soft tissue landmarks on designated facial frontal photographs and established 10 reference lines. The midsagittal line was defined as perpendicular to the midpoint of the bipupillary line. Using ML algorithms, the software automatically identified the identical two reference lines and facial landmarks, while the remaining eight reference lines were created using the automatically determined facial landmarks, as shown in Figure 1. During the next phase, a sole researcher carried out two linear and 10 angular measurements on 270 photographs. Consistency and discrepancies among the measurements were assessed through a one-sample t-test, an intraclass correlation coefficient (ICC), and Bland-Altman Plots.

The study evaluates the agreement between conventional and modern approaches to facial asymmetry assessment and midline determination.

As shown in table 1, this work revealed strong overall agreement between researchers but inconsistency in specific facial asymmetry measurements. Notably, most differences were not clinically significant, except for lip canting and pronasale deviation showed no significant relationship.(1)

Table 1: Comparing traditional vs. modern approaches to facial asymmetry assessment: agreement and significance (1)

Measurement Category	Interobserver Agreement ICC	Software vs. Researcher Agreement ICC	Statistical Significance
Asymmetry Index Vertical Go'	Low (0.03)	Low (< 0.70)	Statistically Significant
Gonion Canting	Low (0.62)	Low (< 0.70)	Statistically Significant
Chin Deviation, Right Gonial Angle, etc.	Low (< 0.70)	Low (< 0.70)	Statistically Significant
Pronasale Deviation, Lip Canting, etc.	High (0.75 to 0.88)	High (> 0.70)	Not Statistically Significant
Differences in Measurements	Statistically Significant	Statistically Significant	Statistically Significant



Facial Frontal Photographs Demonstrating Varying Levels of Mandibular Asymmetry

Researcher-Manual Midline Localization and Landmark Placement

Machine Learning-Based Automatic Midline Localization and Landmark Placement

Figure 1 : Traditional vs. modern approaches to facial asymmetry. Adapted from Yurdakurban et al., 2021 (1).

As a conclusion, the study underscores the distinct advantages that ML offers over traditional methods in facial asymmetry assessment. Firstly, it addresses the issue of bias by circumventing the use of potentially asymmetrical facial structures as reference points, thereby promoting a more objective evaluation. Moreover, it enhances accuracy, particularly in the assessment of midline and lower face asymmetry, by circumventing reliance on potentially asymmetrical structures within these regions. By automating landmark creation, it also mitigates errors stemming from manual identification and localization, thus contributing to minimized errors overall. Despite encountering some limitations, the ML approach demonstrates its clinical relevance by achieving agreement with traditional methods across most asymmetrical measurements, thereby bolstering its utility in clinical practice (1).

1.1.2 Smartphone-Based Facial Scanning

Currently, there has been a shift in orthodontic treatment planning towards prioritizing considerations associated with soft tissue. While the 3D diagnostic workflow is increasingly prevalent, its widespread adoption is impeded by the high cost of facial scanners. However, the introduction of smartphone sensors, such as those found in the iPhone X since 2017, provides a more accessible and convenient method for facial scanning at an affordable price point.

Recent innovations in smartphones and tablets, such as LiDAR ('Light Detection and Ranging') and TrueDepth technology, have enabled scanning capabilities. LiDAR, a remote sensing method utilizing pulsed laser light to measure ranges, has particularly enhanced facial recognition technology. As of 2020, the leading face identification algorithm achieves an exceptionally low error rate of merely 0.08%, a significant improvement from the 4.1% error rate seen in the leading algorithm of 2014.

TrueDepth scanning, exemplified by Bellus3D Dental Pro on iPhones or iPads with a 3D capture system, can utilize affordable programs like Bellus3D FaceApp. In just 10 seconds, this intuitive app captures more than 250.000 3D data points as the user gently rotates their head in front of the camera. It then reconstructs a virtual, high-resolution version of the face, offering various viewing options in three dimensions. Furthermore, users can observe the face model with interactive lighting, adjusting viewing angles using the device's gyroscopic sensor (2).

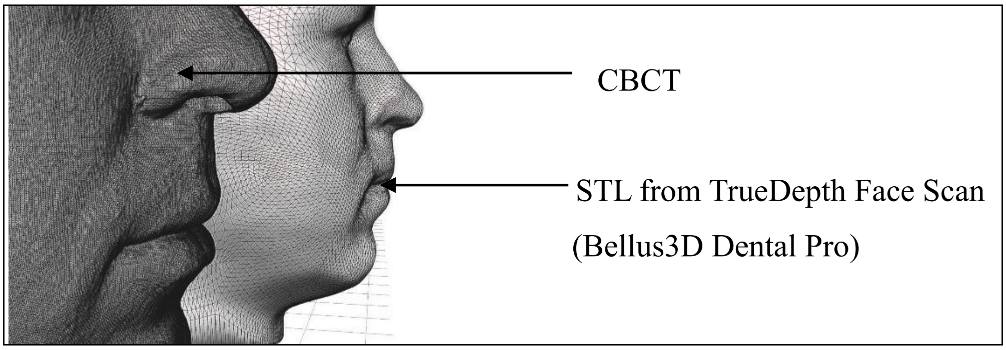


Figure 2: Visible discrepancy in polygon resolution. Adapted from Thurzo et al., 2022 (2).

Thurzo et al. (2022) conducted a study with the goal of assessing the precision of facial scans produced using TrueDepth sensors and the Bellus Dental Pro app, in comparison to Cone Beam Computer Tomography (CBCT) surface imaging, as illustrated in figure 2. A chart with 21 facial locations was analyzed to identify deviations, with a specific focus on Aesthetic and Harmony lines.

This excerpt outlines a thorough comparison between TrueDepth (Bellus3D Dental Pro) scans and CBCT scans in orthodontics, focusing on the clinical relevance of deviations, measurement locations, level of deviation, regional differences, accuracy across facial regions, and a double-check comparison using Friedmann's test.

Firstly, the study establishes a criterion where differences exceeding three mm are considered clinically significant, aiming to mitigate potential biases from factors like facial expressions or circadian cycles.

Measurements were taken at specific facial locations including the tip and bridge of the nose, nasolabial and mentolabial sulcus, zygomatic bone, infraorbital and cheek regions, as well as the oral fissure, temporal and orbital regions.

Results indicate varying degrees of deviation between the scans, as presented in figure3. Some areas, such as the tip of the nose, showed minimal deviation (less than or equal to 10%), while others, notably the orbital region, exhibited higher discrepancies (more than 30%).

Furthermore, differences between the right and left sides of paired regions were noted, adding nuance to the analysis.

Overall, accuracy was highest in facial prominences and lower in deeper structures, suggesting a spatial dependency in the reliability of the scans.

Finally, a statistical double-check comparison using Friedmann's test revealed differing levels of consistency across the facial regions, with the oral fissures exhibiting the highest average rank, potentially indicating greater discrepancies in this area compared to others.

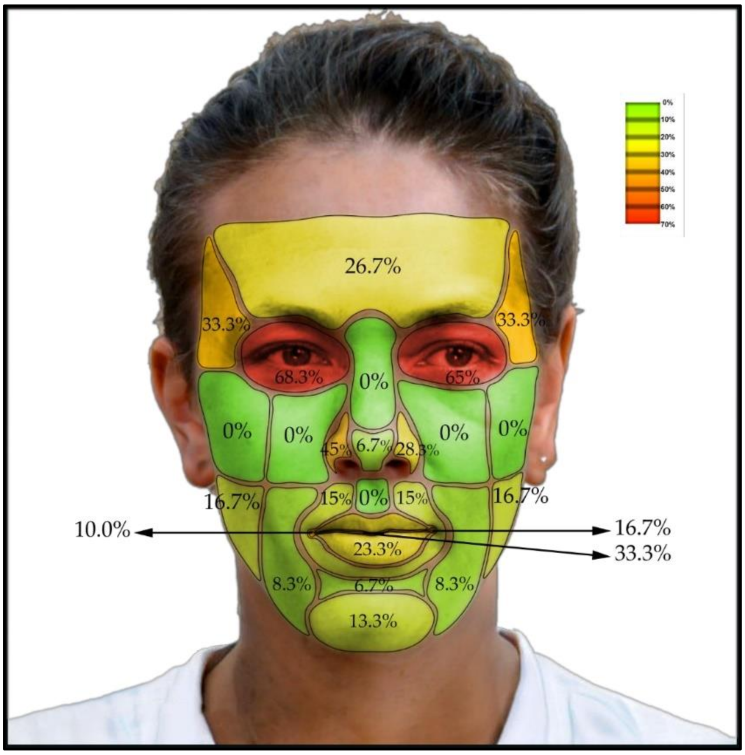


Figure 3: The percentage of variance observed in TrueDepth (Bellus3D Dental Pro) scans compared to CBCT scans. Adapted from Thurzo et al., 2022 (2).

In summary, this study provides a comprehensive evaluation of the accuracy and reliability of TrueDepth and CBCT scans in orthodontic applications, shedding light on their strengths and limitations across various facial regions. Also, the findings underscored notable variances in facial surfaces between CBCT and TrueDepth (Bellus3D Dental Pro cell phone application) scans in certain facial regions, exceeding three mm in magnitude. This indicates that the present TrueDepth sensor by Apple may have restricted clinical utility within orthodontic contexts. Nonetheless, the approach outlined in this study, tailored for orthodontic facial analysis without necessitating precision within three mm, could still be deemed clinically applicable (2).

1.1.3 Comparative Analysis of 3D Facial Scanning Systems

The objective of the research, led by Pellitteri et al. (2023), was to evaluate the precision and consistency of three distinct 3D facial scanning systems. These systems utilized stereophotogrammetry, structured light technology, and a smartphone app coupled with a camera.

Thirty participants underwent facial measurements through two approaches: manual measurement, where anthropometric data was directly collected from their faces, and 3D scanning using three different technologies, including stereophotogrammetry likely employed by the Vectra M3 system, structured light technology potentially utilized by the Face Hunter, and a smartphone application equipped with a camera.

Linear measurements, cited in figure 4, obtained from these scans were then compared with direct anthropometric measurements taken on the participants' faces.

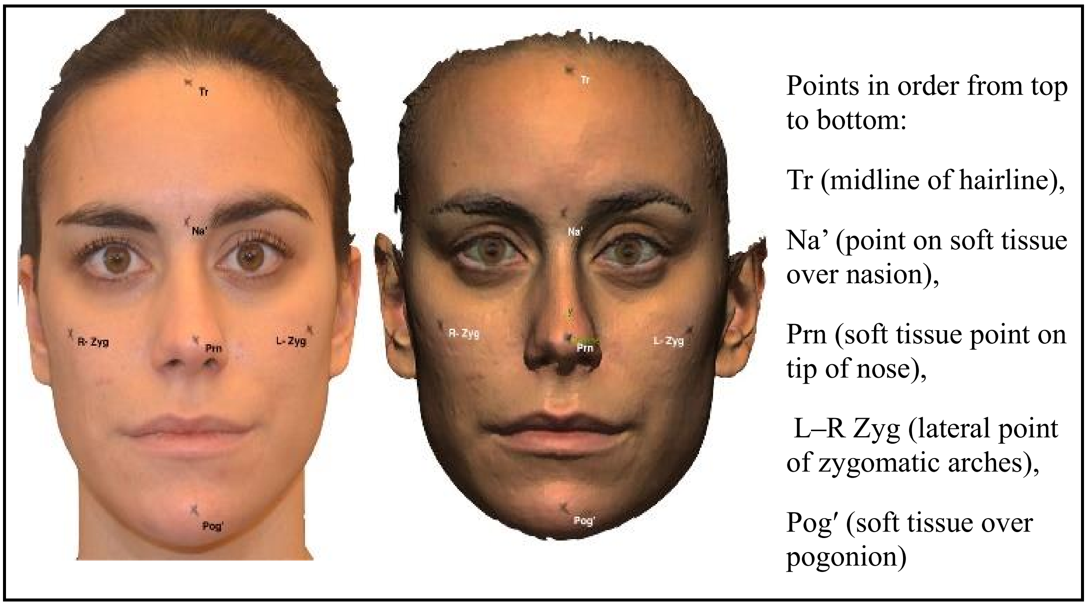


Figure 4: Frontal photograph and facial scan of the subject. Adapted from Pellitteri et al., 2023 (3).

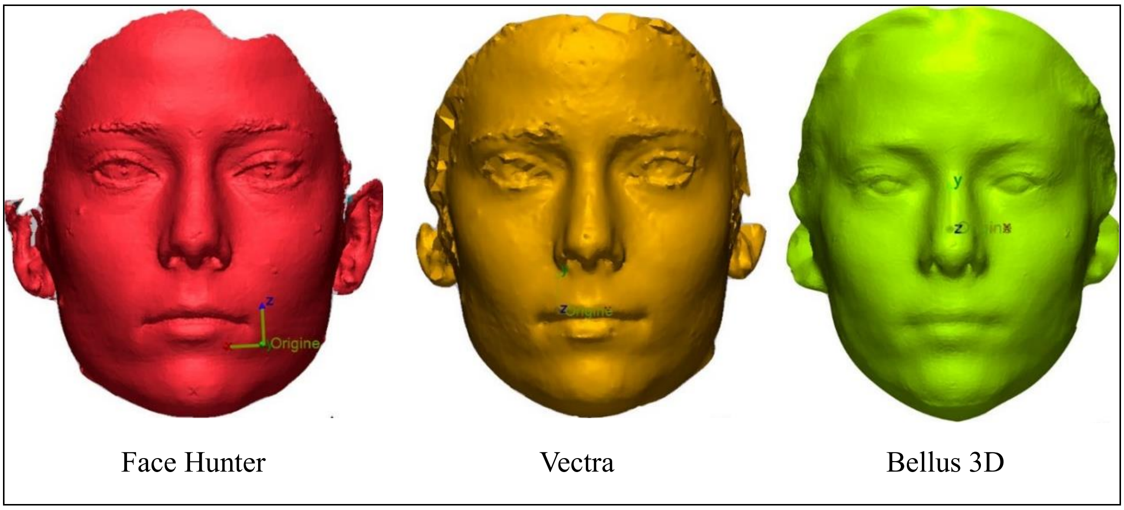


Figure 5: Facial scan of the same subject. Adapted from Pellitteri et al., 2023 (3).

The ANOVA test was employed to compare linear distances with direct anthropometry measurements, shown in figure 5. Results indicated statistically significant values for all distances examined, particularly for the Face Hunter scanner, except for the Prn–Pog′ distance (P= 0.092). Pairwise superimposition of the three facial scans showed nearly

100% overlap within tolerance limits for all comparisons analyzed. The chin exhibited the highest level of accuracy, with consistent reproduction across all scanners, whereas the forehead showed the least accurate reproduction among all scanners.

Each of the three acquisition systems successfully captured 3D facial images, except for the Face Hunter scanner, which displayed statistically significant variations in linear measurements for the Tr–Na′ and L–R Zyg distances compared to direct anthropometric measurements (3).

Another study conducted by D'ettorre et al. sought to compare three-dimensional facial scans captured using stereophotogrammetry with those obtained from smartphone applications that utilize the structured light technology and TrueDepth system.

Following the 'cleaning' phase, facial scans of 40 subjects were obtained using three different systems. This phase ensured that only the face was kept, removing any confounding elements such as ears, soulders, hair, and neck. The study compared the smartphone (iPhone Xs; Apple, Cupertino) equipped with either the Bellus3D Face Application (version 1.6.11; Bellus3D Inc, Campbell) or Capture (version 1.2.5; Standard Cyborg Inc, San Francisco) with a 3dMDtrio Stereophotogrammetry System (3dMD, Atlanta), indicated in figure 6.The time taken for image processing and acquisition was recorded for each system. Additionally, surface-to-surface deviations and distances between 18 landmarks from the 3dMD reference images were measured against those obtained with Bellus3D and Capture.

Figure 6 : 3D scans of the face. Adapted from D’ettorre et al (4).

The smartphone applications demonstrated significantly longer durations for capturing and processing in contrast to the 3dMD system.

Table 2: The scanning, processing, and total time taken by the three different software applications employed in this study (4).

Application	Scan Average	Scan SD	Processing Average	Processing SD	Total Average	Total SD
3dMD	0.0015a	0.00	20.58	1.30	20.59	1.30
Bellus3D	20.28	0.56	55.47	3.58	75.75	3.67
Capture	40.34	2.99	53.57	4.19	93.91	5.56

Analysis of the surface-to-surface deviation between Bellus3D and 3dMD revealed that within the one mm and 0.5 mm discrepancy ranges, there was an overlap percentage of 80.01 (± 5.92) % and 56.62 (± 7.65) %, respectively. Capture images displayed an overlap percentage of 81.40 (± 9.59) % and 56.45 (± 11.62) % within the ranges of one mm and 0.5 mm, respectively.

Acquiring facial images using the 3dMD device is rapid and precise, yet it can be cumbersome and costly. The latest smartphone applications, combined with TrueDepth sensors, show encouraging outcomes, although they demand greater precision from the operator and necessitate enhanced patient compliance due to prolonged acquisition times. Their primary advantages lie in cost-effectiveness and portability (4).

Automated facial analysis enhances orthodontic practice by providing efficient, accurate, and personalized diagnostic capabilities. Utilizing sophisticated algorithms, it streamlines data processing, ensuring standardized and objective assessments of facial features. This results in evidence-based treatment planning, enabling orthodontists to deliver more precise and tailored care to patients based on their individual facial anatomy. Overall, automated facial analysis represents a significant advancement in orthodontics, optimizing workflow efficiency and treatment outcomes.

1.1.4 Treatment needs from exobuccal images

1.1.4.1 Need for Class II and Class III treatment from mobile photos.

Identifying skeletal orthodontic deformities early is crucial due to functional and aesthetic impacts.

Research carried out by Kılıç et al. (2023) aimed to tackle the challenge of parents seeking routine orthodontic checkups for their children after the optimal treatment age. In response, they created a mobile application utilizing ML for an initial assessment of skeletal malocclusion based on a single photograph.

A retrospective analysis was performed on 524 children, aged five to twelve years, to assess the precision of the mobile application based on ML. The application detects different points in photos taken by the mobile camera and offers a signal indicating the presence of skeletal malocclusion in the diagnosis.

The study trained two ML models, Linear Regression Classifier (LRC) and Random Forest Classifier (RFC) to differentiate Class III vs not Class III and Class II vs Class I. Results are shown in tables 3 and 4.

Table 3: Class III vs. not Class III: Model Accuracy Comparison (5).

Method	Accuracy
LRC	0.8023
LRC Bagging	0.8140
LRC Boosting	0.7209
RFC	0.8023
RFC Bagging	0.7907

This table shows how well different ML models classified patients with or without Class III malocclusion. LRC Bagging achieved the highest accuracy (81.4%) in distinguishing between the two groups.

Table 4: Class II vs. Class I: Model Accuracy Comparison (5).

Method	Accuracy
LRC	0.69
RFC Boosting	0.8023
Extra Trees Classifier - Boosting	0.7907
Gradient Boosting Classifier - Boosting	0.8023
AdaBoost Classifier - Boosting	0.7093
Voting Classifier Blending hard	0.814

This table summarizes the key finding regarding model performance in classifying Class I vs Class II malocclusions. It highlights the Voting Classifier Blending method achieved the highest accuracy (0.814) among all the evaluated methods.

As a conclusion we can say that the app furnishes parents with details regarding orthodontic issues, treatment age, and diverse treatment choices. This empowers parents to consult with an orthodontist sooner and make well-informed decisions (5).

1.1.4.2 AI vs. Human Assessment of Facial Attractiveness in Cleft Patients

Research undertaken by Patcas et al (2019) had as an objective to assess the facial attractiveness of cleft patients' post-treatment compared to control subjects. Using AI and compare these outcomes with evaluations from laypeople, orthodontists, and oral surgeons.

As represented in figure, to achieve this, frontal and profile images of 20 treated left-sided cleft patients and 10 controls were subjected to facial attractiveness analysis. This analysis utilized convolutional neural networks trained on more than 17 million attractiveness ratings.

The AI-generated results were juxtaposed with evaluations from 15 laypeople, 10 oral surgeons, and 14 orthodontists utilizing a visual analogue scale, with a total of 2323 scorings.

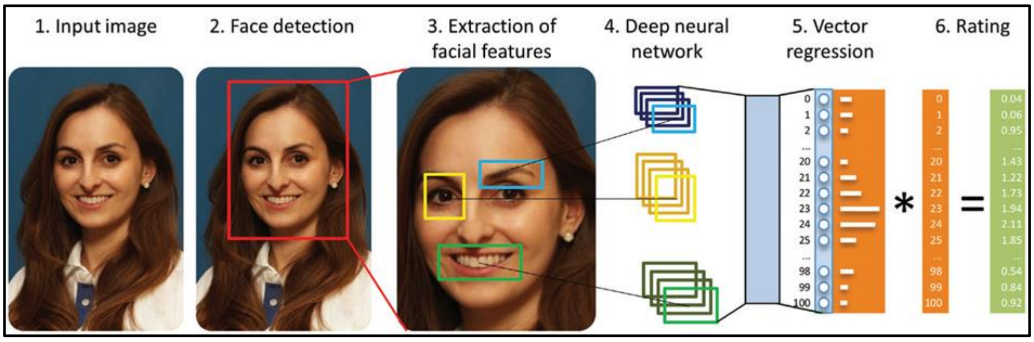


Figure 7: Processing pipeline of the deep neural network applied. Adapted from Patcas et al., 2019 (6)

AI evaluations of cleft patients (mean score: 4.75 (± 1.27)) closely resembled human ratings (laypeople: 4.24 (± 0.81), oral surgeons: 4.74 (± 0.83), orthodontists: 4.82 (± 0.94)) and showed no statistical differences. For controls, human ratings were significantly higher than AI, with AI providing lower scores compared to cleft subjects. Variance was substantial in all human rating groups, especially in the assessment of cleft patients (coefficient of variance—laypeople: 38.73 (± 9.64), oral surgeons: 42.19 (± 9.80), orthodontists: 32.56 (± 8.21)).

In summary, the AI-based results exhibited close alignment with the average scores from all three rating groups for cleft patients, indicating strong concurrence with assessments by professional panels. However, for control cases, the AI-based results generally showed lower scores compared to cleft patients.

The variability observed in panel ratings underscored significant imprecision attributed to a problematic lack of uniformity (6).

1.1.4.3 Machine Learning for Orthodontic Treatment needs

Photography is essential for evaluating pre-operative dental conditions and maintaining oral health records, especially for diagnosing and planning orthodontic treatments. However, manual facial measurements can be error-prone and tedious. To address these challenges, new ML algorithms have been developed to automate facial landmark identification and measurements on 2D patient images, streamlining the process and improving accuracy.

A study conducted by Rao and al., (2019) successfully identified 418 facial landmarks, as represented in figure 8 and 9, with 100% facial recognition accuracy using the YOLO (You Only Look Once) deep learning algorithm. Of the 220 landmark measures performed, the system generated measurements within different error ranges: 21.81% in the zero to one mm range, 34.09% in the two to three mm range, 41.81% in the four to five mm range, and 2.2% in the six mm range.

The study's results demonstrated the system's effectiveness in reliable and fast identification of landmarks and analysis, providing valuable training for students in clinical facial analysis.

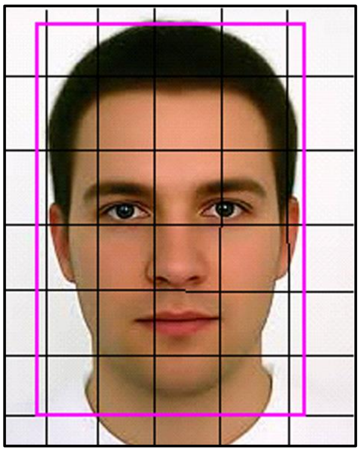


Figure 8: The detected face region. Adapted from Rao et al., 2019 (7)

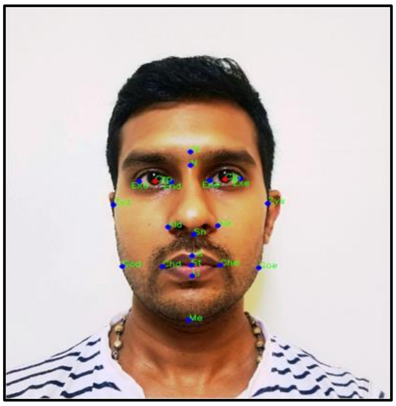


Figure 9: Facial landmark points identified and located on the subject's image. Adapted from Rao et al., 2019 (7).

In conclusion, the automated system, powered by an efficient algorithm, offers a significant advancement in orthodontic photometric points and facial measures analysis. The integration of YOLO in deep learning processes allowed for handling images of various qualities and complexities, enhancing the system's robustness and real-time capabilities. The system, designed to be interactive, engaging, and user-friendly, fosters self-directed learning and generates interest in understanding facial measurements within the context of diagnosis and treatment purposes (7).

1.2 Endobuccal diagnostic

The realm of orthodontics has been revolutionized by the integration of AI, particularly in the domain of endobuccal diagnostics. This section delves into the utilization of AI for assessing treatment needs from images and automating the classification and archiving of diagnostic images.

1.2.1 Treatment needs from endobuccal images

Proper diagnosis, identification, and evaluation of malocclusion play a pivotal role in maintaining optimal oral health. Traditionally, malocclusion treatment needs have been assessed through direct examination by a specialist.

Alternatively, a study led by S.Talaat et al., (2021) introduces a groundbreaking approach, a fully automated system utilizing convolutional neural networks (CNNs) for detecting, localizing, and assessing malocclusion and orthodontic needs. The research focuses on developing and validating an AI application designed for the automated identification of malocclusion and assessment of treatment requirements.

They used intraoral raw images from 700 subjects, categorized into front occlusion, right occlusion, left occlusion, lower occlusal and upper occlusal images. Images that did not adhere to the study protocol were eliminated, resulting in a set of 576 images. Each image underwent independent annotation by both an investigator and an orthodontic specialist.

Malocclusion was detected and pinpointed in each image, as evidenced in figure 10, covering various conditions including spacing, crowding, increased overjet, deep bite, open bite, and crossbite.

The chosen model for this research study was the "You Only Look Once" model.

Figure 10: Resulting testing images showing fully automated prediction boxes depicted in thin red marking the malocclusions. Adapted from Talaat et al., 2021 (8).

The CNN model exhibited outstanding performance, with an ICC surpassing 0.9, demonstrating its capability to detect and localize malocclusions with 99.99% accuracy, 99.79% precision, and 100% recall.

This achievement introduces a novel avenue for home care, enabling patients to conduct automated self-assessments using images captured on their mobile devices. Following specific instructions, patients can promptly receive a summary of identified issues and hints regarding treatment difficulty. Additionally, this technology proves valuable for health insurance companies, enabling automated pre-authorization and pre/post-treatment assessment (8).

1.2.2 Classifying and archiving images

In the realm of orthodontics, maintaining a continuous flow of image acquisition is imperative for effective treatment monitoring and planning. However, the current conventional system relies heavily on manual processes such as image classification, archiving, and monitoring, a process that demands sustained attention and accuracy. The fatigue factor in manual procedures heightens the risk of oversight and misclassification, impacting the precision of treatment plans. Consequently, the limitations of this conventional approach underscore the pressing need for a more efficient and error-resistant system, prompting the exploration of advanced technologies such as AI to revolutionize orthodontic image management.

Amid these complexities, we turn our attention to the pioneering contributions of two authors, which underscore their dedication to advancing orthodontic image management through inventive research and technological innovations.

One such figure is Shihao Li, (2022) whose work between January and December 2019 involved the collection of orthodontic images from 1,000 patients treated at Sichuan Hospital of Stomatology, Simai Clinic, and Yingke Clinic. Additionally, an external data set comprising 100 patients from Haoya Clinic was included. This comprehensive dataset, comprising 15,819 images across 14 categories, as shown in figure 11, underwent rigorous training, validation, and testing for the development of a DeepID-based orthodontic image classification model. To ensure the reliability of the data, all images were manually classified by experienced orthodontists, with oversight from a senior specialist. The model was exclusively applied to images that had undergone manual review by experienced orthodontists to ensure sufficient quality and suitability.

The study compared the deep learning model's performance against orthodontists with over five years of experience. The fully automated method based on deep learning model achieved image classification in just 0.08 minutes, 236 times faster than the human expert, with an accuracy of 99.4% and a macro-AUC of 1.00.

Furthermore, in order to thoroughly assess the effectiveness of our deep learning model, the study compared the efficacy of human-only and human-machine methods for classifying, selecting, removing, and documenting orthodontic images. On average, three human experts aided by deep learning required 8.10 minutes to classify and monitor images from the external dataset consisting of 100 patients. This was found to be more efficient compared to manual classification performed solely by human experts, which took 18.93 minutes on average. Additionally, the assistance of deep learning led to one% improvement in classification accuracy and a 0.1 increase in the macro-AUC value (9).

Figure 11: Examples of slideshows showcasing the classification and monitoring of orthodontic images using deep learning. Adapted from (9).

Also, a study by Ryu J et al., (2022) incorporated 4,448 clinical photos from 491 orthodontic patients at Seoul National University Dental Hospital, taken by various doctors. The training and validation phases employed the Adam optimization method and Categorical Cross-entropy loss function, resulting in remarkable accuracies of 99.3% for facial and 99.9% for intraoral photos. The model demonstrated success rates of 97% for facial front and smile photos, 98% for three-quarter facial photos, and 99% for intraoral right photos. However, a lower success rate of 94% was observed for intraoral front photos and 97% for intraoral left photos. Validation accuracy remained high at 99.8%.

The model demonstrated proficiency in detecting diverse dental conditions such as braces, teeth malformations, and removable appliances, as illustrated in figure 12.

Figure 12: Examples of input photos depicting various arrangements, alignments, appliances, and statuses of teeth. Adapted from (10).

Challenges in distinguishing nuanced facial expressions and front intraoral photos highlight the need for ongoing exploration into the model's decision-making mechanisms.

Despite these considerations, the study emphasizes the model's overall success in recognizing varied dental conditions (10).

1.3 Radiological diagnostic

Identifying landmarks on diagnostic images such as cephalograms, models, and CBCT scans is crucial for diagnosis and treatment planning. However, manual, or visual analysis of these images is time-consuming and labor-intensive. Moreover, it relies on the expertise and subjective judgment of the clinician, which can lead to errors and inter-expert variability. Given the critical importance of accurately interpreting orthodontic records, inaccurate image analysis can potentially impact the treatment outcome adversely.

Therefore, there is a pressing need to establish a reliable and reproducible framework that can efficiently detect landmarks and perform the necessary measurements within an acceptable time frame. While various approaches have historically been employed to address these challenges, in recent years, AI -based fully automated methods have emerged as the leading contenders.

1.3.1 Advancements in AI-based Analysis

The research conducted by Jiang et al. (2023) aimed to develop a reliable and practical AI system for automated cephalometric analysis. This effort resulted in the creation of an advanced AI system, which began by compiling a dataset of 9,870 cephalograms from 20 medical institutions, capturing diverse malocclusions and taken using different radiography machines. Subsequently, 30 landmarks were manually annotated on all cephalogram samples to train the AI system, comprising a two-stage convolutional neural network and a software-as-a-service platform.

Furthermore, over 100 orthodontists contributed to refining the landmark localizations produced by the AI and retraining the system accordingly. The developed automatic cephalometric analysis system, known as CephNet, exhibited high accuracy in landmark localization, with an average location error of 0.94 (± 0.74) mm, surpassing previous studies. Additionally, CephNet achieved an average successful detection rate (SDR) of 89.33% for 28 landmarks, showcasing its potential for clinical application. The accuracy and robustness of CephNet were credited to the utilization of high-quality training datasets, advanced network architecture, and the collaborative efforts of orthodontists in refining the AI-generated landmark localizations. Additionally, CephNet's performance was evaluated across various clinical scenarios, demonstrating consistent performance across cephalograms with different qualities, resolutions, and malocclusions. Overall, the results suggest that CephNet holds promise in significantly enhancing the efficiency of orthodontic diagnosis and treatment planning.

Table 5: Description of cephalometric landmarks (11).

Landmark	Abbreviation	Description
Sella	S	Point in the center of the sella turcica in the sphenoid bone
Nasion	N	Point at the junction of the frontal and nasal bones
Condylion	Co	Most posterior superior point of the condyle of the mandible
Upper incisor	U1	Tip of the crown of the upper central incisor
Porion	Po	Superiormost point on the external auditory meatus
Root apex of upper central incisor	U1A	Apex of the root of the upper central incisor
Orbitale	Or	Lowermost point on the rim of the bony eye socket
Lower incisor	L1	Tip of the crown of the lower central incisor
Articulare	Ar	The most posterior point on the condyle of the mandible
Root apex of lower central incisor	L1A	Apex of the root of the lower central incisor
Anterior nasal spine	ANS	The most pointed forward projection on the anterior maxilla
Pronasale	Prn	The most anterior tip of the soft tissue of the nose
Posterior nasal spine	PNS	The most posterior projection on the posterior maxilla
Subnasale	Sn	The inferior point on the columella (the fleshy part between the nostrils)
Subspinale	A	The deepest point of the curve of the lower lip
Superior labial sulcus	A’	The groove between the upper lip and the nose
Superior prosthion	Spr	The most anterior point on the alveolar process of the upper jaw between the central incisors
Upper lip	UL	The soft tissue of the upper lip
Infradentale	Id	The deepest point between the lower lip and the chin
Labrale superius	Ls	The upper border of the vermilion of the upper lip
Supramentale	B	The most superior point on the curve of the lower jaw
Lower lip	LL	The soft tissue of the lower lip
Pogonion	Pog	The most anterior point on the mandible on the midline
Labrale inferius	Li	The lower border of the vermilion of the lower lip
Gnathion	Gn	The lowest point on the mandible on the midline
Pogonion of soft tissue	Pog’	The most anterior point of the soft tissue of the chin
Menton	Me	The lowest point on the bony chin
Gonion (Go)	Go	The angle where the body and ramus of the mandible meet

In summary, this automated cephalometric analysis system, backed by extensive training data and a novel algorithm, demonstrated remarkable precision and suitability.

It is anticipated that this system will streamline the tasks of orthodontists, markedly improving their productivity (11).

1.3.2 Evaluation of AI-Human Collaboration

A study by Le et al. (2022) aimed to evaluate how human-AI collaboration impacts cephalometric landmark detection, particularly on lateral cephalograms. It assessed the Deep Anatomical Context Feature Learning (DACFL) model's effectiveness, compared beginners' performance working alone versus with AI, and investigated the collaboration's benefits in enhancing landmark detection rates. Overall, the study aimed to highlight the potential of AI-human collaboration in improving personalized medicine in dentistry and orthodontics.

This study demonstrated that the DACFL model attained an SDR of 73.17% within a 2 mm threshold on our dataset. Additionally, collaboration between beginners and AI enhanced the SDR by 5.33% within the same threshold, along with improving the SCR (successful classification rate) by 8.38% compared to beginners. These findings indicate the DACFL model's suitability for clinical orthodontic diagnosis and highlight the potential benefits of AI-experienced orthodontist collaboration. Further research is needed to validate these advantages (12).

1.3.3 Comparison of Manual Analysis to Automated Cephalometric Analysis

An investigation by Tsolakis et al. (2022) aimed to compare the accuracy of automatic cephalometric analysis with CS Imaging V8 software to manual analysis, evaluating reliability, precision, and agreement between methods for cephalometric landmarks and measurements, with consideration of clinical implications.

The study involved 100 subjects, comprising 43 males and 57 females, with a mean age of 15.9 (± 4.8) years. Operator reliability was assessed using intraclass correlation on 20 randomly chosen subjects, demonstrating excellent agreement across all measurements. Sixteen cephalometric landmarks, corresponding to 17 angular and two linear measurements, were identified, as indicated in figure 13. Statistical analysis was conducted using SPSS software, with the Bonferroni method applied for multiple comparisons between automatic and manual methods. Intra-method agreement was assessed using the ICC.

Results revealed a strong correlation between automatic and manual methods for various cephalometric measurements. Specifically, for the American Board of Orthodontics analysis, there was no significant difference in several measurements, including SNA, SNB, ANB, SN-MP, U1-SN, U1-NA, L1-MP, and L1-NB, while differences were observed for FMA and L1-MP. Similarly, for European Board of Orthodontics analysis, no significant difference was found for SNPg, ANPg, SN/ANS-PNS, SN/Go-Gn, U1/ANS-PNS, L1/GoGn, and L1/APg measurements, but differences were noted for ANS-PNS/GoGn and U1-L1. Overall, most measurements exhibited strong correlation (ICC > 0.70) between the two methods.

The study suggests that automatic cephalometric analysis using CS Imaging V8 software is comparable to manual analysis, demonstrating high correlation and agreement across most measurements (13).

Also, a paper published by Bao et al. (2023) aimed to assess the accuracy of automated cephalometric analysis utilizing artificial intelligence. Specifically, researchers compared an automatic localization program with Dolphin software, a commonly used computer-assisted cephalometric analysis program. They evaluated the accuracy of landmarks and measurements pertaining to bone, teeth, and soft tissue to explore the potential clinical application of AI cephalometric analysis. Through this assessment, the researchers aimed to ascertain the reliability and effectiveness of automated cephalometric analysis as a time-saving tool for orthodontic practitioners.

The study assessed the precision of automated cephalometric analysis utilizing AI, utilizing reconstructed lateral cephalograms derived from CBCT scans. Here are key numerical findings from the study:

- Among 23 measurements, 15 fell within the clinically acceptable threshold of two mm or two degrees.

- Consistency rates within the 95% limits of agreement exceeded 90% across all measurement parameters.

- Bland-Altman plots illustrated that measurement bias remained within the 95% limits of agreement in over 90% of cases.

- The research demonstrated that automatic analysis software effectively collected cephalometric measurements, meeting clinical standards.

- Nevertheless, it was acknowledged that automated cephalometry cannot entirely replace manual tracing. Additional manual oversight and adjustment for automated programs can enhance accuracy and efficiency.

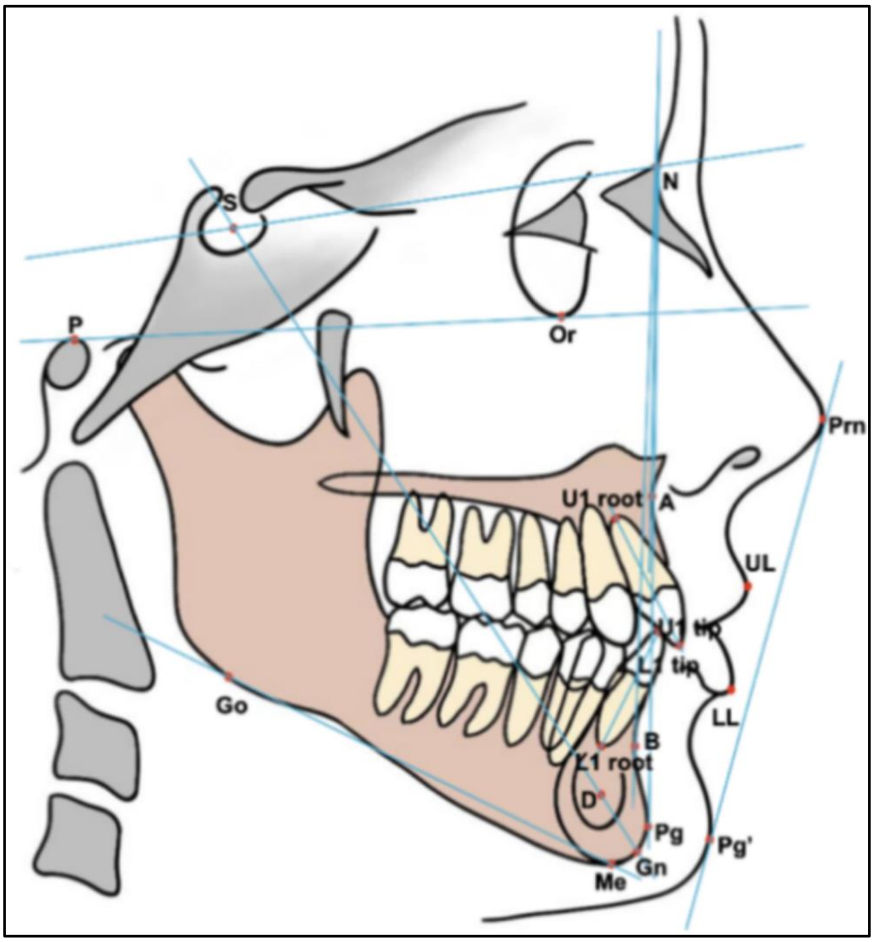


Figure 13: Cephalometric landmarks and measurements in terms of bone, teeth, and soft tissue. Adapted from Bao et al., 2023 (14).

These numerical findings highlight the promising performance of automated cephalometric analysis utilizing AI in delivering precise and efficient cephalometric measurements for clinical application (14).

1.3.4 Future Directions in Orthodontics

Al-Ubaydi et al. (2023) evaluated the precision of tooth models segmented by an AI program, CephX®, versus intraoral scans and Insignia outcomes. Focusing on Class I malocclusion cases with mild-to-moderate crowding, the study aimed to assess the accuracy of AI-based tooth segmentation compared to traditional methods like CBCT scans. It aimed to determine the reliability of AI in providing detailed tooth measurements and its potential impact on orthodontic diagnosis and treatment planning.

In this study, the precision of segmented tooth models was evaluated through various methods. Utilizing the AI program CephX®, a total of 280 segmented tooth models were produced based on intraoral scans and CBCT scans obtained prior to orthodontic treatment. Each tooth in the segmented models underwent measurements from three aspects - apexo-occlusal, mesiodistal, and labiolingual - in both DICOM and STL formats, allowing for a comprehensive assessment of accuracy and reliability. Additionally, root volume measurements were conducted using the CephX® software and the Insignia™ system, enabling a comparison to evaluate the effectiveness of AI in providing detailed root volume data crucial for treatment planning. Statistical analysis, including ICC, was performed to assess agreement between volume measurements of segmented teeth by CephX® and the Insignia™ system, providing insights into the reliability of AI-generated tooth models compared to traditional methods. Through these approaches, the study contributes valuable insights into the validity and reliability of automatic tooth segmentation techniques in orthodontic practice, as presented in figure 14.

The study revealed several significant findings regarding the precision and reliability of segmented tooth models generated through AI. Firstly, there was strong agreement between the STL tooth models produced by CephX® and the Insignia™ system, indicating a high level of consistency (ICC = 0.881). Secondly, while segmented 3D models from CBCT images tended to underestimate tooth sizes, this discrepancy did not clinically impact calculations like the discrepancy index or Bolton index. Thirdly, root volume measurements obtained from both CephX® and the Insignia™ system showed excellent agreement, emphasizing AI's reliability in producing detailed tooth measurements. Lastly, the study's results aligned with previous research, corroborating the tendency for 3D CBCT segmented models to underestimate tooth sizes, particularly in capturing anatomic contact points. Collectively, these findings underscore the comparable accuracy of automatic tooth segmentation methods using AI, suggesting their potential to enhance orthodontic diagnosis, treatment planning, and assessment in the future.

Segmentation of teeth utilizing AI technology presents numerous advantages in orthodontics and dental imaging. Firstly, AI-based segmentation techniques offer precise and accurate delineation of individual teeth from surrounding structures in imaging data, facilitating detailed analysis and measurements. Secondly, automated segmentation with AI significantly reduces the time and effort required for manual segmentation, enhancing workflow efficiency. Thirdly, AI algorithms ensure consistency in tooth segmentation across different datasets and imaging modalities, reducing variability, and improving measurement reliability. Fourthly, AI-based segmentation eliminates subjective biases inherent in manual processes, leading to more objective and standardized tooth models for analysis. Moreover, accurate tooth segmentation supports better treatment planning in orthodontics by providing detailed information on tooth morphology, alignment, and relationships, thereby aiding in the development of personalized treatment strategies. Additionally, segmented tooth models can seamlessly integrate with computer-aided design/computer-aided manufacturing (CAD/CAM) systems for orthodontic appliance and restoration fabrication, further enhancing treatment outcomes. Furthermore, AI-based tooth segmentation supports advanced research in dental imaging and orthodontics, enabling studies on tooth morphology, growth patterns, and treatment outcomes, while serving as a valuable educational tool for dental anatomy and orthodontic diagnostics. In summary, AI-driven tooth segmentation offers improved precision, efficiency, consistency, objectivity, treatment planning capabilities, integration with CAD/CAM systems, and support for research and education in orthodontics and dentistry (15).

In the foreseeable future, it's plausible that superimposition or similar methods will supplant, or supplement linear and angular measurements conducted on 3D images. Automated segmentation of bone, teeth, or any anatomical structure from CBCT scans will become commonplace, streamlining processes and mitigating biases. Likewise, the identification of anatomical landmarks and measurements through AI and computer vision will be automated. CBCT imaging of digital models may emerge as an alternative to digitization with optical devices, eliminating the need for additional dedicated dental digitizers. Customized brackets and arch wires bent by robots will be manufactured based on these digital models. In the coming decades, personalized treatment and biomechanical planning may become fully integrated, possibly even within one's own practice (16).

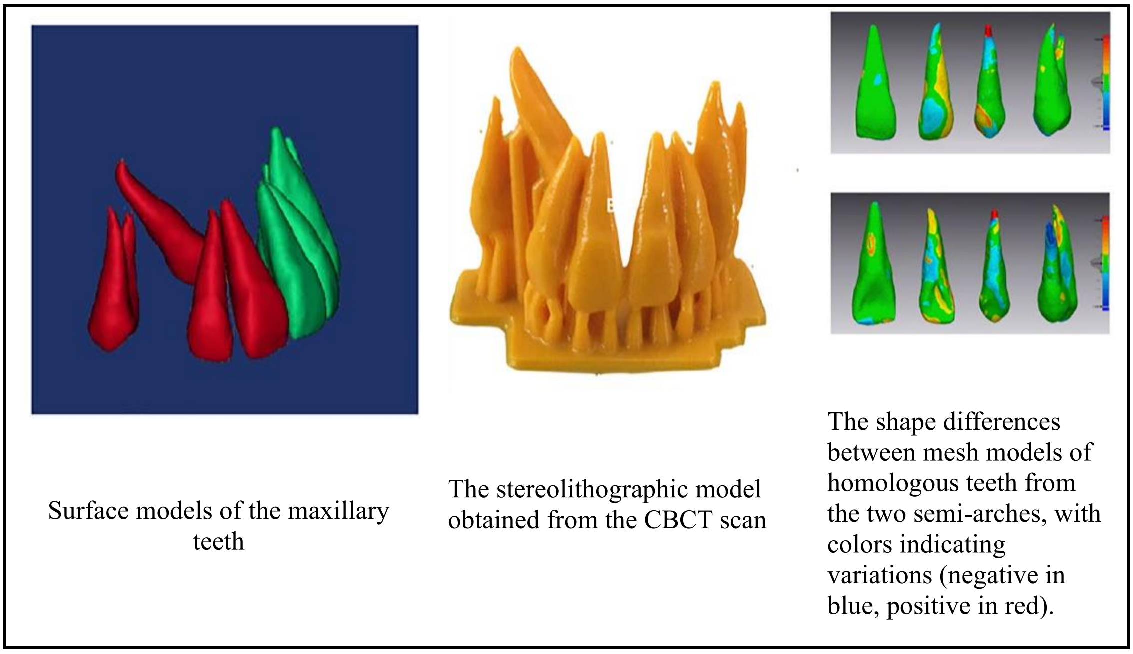


Figure 14: Maxillary teeth segmentation from CBCT-derived models. Adapted from Leonardi, 2019 (16).

1.4 Treatment

The integration of AI in orthodontics has brought forth in a new era of precision and efficiency in the treatment of dental conditions. In the realm of treatment, AI plays a pivotal role by offering personalized planning solutions, optimizing treatment simulations, automating critical tasks such as bracket placement and wire bending, and providing real-time monitoring capabilities. This transformative technology not only enhances the accuracy of tooth movement but also allows for dynamic adjustments based on individual responses to treatment.

1.4.1 Personalized treatment plan

Personalized treatment plans in orthodontics are essential for addressing individual patients' unique dental needs and goals. By tailoring treatment plans, dental professionals ensure that patients receive customized care designed to meet their specific oral health requirements. This individualized approach enhances the effectiveness of treatments and empowers patients by involving them in decision-making. Personalized treatment plans also facilitate effective communication, patient education, and simplified financial management, ultimately leading to more efficient and effective delivery of care for optimal oral health.

In the context of orthodontics, the use of 3D digital treatment simulation technology allows for the design of tailored treatment plans customized to the specific requirements of each patient. This advanced technology enables orthodontists to visualize and customize treatment plans, contributing to more tailored and effective orthodontic care.

Furthermore, the incorporation of AI into orthodontics holds promise for optimizing treatment planning. by reducing variability in practitioners' decisions and improving the consistency and effectiveness of orthodontic treatments. AI can be utilized to support human experience in developing predictive models for orthognathic surgery planning and orthodontic extraction treatment decisions, highlighting its extraordinary potential in personalized treatment planning.

While personalized treatment planning and the integration of AI offer significant benefits, it is important to recognize the need for human input and expertise in addressing unexpected situations, incorporating patient preferences, and ensuring high standards of treatment planning and execution. Patients may still prefer human orthodontists to explain their treatment in detail, answer questions thoroughly, and provide reassurance during the process, emphasizing the complementary role of AI and human professionals in delivering personalized orthodontic care (17).

1.4.2 Teeth extraction need and selection

The decision to extract teeth in orthodontic treatment is crucial but often debated due to its irreversible nature. Clinicians traditionally rely on various factors such as clinical assessments and radiographs to make these decisions, which depend on their expertise. However, incorrect decisions can lead to adverse outcomes, including aesthetic and functional issues, highlighting the importance of careful consideration in treatment planning.

Currently, there is no standardized protocol for tooth extraction decisions, resulting in variability among clinicians and inconsistency in treatment approaches. Consequently, this presents a significant challenge for students, residents, orthodontists, and dentists worldwide, leading to gaps in knowledge and interpretation of data. To address this issue and promote consistency in decision-making, innovative approaches are needed to formalize and standardize the process.

Since 2010 Xie et al. developed a decision-making expert system to assess the necessity of extraction for malocclusion patients aged 11 to 15 years. Artificial Neural Networks (ANNs) utilize the error backward propagation learning technique to minimize the occurrence of errors. As per the research findings, determining whether extraction or non-extraction treatment is required exhibited an accuracy rate of 80%. In 2016, Jung et al. utilized ANN to predict specific extraction patterns with an accuracy of 84%.

In 2019, Li et al. investigated the use of multilayer perceptron ANNs to predict orthodontic treatment plans. Their focus was on determining extraction needs and extraction patterns.

The ANN model utilized in orthodontic treatment planning incorporates 24 feature variables extracted from patients' medical records, encompassing demographic data, extraoral and intraoral photographs, pretreatment casts, and cephalometric measurements. These features encompass a range of factors such as "crowding, upper arch," "crowding, lower arch," "U1-NA°," "ANB," "overbite," "lip incompetence," "curve of Spee," and "nasolabial angle". To ensure uniformity in data representation, nonquantitative information is transformed into numerical values through an encoding method prior to model training. Additionally, the significance of each feature in predicting extraction or non-extraction, extraction patterns is evaluated through ranking their relative contributions to the decision-making process.

The neural network model demonstrates high performance in predicting extraction or non-extraction plans, with an accuracy of 94.0%. The optimal diagnostic threshold for this model is 0.692, achieving a sensitivity of 94.6% and a specificity of 93.8%. The key features influencing these predictions include factors such as "crowding, upper arch," "ANB," and "curve of Spee," which play a crucial role in determining whether a case requires extraction or non-extraction treatment, providing valuable insights for orthodontic treatment planning. Additionally, the model shows predictive accuracies of 83.3% for extraction patterns. These accuracies outperform some traditional prediction methods, with the extraction prediction accuracy of 94.0% being higher than previous models. The AUC of 0.982 for extraction prediction also surpasses results from studies using other algorithms. Overall, the neural network model demonstrates superior performance in predicting extraction compared to traditional methods, providing valuable support for orthodontic treatment planning (18).

In 2022, Del Real et al presented a study on the use of AI for predicting the necessity of dental extractions during orthodontic treatments, based on gender, cephalometric records, and model variables. Data from 214 patients were used to develop prediction models using ML software (Auto-WEKA). The findings demonstrated a 93.9% accuracy in discerning the necessity of extraction, leveraging both model-based and radiographic information. When exclusively relying on model variables, the accuracy reached 87.4%, whereas employing only cephalometric data yielded an accuracy of 72.7%. Predictive models demonstrated that combining both enhances the accuracy of predicting the need for orthodontic extractions.

The study also emphasizes the importance of automated ML systems (AutoML) to ease healthcare professionals' access to AI methods and technologies. This enables the creation, testing, and execution of AI systems in their practices without requiring assistance from skilled experts. The study results suggest significant potential for the use of AutoML systems in orthodontics, providing reliable and accurate prediction models for challenging clinical decisions, such as dental extractions.

In summary, this research showcases how AutoML simplifies model generation, minimizing operator dependency and enabling the creation of multiple precise prediction models. This advancement holds particular promise for healthcare professionals navigating complex clinical decision-making, such as in orthodontic extractions (19).

Also in 2020, Suhail et al. conducted a study involving 287 patients, collaborating with five experts who assessed 19 pre-determined diagnostic attributes using patient photographs and cephalometric images. These experts also provided primary and alternative treatment options, making binary decisions between extraction and non-extraction. From the extraction plan, they chose among 13 alternatives based on the teeth identified for extraction as shown in Figure 15.

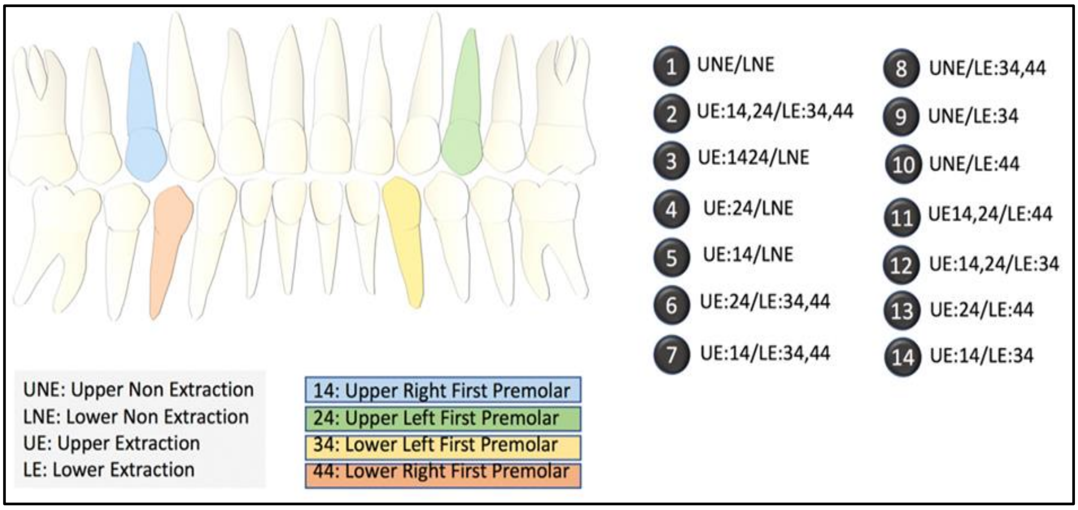


Figure 15: Index of various extraction options. Adapted from Suhail et al., 2020 (20).

Moreover, they offered opinions on the alternative outcome, allowing for robust outcome accuracy testing amid expert opinion variability. Despite similar studies including numerous features, our deliberate limitation of features aimed to simplify data collection and implementation in clinical settings, reducing computational requirements and redundancy. By leveraging diverse features with various ML models, we extracted additional information and created nonlinear predictors for regression by incorporating second-degree interactions. While overfitting was detected, regularization addressed this issue, and ensemble learning, and weight regression proved beneficial. The constraints of our feature set and ML algorithm achieved extraction procedure prediction accuracy comparable to that of diverse experts, supported by ensemble classifiers like random forest. Additionally, simpler ensemble models outperformed more complex ones, indicating the effectiveness of our approach. Methods like bagged batch training and dropouts could potentially augment the performance of neural network models when compared to random forest models (20).

1.4.3 Automated bracket placement

1.4.3.1 Indirect bonding

AI models play a crucial role in diagnosing and classifying malocclusions by analyzing diverse diagnostic data, including radiographic images, facial photographs, and dental models. Through training on extensive datasets, AI can recognize and categorize various malocclusion types, aiding orthodontists in treatment planning and selecting suitable treatment approaches. AI-driven software can produce virtual 3D models of patients' teeth, allowing for simulation of orthodontic treatment progression and outcomes.

Additionally, AI algorithms can automate bracket placement by assessing dental models and predicting the best bracket positions based on individual tooth anatomy (21).

Indirect bonding was developed to enhance the precision of bracket placement, particularly in cases of significant irregularities on the lingual or labial tooth surfaces. This technique can be executed with or without individual tooth setups. While conventional indirect bonding methods aim to reduce errors associated with direct bonding, individualized setups in indirect bonding strive to attain an optimal straight archwire without requiring manual bending. Additionally, this approach enables precise bracket placement, tailored to the patient's aesthetic, occlusal and functional needs. Instead of relying on a bracket position chart, clinicians using this approach consider three key parameters: data from FA (facial axis) point and FACC (facial axes of the clinical crowns) axis detection, amount of tooth displacement, and potential overcorrection in axial, sagittal and vertical orientations.

Incorporating CAD-CAM technology has optimized the entirety of the indirect bonding process, beginning with digital bracket positioning and orthodontic setup, through to the production of indirect bonding trays within the laboratory. The digital modeling of the indirect bonding tray is customized based on the digital orthodontic setup, ensuring precise adjustments like vertical overcorrection of specific brackets, as illustrated in Figure 16 (22).

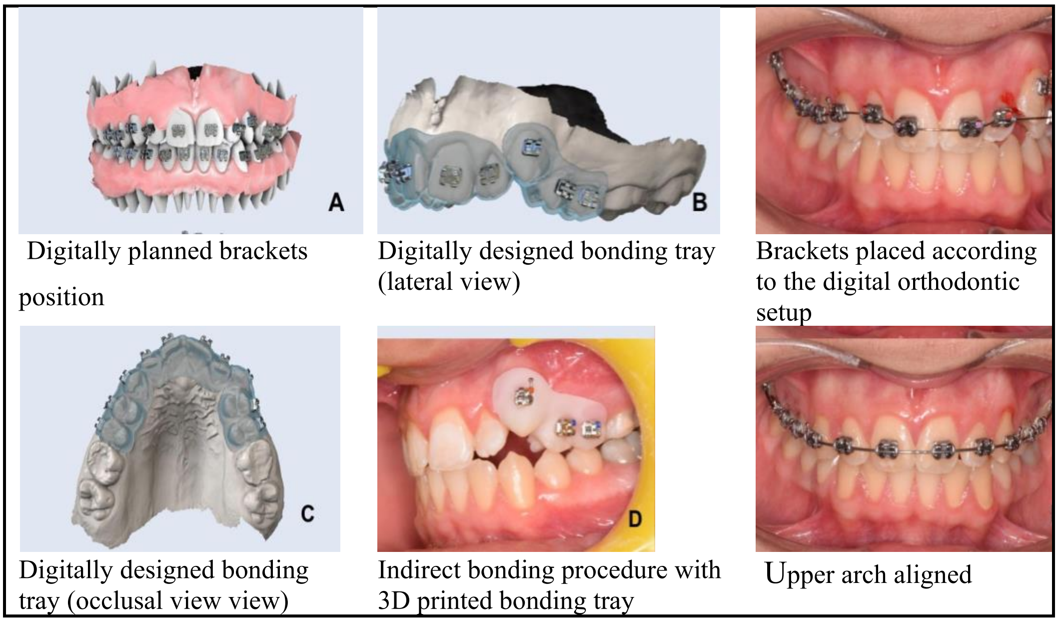


Figure 16: An example of digitally planned bracket positions based on the digital setup and the subsequent 3D printing of an indirect bonding guide using Maestro software (AGE Solutions SRL, Pisa, Italy). Adapted from Ronsivalle et al., 2023 (22)

The integration of digital treatment planning software and 3D printing has transformed orthodontics, particularly the traditional indirect bonding technique. This advancement is multifaceted: digital treatment planning software eliminates manual tray fabrication, allowing for digitally designed trays for indirect bonding (IDB). Digital IDB protocols enable precise bracket positioning based on simulated treatment plans, enhancing bracket placement accuracy. Digital IDB techniques simplify the process by eliminating numerous steps, reducing errors during bonding appointments. Tailoring fixed appliances to match the eventual treatment outcome is facilitated by digital treatment planning software, enhancing overall treatment strategies. In-office 3D printing for transfer trays reduces costs, streamlines workflow, and minimizes the need for multiple visits for bracket placement adjustments. Digital IDB techniques enhance the patient experience by minimizing repositioning during treatment and ensuring accurate bracket positioning. Overall, this integration represents a significant advancement, offering orthodontists a more precise, efficient, and patient-centered approach to fixed appliance treatment.

AI revolutionized the development of indirect bonding trays, providing several significant benefits. Algorithms automate bracket positioning by analyzing digital models, recommending optimal positions based on treatment objectives, tooth morphology, and occlusal relationships, thereby reducing manual effort in tray design. AI employs predictive modeling to simulate tooth movement and treatment outcomes, aiding orthodontists in planning ideal bracket positions and enhancing the precision of indirect bonding tray designs. By processing extensive datasets, including patient information and treatment histories, AI recognizes trends and patterns to create personalized indirect bonding trays tailored to each patient's unique requirements. AI algorithms also analyze treatment plans, offering suggestions for bracket position adjustments to optimize tooth movement, reduce treatment duration, and improve efficiency. AI-powered systems perform quality control checks on indirect bonding tray designs, ensuring accurate and consistent bracket positioning aligned with the treatment plan, minimizing errors, and enhancing treatment outcomes. Leveraging AI capabilities, orthodontists can create personalized treatment plans tailored to each patient's unique dental anatomy, treatment goals, and biomechanical factors, resulting in more effective designs for indirect bonding trays and improved patient care.

Integrating AI technologies into indirect bonding tray development streamlines the design process, enhances treatment planning accuracy, optimizes treatment outcomes, and ultimately improves the overall efficiency and effectiveness of orthodontic care (23).

1.4.3.2 Bonding facilitated by Augmented reality

The precise placement of brackets is crucial for effective orthodontic treatment. The direct bonding method utilizes a gauge to determine the correct bracket placements directly within the mouth. This technique provides benefits like the absence of interference with guiding trays, accommodation for crowded teeth, and the ability to promptly adjust bracket positions, as shown in figure 17. Nonetheless, several factors, including the gauge's measurement scale, tooth morphology, and operator experience, can impact the accuracy of this technique, potentially resulting in placement errors influenced by factors such as technician skills, operator finger pressure, and transfer tray material.

On the other hand, the Augmented Reality (AR)-assisted bracket navigation system integrates the advantages of both bonding techniques while addressing their limitations.

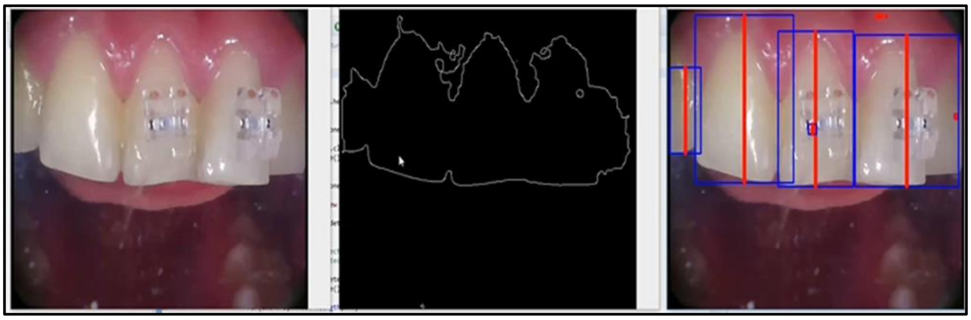


Figure 17: Registration method, employing real-time natural feature registration to overlay the ideal bracket position of the virtual object onto the tooth surface. Adapted from Lo et al., 2021 (24)

This method utilizes a real-time corner detection algorithm to ensure real-world integrity and achieve high registration accuracy.

In a study by Lo et al., (2021) comparing expert and novice orthodontists, the average error was 0.29 mm and 0.51 mm respectively, showing a particularly high level of accuracy. This study is clinically significant as the typical acceptable placement error is around 0.5 mm. By utilizing digital modeling with an intra-oral scanner instead of computed tomography to determine bracket positions, radiation exposure is avoided.

The AR system employs a wireless intraoral camera for capturing oral images for data processing. Real-time natural feature registration is used for superimposing the ideal bracket position on the tooth surface. The findings indicated that in the expert group, the control group exhibited vertical deviations of 0.40 mm, while the AR group showed deviations of 0.29 mm, representing a 28% enhancement rate. In the novice group, deviations measured 0.90 mm and 0.51 mm for the control and AR groups, respectively, resulting in a 43% improvement rate.

Also, this study compared the Boone method (standard) with a new AR-assisted bracket navigation system, measuring the distance between the planned and actual bracket position in two directions: mesiodistal (X) and incisogingival (Y). With a total sample size of 62 patients, including subgroups of 31 novice orthodontists and more experienced practitioners, the results showed in table 6 revealed no statistically significant differences between the two methods in the mesiodistal direction for either expertise level. However, in the incisogingival direction, both methods demonstrated better accuracy for experienced orthodontists compared to novices. Notably, the AR method exhibited statistically significant improvement for both novice and experienced orthodontists compared to the Boone method. These findings suggest that the AR method may offer notable advantages in terms of accuracy, particularly for less experienced orthodontists.

Table 6: Comparison of bracket positioning accuracy between boone method and ar-assisted navigation system (24).

Method	Direction	Mean ± IQR (mm) (Total)	Mean ± IQR (mm) (Novice)	Mean ± IQR (mm) (Experienced)	p-value (Novice vs. Experienced)
Boone	X (Mesiodistal)	0.32 ± 0.18	0.28 ± 0.09	0.36 ± 0.21	0.414
AR	X (Mesiodistal)	0.26 ± 0.11	0.27 ± 0.16	0.25 ± 0.10	0.920
Boone	Y (Incisogingival)	0.64 ± 0.37	0.90 ± 0.06	0.40 ± 0.29	<0.001
AR	Y (Incisogingival)	0.35 ± 0.15	0.51 ± 0.24	0.29 ± 0.08	<0.001

Remarkably, the implementation of the AR-assisted system narrowed the accuracy disparity between novice and expert orthodontists when compared to conventional methods like the Boone gauge, showing no notable variances in the horizontal direction regardless of experience level or system utilized (24).

1.4.4 Automated wire bending

AI is increasingly influencing orthodontics, particularly in the realm of arch wire bending. By harnessing AI algorithms, orthodontists can automate and optimize the process of bending arch wires to achieve precise and customized tooth movements. AI-driven systems analyze personalized patient data, including dental impressions and treatment goals, to generate bending instructions tailored to individual cases. This technology enhances the accuracy, efficiency, and consistency of arch wire bending, ultimately improving treatment outcomes for orthodontic patients.

The SureSmile Orthodontic Arch Wire Bending Robot System employs a sophisticated 3D computer monitoring system that captures precise images of teeth, enabling orthodontists to meticulously plan the most efficient series of movements. The process begins with the Ora scanner or Cone Beam Computed Tomography, which generates a detailed 3D computer model of the teeth, aiding in the analysis of their orientation and root positions. SureSmile then offers a virtual simulation of the progression of tooth movement, allowing operators to select the most accurate treatment plan. Subsequently, SureSmile technology instructs the Robot to bend a shape memory alloy at 1000 degrees Fahrenheit in accordance with the customized prescription. This approach significantly reduces treatment time by planning the shortest and most precise path of movement, resulting in fewer adjustments and consequently less discomfort for patients. On the other hand, the LAMDA system, facilitates rapid and accurate bending of Orthodontic Arch Wire, although it cannot handle Orthodontic Arch Wire with closed loops due to its limitation to motion in the XY plane. Meanwhile, the Orthodontic Arch-Wire Bending Robotic System, based on MOTOMAN UP6, incorporates arch-wire bending actuators and a computer connected to the MOTOMAN UP6 robot. The system conducts clamping and bending of the arch-wire, involving thorough examination and simulation of bending characteristics, angle optimization, robot kinematics, and positions of bending point. Finally, the Cartesian type Orthodontic Arch Wire Bending Robotic System consists of the arch-wire bending system, supporting structure of the Orthodontic Arch Wire, bending die, rotary, feed, and base, all integrated with sophisticated software for designing the robot's structure (25).

1.4.5 Automated mini-implants placement

Orthodontic mini implants play a role in improving the predictability and expanding the indications of orthodontic treatments, providing advantages regardless of patients' adherence. These implants enable a range of orthodontic tooth movements, such as rapid maxillary expansion, segment protraction, and molar distalization. Palatal mini-implants have become increasingly popular due to their stability compared to buccally inserted counterparts, with studies indicating that stability is influenced by factors such as implant diameter, soft tissue thickness, bone thickness, and density.

However, the stability of orthodontic mini implants primarily relies on mechanical retention, underscoring the importance of sufficient palatal bone quantity for achieving primary stability. Therefore, the determination of suitable sites for palatal mini implants should consider soft tissue thickness and palatal bone. Manual measurement of palatal thickness lack's reliability, necessitating an urgent need for an automated method.

Research by Tao et al, (2023) aimed to create an AI system capable of segmenting the palate and measuring its thickness, with a thorough assessment of the deep learning model's performance.

The findings showcased excellent precision in the segmentation of both palatal bone and soft tissue, as evidenced by metrics like Dice Similarity Coefficient, Average Symmetric Surface Distance, Sensitivity, and Positive Predictive Value, which yielded values of 0.78, 1.15, 0.86, and 0.76, respectively, for the adult group, showing favorable values.

The utilization of this AI system enabled the creation of personalized 3D maps illustrating available sites suitable for mini implants, offering valuable guidance for clinicians in site selection and personalized surgical guide design, as illustrated in figure 18.

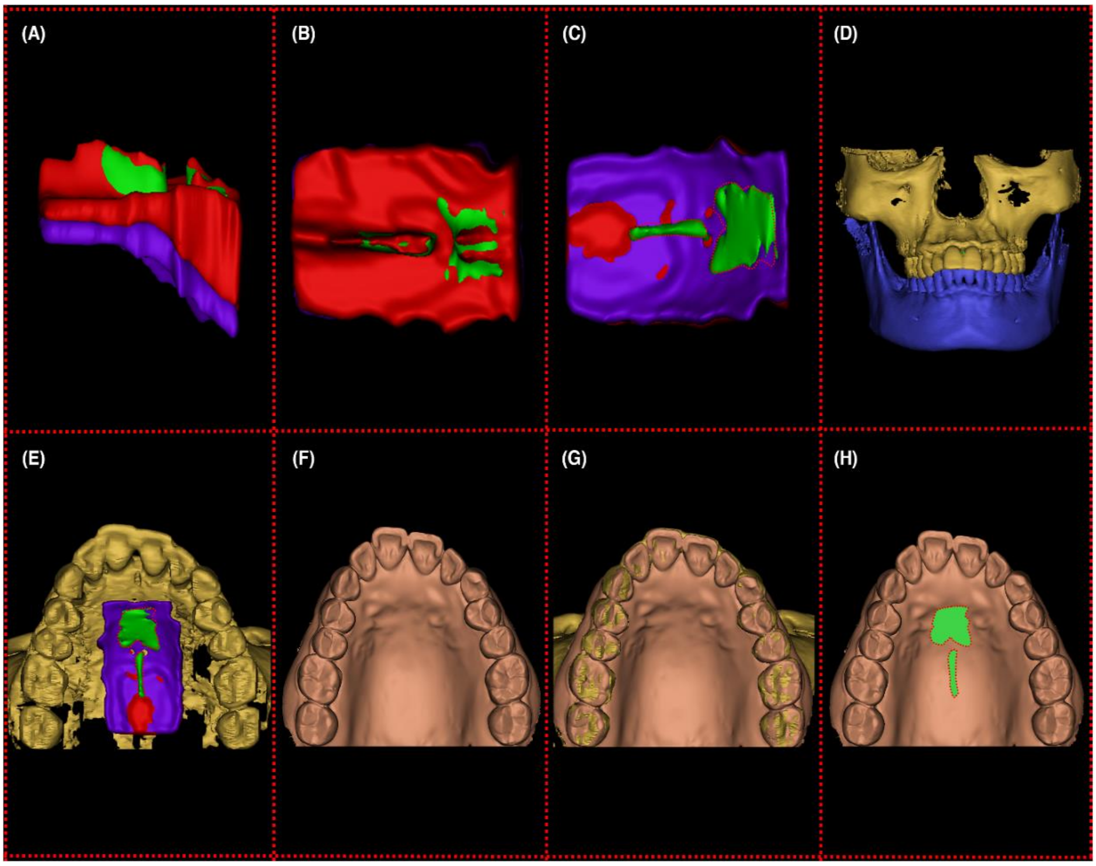


Figure 18: A randomly selected example of the available sites for palatal mini-implant from the test set. Adapted from Tao et al., 2023 (26).

Furthermore, in a prior study, the measurement of palatal thickness through manual methods proved to be time-consuming, requiring over four hours for each patient. In contrast, in this study, the use of AI-assisted segmentation for the palate and the measurement of palatal thickness were accomplished within a matter of seconds.

In conclusion, the widespread use of palatal orthodontic mini implants necessitates accurate determination of insertion sites. This study addresses this need through the development and evaluation of an AI system, showcasing its potential to enhance precision in site selection for personalized palatal mini implant procedures (26).

1.4.6 Orthognatic surgery

The primary aim of orthognathic surgery is to restore proper dental occlusion, align bone structures, and achieve harmony in facial soft tissues. Criteria such as Angle's Class I for dental occlusion and cephalometric measurements for bone positioning serve as benchmarks in this evaluation and can guide therapeutic goals. In the field of maxillofacial surgery, several publications explore the utilization, models, and importance of AI across different aspects of the field.

CAD-CAM technologies assist surgeons in surgical planning and fabricating dental-guided templates to reposition maxillary and mandibular segments. However, achieving precise bone repositioning accuracy and accurately simulating tissue responses to positional changes remain areas of uncertainty.

AI plays a prominent role in three crucial stages of the digital workflow in maxillofacial surgery: CBCT reconstruction, bone segmentation, and surgical simulations. These processes are essential for surgical planning, design, and the fabrication of surgical splints. Additionally, this study will explore anatomical structure identification, differentiation between orthodontic-only and orthodontic-surgical treatment options, facial attractiveness, and custom orthodontic and surgical appliances.

1.4.6.1 Anatomical structure identification

The process of manually annotating landmarks is time-consuming and susceptible to human bias. However, recent studies employing AI in landmarking have proliferated and significantly enhanced its accuracy. AI can now discern and recognize anatomical structures with a level of precision comparable to human experts. This capacity includes identifying landmarks in images containing fixed retainers, brackets, screws, and surgical hardware, achieving impressive mean error values and high levels of accuracy.

Moreover, AI facilitates the identification of anatomical structures in radiographic examinations, serving as either input features or enhancing specific regions of interest to optimize AI performance. This capability holds promise in predicting the necessity for orthognathic surgery based on detected anatomical features or structures, thereby aiding in treatment planning and decision-making processes (27).

1.4.6.2 Distinguishing between orthodontic-only and orthodontic-surgical treatment options

Accurate evaluation of an orthognathic surgery patient is essential for devising an optimal treatment strategy and attaining superior outcomes. Numerous factors must be considered, including developmental stage, radiographic findings, morphological characteristics, and occlusal considerations.AI can effectively categorize patients' skeletal patterns, discerning the severity of developmental deviations in cranial structures. Research consistently demonstrates AI's ability to predict skeletal maturation in cervical vertebrae maturation images with high-performance metrics, despite the documented low intraobserver and interobserver agreement among trained human evaluators (28).

1.4.6.3 Facial attractiveness

AI in orthognathic surgery predicts surgical outcomes and assesses facial attractiveness by analyzing facial morphology and soft tissue changes. This improves treatment for facial discrepancies, boosts clinical confidence, and aids treatment decisions. Facial attractiveness, crucial in orthognathic surgery, is typically evaluated using visual analog scales.

Kato et al. (2023) conducted a study that not only assessed facial attractiveness but also estimated age using dedicated CNN trained on extensive datasets. The investigation utilized pre- and post-treatment images of 146 sequential orthognathic patients. Results showed that 74.7% of the patients experienced improved facial attractiveness after surgery, along with a reduction in estimated age. Additionally, AI improves objectivity and reproducibility in the analysis of soft tissue simulation, further contributing to the precision of orthognathic surgery outcomes.

Modern planning software now incorporates deep learning technology to simulate profile changes. Various methods such as structure light scanning, laser scanning, and stereophotogrammetry are used for surface modeling. These methods may be landmark-based or utilize volumetric models like finite element models, mass tensor models, and mass-spring models to forecast alterations in soft tissue by establishing correlations between hard and soft tissues. Factors like gender, age, the extent of jaw displacement and preoperative facial characteristics can influence soft tissue simulation.

However, current software may not consider all these factors, indicating a need for improvement in accuracy.

Deep learning offers promise in enhancing soft tissue simulation accuracy by incorporating complex patterns from clinical cases. DL-based algorithms can predict facial changes, evaluate the influence of orthognathic surgery on facial attractiveness and age estimation and generate predictions autonomously. Despite the need for extensive patient databases, DL enhances the precision of virtual soft tissue simulations in contrast to ML algorithms.

AI enhances the accuracy of analyses in orthognathic surgery, improving surgical techniques, precision, and patient satisfaction.

Fully AI-assisted workflows may enable personalized treatment plans with realistic surgical simulations, while also allowing for evaluation of postoperative stability over time (29).

1.4.6.4 Custom orthodontic and surgical appliances

CAD/CAM technology, particularly 3D printing, has revolutionized medical device manufacturing, enabling innovative treatments like clear aligner therapy and lingual therapy. In orthognathic surgery, CAD/CAM technology is used for treatment planning and transfer methods, with Virtual Surgical Planning being a powerful tool, especially in complex cases, as illustrated in figure 19. VSP facilitates remote collaboration between practitioners, streamlining communication and enhancing efficiency.

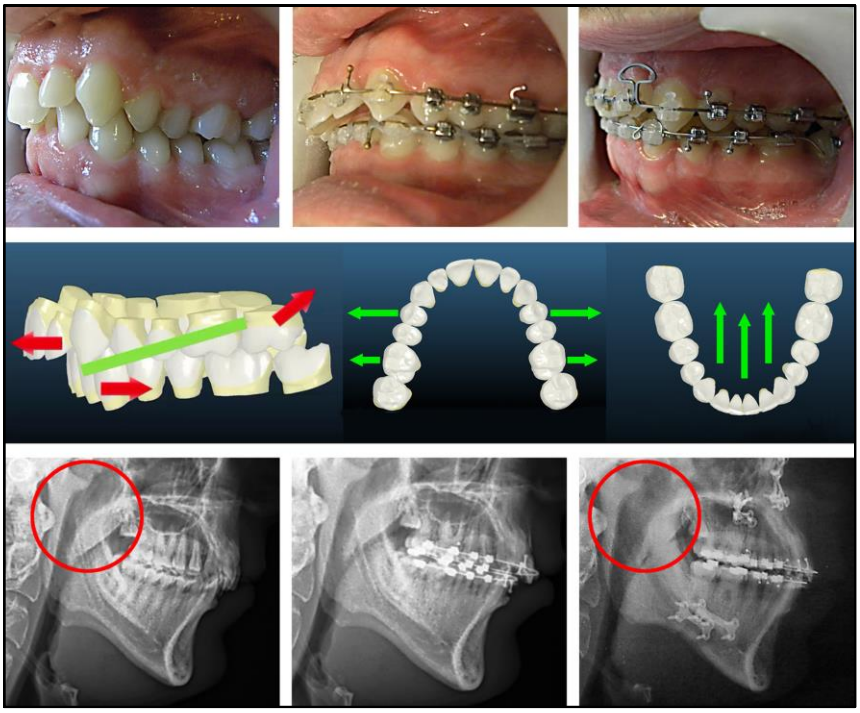


Figure 19: With CAD/CAM technology the biomechanics of alveolar decompensation could be incorporate on the appliance Insignia (Ormco). Adapted from (Bouletreau et al., 2019)

Regarding implementation, which refers to the practical application of the planning, CAD/CAM technology has made considerable advancements over the past decade. Currently, there are several transfer methods accessible, such as CAD/CAM surgical splints, CAD/CAM splints incorporating external bone support, patient-specific titanium miniplates for osteosynthesis, and surgical navigation systems, as shown in figure 20 (30).

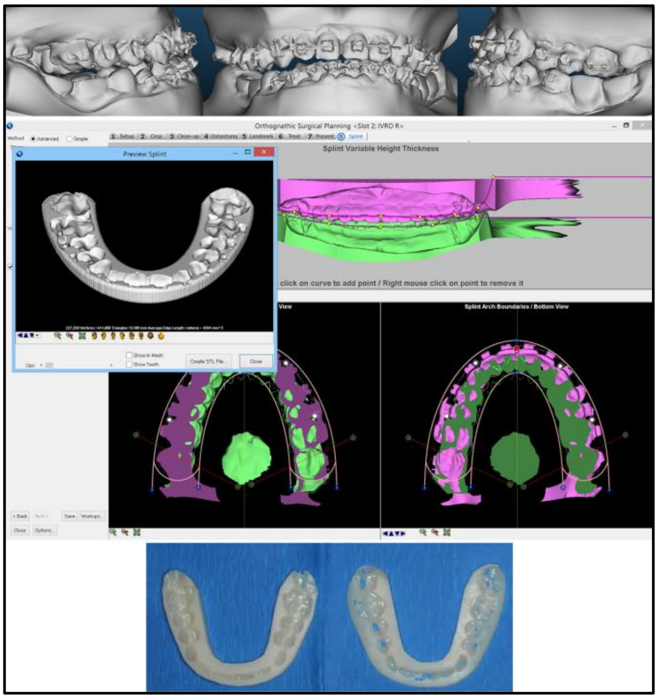


Figure 20: Realization of digital casts (Ormco), virtual construction of the surgical splint (Dolphin imaging), 3D printing of surgical splints (AAO). Adapted from Bouletreau et al., 2019 (30).

1.4.7 Aligners

Utilizing accurate 3D scans and virtual models, the production of customized aligners with tailored treatment plans via 3D printing becomes straightforward. Extensive data processing generates an algorithm that intelligently determines the optimal movement of a patient's tooth or teeth, identifying specific pressure points and the appropriate pressure to be applied. This AI-driven analysis guides precise treatment execution and facilitates progress monitoring, potentially shortening treatment duration.

Pressure resin tags are applied to the tooth surface to facilitate the application of pressure. With digital impressions replacing conventional ones and associated laboratory procedures, treatment outcomes can be predicted through software analysis (31).

Hyein Woo et al. (2023) conducted a study with the objective of assessing the precision and efficacy of automated digital setup software in orthodontic care. The research involved a comparison of three automated software programs: Ortho Simulation (fully automated setup), Outcome Simulator Pro (fully automated setup) and Autolign (semi-automated setup). These were compared with manual setup models performed using Maestro 3D Dental Studio, acknowledged as the gold standard. The study aimed to evaluate the impact of AI techniques on orthodontic treatment planning.

To assess the quality of alignment, the setup models underwent evaluation using the Peer Assessment Rating (PAR) index. This index provides an objective quantification of malocclusion, considering five categories: centerline, overbite, overjet, buccal occlusion, and displacement.

Table 7: Comprehensive Evaluation of Alignment and Occlusion in Initial and Setup Models Using Manual, Semi-Automated, and Fully Automated Software Approaches (32).

	Initial	Maestro 3D	Autolign	Outcome Simulator Pro	Ortho Simulation
Displacement (X1)	10.67±3.77	0.20±0.61	0.10±0.31	0.03±0.18	1.03±1.10
Buccal occlusion (X1)	1.63±1.52	0.17±0.38	1.40±1.10	1.60±1.33	1.30±0.75
Overjet (X6)	1.80±1.19	0.03±0.18	0.00±0.00	0.37±0.81	0.07±0.25
Overbite (X2)	1.00±1.17	0.03±0.18	0.03±0.18	0.10±0.31	0.07±0.25
Centerline (X4)	0.37±0.56	0.03±0.18	0.00±0.00	0.00±0.00	0.00±0.00
Total	26.17±8.69	0.77±1.89	1.60±1.13	3.97±5.40	2.47±1.74

The results table offers a comprehensive evaluation of alignment and occlusion in both the initial models and setup models, employing manual, semi-automated, and fully automated software approaches.

The Total PAR index for the initial models was 26.17. The Total PAR index for the manual setup model, 0.77, serves as a benchmark for comparison. This value represents the level of improvement achieved through manual setup methods.

While Autolign is semi-automated, it likely shows improvements in alignment and occlusion reduction of 94%, compared to fully automated software but may not achieve the same level of reduction as manual methods.

The Total PAR indices for the setup models generated by the fully automated software programs (Outcome Simulator Pro, and Ortho Simulation) would likely show a significant reduction compared to the initial. The study mentioned a reduction of 85%, and 91% for Outcome Simulator Pro, and Ortho Simulation, respectively. These high percentage reductions indicate substantial improvements in alignment and occlusion achieved by the fully automated software.

The Total PAR index is crucial for assessing the overall quality of alignment and occlusion in orthodontic models. Lower Total PAR indices in the setup models suggest better alignment and occlusal outcomes, which are essential for successful orthodontic treatment.

Comparison with Fully Automated Software: y comparing the Total PAR indices of the fully automated software models with the initial and manual setup models, the study demonstrates the superior effectiveness of fully automated software in achieving optimal alignment and occlusal results. The high percentage reductions in the PAR indices for the fully automated software programs highlight their ability to significantly improve orthodontic setup models.

In summary, the table underscores the remarkable impact of fully automated software programs in enhancing alignment and occlusion in orthodontic models. The substantial reductions in the Total PAR indices emphasize the efficiency and effectiveness of fully automated software in achieving orthodontic treatment outcomes (32).

A study led by Dhingra et al. (2022) was to compare the differences in tooth movements of Twenty-five adult patients treated with Invisalign® restructuring the virtual setup across the following four software packages: Ortho Analyzer®, Ortho Insight 3D®, SureSmile®, and ClinCheck® Pro.

Best fit superimpositions were performed using Geomagic® Control X.

According to the findings, adjustments were made to the tooth position in the three software platforms to match the virtual setups created in ClinCheck® Pro. Comparison was made regarding tooth movements, along with an assessment of the number of aligners and attachments automatically generated by each of the software packages.

The Kruskal-Wallis one-way analysis of variance revealed significant differences in extrusion/intrusion and translation lingual/buccal among the four software packages. Pairwise comparisons indicated that all software packages differed in terms of intrusion/extrusion direction, as well as significantly varied in their values for translation lingual/buccal movement.

Yet, the four remaining movements: translation distal/mesial, rotation distal/mesial, angulation distal/mesial, and inclination lingual/buccal did not exhibit significant differences across the software packages.

The equivalence of the virtual setups was verified by overlaying the models on Geomagic Control X. The range was limited to -1.0 mm to 1.0 mm, with a comparison tolerance set from -0.25 mm to 0.25 mm. Analysis yielded positive and negative average values of 0.064 mm and -0.055 mm, respectively. The absolute average difference between the models was determined to be 0.011 (± 0.086) mm.

Significant differences were observed in the number of maxillary and mandibular aligners generated by each of the four software packages, as revealed by pairwise comparisons. Moreover, the study investigated the number of attachments generated automatically by ClinCheck Pro and SureSmile. The Kruskal-Wallis one-way analysis of variance indicated a significant difference ($p \leq 0.000$) between SureSmile and ClinCheck Pro in terms of the number of attachments generated. Ortho Analyzer and Ortho Insight 3D were not considered in this analysis as they do not have the capability to automatically generate attachments (33).

2 Artificial intelligence and orthodontics: Perspectives

In this section, we delve into the domain of AI within the field of orthodontics, exploring its potential multifaceted applications and impact. From leveraging AI for enhanced radiological analysis to its role in guiding interceptive orthodontic interventions and multifactorial treatment strategies, we embark on a journey through the innovative avenues that AI opens in orthodontic practice. Additionally, we explore the integration of microsensor technology and the IOT in orthodontics, along with the emergence of app monitoring solutions, shedding light on how these advancements are reshaping the landscape of orthodontic care delivery and patient management.

2.1 Radiology

In the future, it is expected that superimposition or similar methodologies will either substitute or complement linear and angular measurements derived from 3D images. The segmentation of anatomical structures, such as bone or teeth, in CBCT scans will become an automated process, saving time, and eliminating biases. AI and computer vision will contribute to the automatic identification of anatomical landmarks and measurements. CBCT imaging of digital models could become a substitute for optical digitization devices, possibly removing the requirement for a dedicated optical dental digitizer. In the future, personalized brackets, and arch wires, molded by robots, will be crafted using these digital impressions. Over the next few decades, personalized treatment and biomechanical planning may become increasingly feasible, even within a clinician's own practice (16).

2.2 Multifactorial treatment

Given that the majority of software defaults to a non-extraction option in digital setups, numerous studies have specifically targeted patients undergoing non-extraction treatment with moderate crowding and no sagittal skeletal discrepancies. As a result, the exclusion of complex cases with skeletal irregularities may lead to a potential underestimation of errors. It's crucial to highlight that software lacks critical clinical information about patients, including functional issues, skeletal patterns, facial soft tissues, and periodontal conditions. Consequently, evaluations were limited to the system's capabilities in aligning and leveling arches only. Additionally, software fails to account for biological limitations in tooth movement. It is the responsibility of the clinician to conduct comprehensive patient diagnoses and make well-informed decisions about the treatment plan. The automated setup software acts as a valuable tool to aid clinicians by offering a visual representation of the anticipated treatment outcome, aligning with the objectives set by the clinician (32).

Orthodontic practitioners are actively exploring AI's potential in interceptive orthodontic treatment, aiming to optimize diagnostic processes and treatment planning through insights extracted from diverse data sources. AI applications seek to discern significant patterns from historical studies, shedding light on complex dental and skeletal growth trajectories. However, a challenge lies in determining optimal data representation for machine comprehension amidst the intricate interplay of bones, teeth, and muscles. Successful orthodontic interventions rely on identifying the opportune growth period and understanding the nuanced bone-tooth interface quality. Ongoing efforts include evaluating cancellous bone quality linked to vertebral maturation and comprehending distinct skeletal segment maturation timelines. Incorporating genetic data, alongside clinical and anamnestic information, enables a holistic understanding of orofacial biological balance, paving the way for AI-driven personalization in orthodontic interventions. Advanced imaging techniques coupled with ML methods offer transformative potential for interceptive orthodontics, promising more precise and personalized treatment approaches. However, true advancement requires addressing the complexity of dental-musculoskeletal tissue and integrating new imaging techniques and genetic data effectively.

Understanding and predicting orthodontic condition progression necessitates consideration of various parameters beyond single measurement modalities or data types, including geometrical data from cephalometric, CBCT scans, and anamnestic data. The complexity of dental-musculoskeletal tissue arises from morphological development, functional characteristics, and genetic factors. While contemporary AI algorithms delve into these aspects, challenges remain in determining relevance, saliency, or causal importance of variables. Theoretical advancements, employing techniques from statistical physics, offer potential for inferring partial information to aid in individual prognosis. In vivo magnetic resonance imaging (MRI) surpasses X-ray CT and CBCT by elucidating both geometric and physiological tissue attributes at scales beyond voxel resolution. Computational models in orthodontics must consider skeletal feature evolution over time and the complex interplay of mechanical properties within bones and teeth. The trajectory of orthodontic practice demands a revolution towards personalized medicine, necessitating the integration of new imaging techniques, genetic data, and effective filtration of valuable information for a redefined orthodontic vision (34).

The utilization of AI in orthodontics is already reshaping modern practices, assisting in diagnosis, treatment planning, and outcome prediction. However, the collaboration between AI-powered systems and well-trained orthodontists is crucial to achieve optimal patient outcomes. The ongoing development of AI technologies in orthodontics holds immense promise for enhancing treatment precision, efficiency, and personalization.

2.3 IOT

A microsensor is a tiny device that detects and measures physical or chemical properties in its surroundings. It's widely used in various applications due to its small size, precision, and versatility, such as in healthcare, environmental monitoring, and consumer electronics, as represented in figure 21.

The integration of these microsensors and AI in orthodontics offers a transformative approach to interceptive treatments by leveraging real-time data collection, personalized treatment planning, remote monitoring capabilities, and enhanced patient engagement. This constructive collaboration between technology and orthodontic care has the potential to optimize treatment outcomes and revolutionize the field of orthodontics towards more efficient and patient-centric practices.

The IOT stands as an innovative technology, operating on the Internet and exerting a substantial impact across various scientific and technological domains. In the realm of oral healthcare, the IOT assumes a pivotal role, particularly in data monitoring and collection, offering dentists novel techniques for risk assessment. Notably, recent attention has been directed toward the application of these technologies in orthodontic brackets. Bahrami et al. proposed a hypothesis suggesting the creation of an integrated electric circuit within orthodontic brackets to control the speed, direction, and extent of tooth movement. This innovative fusion of IOT, nano-electronics, and orthodontics could potentially revolutionize the field. Envisioned as a remote-controlled device, the smart bracket incorporates a vibrator circuit for controlling tooth movement speed and a motion circuit with a power system for regulated tooth movement. In the future, progress in nano-robots and intelligent systems may supplant conventional orthodontic appliances, ushering in the era of smart brackets. Integrating smart orthodontic brackets into the IOT framework offers potential for gathering real-time data on tooth movement, facilitating remote monitoring and personalized treatment plans. ML algorithms and predictive modeling can assess this data, offering valuable insights for optimizing orthodontic treatment, potentially shortening treatment duration, and improving patient satisfaction. Additionally, the IOT can enhance communication and collaboration among orthodontists, dental teams, and patients, leading to better patient adherence and ultimately resulting in enhanced treatment outcomes (35).

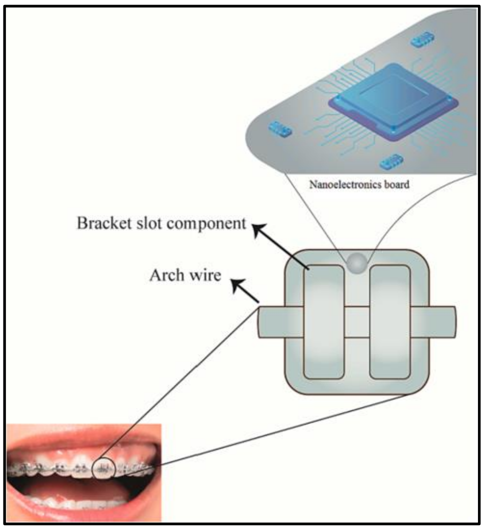


Figure 21: Smart orthodontic brackets. Adapted from Bahrami & Bahrami, 2023) (35).

AI encompasses computer and software capabilities to comprehend information, reason, and act intelligently. In dentistry, Dental Monitoring in Paris utilizes intraoral photos taken by patients to remotely monitor dental conditions, primarily during aligner treatments. It tracks tooth movement, identifies issues like lost attachments and poor oral hygiene, and delivers customized instructions to patients while notifying orthodontists, who can intervene as needed. This technology also aids in retention phase monitoring and dental health concerns. Ongoing research explores potential benefits such as reduced clinician involvement and patient convenience. Additionally, thermal monitors embedded in removable retainers, coupled with AI-enabled remote scans, offer innovative methods for patient and retainer oversight. These monitors gauge patient compliance with retainer usage by detecting normal intraoral temperature during wear.

Future advancements are needed to improve reliability and data access, as current data are only accessible during in-person appointments (36).

2.4 App monitoring

Orthodontists are integrating innovative technologies to enhance patient care, catering to a growing demand for treatments with fewer in-office visits. Technologies like biometric devices and orthodontic treatment-monitoring software are transforming the patient experience. Remote monitoring, particularly useful for procedures with virtual checkups, reduces office visits and addresses emergencies promptly. The latest monitoring technology combines mobile apps with AI, enabling orthodontists to remotely track patients' progress using scanning videos taken through a smartphone app. This system provides alerts for preset objectives or issues, enhancing the efficiency of orthodontic care.

The investigation carried out by Moylan et al., (2019) aimed to assess the monitoring software's measurement accuracy by comparing linear measurements on plaster models using in-office methods. Intercanine and intermolar distances were measured as follows: the straight distance between the cusp tips or wear facet centers of right and left canines for intercanine distance and the straight distance between the mesiobuccal cusp tips of left and right maxillary first molars for intermolar distance. The use of monitoring applications in orthodontics, facilitated by a secure web server, allows for closer patient follow-up, potentially reducing office visits. Setting notification preferences for specific treatment milestones can eliminate unnecessary appointments, and the software can aid in evaluating orthodontic emergencies remotely. Furthermore, the software may analyze tooth movement changes during retention, determining the need for in-person consultations and nurturing the doctor-patient bond. The manufacturer estimates an error margin of approximately 0.58 for tip, rotation, and torque, and about 0.05 mm in the 0.07 mm in the posterior and anterior regions for linear measurements (37).

Figure 22: The patient captures a video scan using a smartphone application. Adapted from Moylan et al., 2019 (37).

Figure 23: Three-dimensional matching involves superimposing models of previous tooth positions onto current photos to illustrate tooth movement in 3D. Adapted from Moylan et al., 2019 (37).

Recent surveys foresee a substantial rise in teledentistry, with an estimated 78% of patients embracing this trend within the next five years. Notably, Petya et al.'s research indicates that 89% of patients believe interactive dental care through specific apps can notably enhance their oral health.

In the realm of orthodontics, Dental Monitoring (DM) stands out as a revolutionary solution. Bridging safe teledentistry and AI, DM utilizes an advanced knowledge-based algorithm to precisely semi-automate orthodontic treatment monitoring. As the pioneering Software as a Service (SaaS) application for remote dental treatment monitoring, DM ensures compliance with healthcare regulations like Health Insurance Portability and Accountability Act (HIPAA) and General Data Protection Regulation (GDPR). This AI-powered system allows orthodontists to remotely monitor treatments using intra-oral pictures, enhancing efficiency and accuracy.

DM's innovative approach includes real-time, validated information, contributing to the partial automation of communication among healthcare professionals and patients. Positioned at the forefront of remote dental care, DM seamlessly integrates teledentistry and AI, prioritizing compliance, patient privacy, and optimized orthodontic outcomes.

Hence, it plays a key role in automating interactions among healthcare professionals, staff, and patients. Distinguishing itself from other dental applications, it stands out by delivering real-time validated information through its sophisticated knowledge-based algorithm.

Dental Monitoring presents a promising solution for elevating doctor-patient interactions, showcasing potential for improved clinical outcomes, high patient satisfaction, and cost savings. This innovation integrates advanced technology seamlessly into patient monitoring, heralding transformative benefits for healthcare providers and patients.

In this study, we will discuss two systems: the Dental Monitoring system and StrojCHECK.

2.4.1 The Dental Monitoring System

A complete DM system involves several steps. Initially, the patient receives a cheek retractor along with a DM ScanBox©, figure 24, aimed at streamlining the process of capturing intraoral images using a smartphone while ensuring standardized results.

Figure 24: Dental monitoring (DM) ScanBox© and cheek retractor. Adapted from Caruso et al., 2021 (38).

Clear instructions, including tutorial videos, guide the patient through the scanning process, which is compatible with all smartphones.

Upon downloading the DM app, the patient follows one of four protocols, each catering to specific characteristics and complexities. These range from Photo Monitoring Light to 3D Monitoring Full, addressing varying levels of clinical analysis, scan frequency, and aligner replacement dynamics.

DM's orthodontic protocols encompass automatic detection of issues such as brace debonding, damage to dental appliances, oral hygiene, and other clinical parameters. During clear aligner treatments, remote monitoring is crucial at each aligner change, allowing clinicians to assess fit, attachment integrity, and overall treatment progress.

The DM system employs a knowledge-based algorithm, blending robotic process automation and DL. Automation of robotic process integrates workflow, rules, and a presentation layer, acting as a semi-intelligent user. Deep learning, a sophisticated form of AI, utilizes neural networks trained on millions of dental images to make informed assessments based on predefined clinical situations.

The patient initiates remote scans, with the system processing raw images, detecting teeth and clinical parameters, and analyzing data through AI. Instructions are then sent to the patient and the orthodontic team based on the chosen protocol. The data transmission from the patient's oral cavity to servers is remote, involving multiple steps to ensure data quality and accuracy.

Orthodontists receive notifications when clinical attention is required, maintaining continuous interaction among patients, the app, and dental professionals. This comprehensive approach ensures effective remote monitoring and timely intervention in orthodontic treatments (38).

2.4.2 StrojCHECK

The StrojCHECK® mobile app, developed by 3Dent Medical, serves as a free tool for orthodontic patients and practitioners. Initially designed in 2015 by Andrej Thurzo, the app started as a simple reminder system but has since evolved into a comprehensive solution for coaching patients undergoing clear aligner therapy.

Research conducted by Thurzo et al. in 2021 examines the effects of incorporating decision tree algorithms, computer-based learning, and other enhancements in computerized learning into an already established mobile application called StrojCHECK®.

The primary objective of the study was to assess the clinical effectiveness of integrating decision-making processes into an established healthcare application designed for orthodontic treatment. Additionally, the secondary aim was to employ an AI system, to analyze the clinical condition with high frequency using video scans of patients' teeth and orthodontic appliances. The findings of the study contradicted the initial hypothesis, suggesting that there was no significant difference in the performance of patients using the app after the AI update compared to before the update. However, the incorporation of decision-making processes into an established healthcare application provided novel data on the behavior of orthodontic patients, allowing for unprecedented analysis opportunities. A novel method for clinical research involving video scans made by patients has been introduced as a successful scientific tool. This marks the first publication of information regarding the StrojCHECK application, which represents a sophisticated healthcare system powered by computational methods. The findings indicate that the application has a notable impact on assessing patient-app interaction. The quantity of "GO" scans remains largely unchanged, possibly because scan frequency is typically determined by the doctor's instructions, and compliant patients adhere to their prescribed scanning routine. However, there is a slight but statistically significant decrease in the frequency of "NO-GO" scans observed primarily among women, with no significant change noted among men. This observation may be attributed to the likelihood of increased discrepancies between teeth positions and aligners as patients progress further into treatment, leading to a decline in clinical progress over time. Additionally, the results confirmed that there was a significant improvement in performance across all measured parameters following the AI update of the app, except for the GO and NO-GO scans among males.

In anticipation of future advancements, the focus of AI implementation is multifaceted: Firstly, it seeks to enhance early detection of non-compliant patients, enabling proactive intervention. Secondly, by analyzing patterns of app usage, it aims to predict and address potential lapses in adherence before they occur. Furthermore, the integration of AI aims to personalize treatment plans to the unique profiles of individual patients, encompassing both behavioral and clinical aspects for optimized outcomes. Lastly, the development of tailored motivational strategies intends to bolster patient engagement by aligning with their behaviors, daily routines, and specific treatment needs (39).

2.5 Tele dentistry

Teledentistry is transforming dental care by enabling remote consultations and treatment planning, offering convenient access to services. In orthodontics, it streamlines workflows and enhances treatment outcomes through virtual consultations and personalized care.

2.5.1 Advantages of teledentistry

Teledentistry offers significant benefits in orthodontics, particularly in regions with limited access to healthcare providers, enabling patients to connect with specialists globally. This approach streamlines access to second opinions and various orthodontic services, reducing travel expenses and time spent on consultations. During emergencies or pandemics like COVID-19, teledentistry becomes indispensable, delivering essential care remotely. Economically, it minimizes disruptions to work or school and contributes to overall national efficiency. By leveraging technology, teledentistry supports a shift towards preventive rather than curative treatments, enhancing follow-ups for at-risk groups and underserved populations through innovative digital platforms.

2.5.2 Applications of AI in Teledentistry

2.5.2.1 Screening, Diagnostic Workup and Triaging

Remote oral screening holds significant promise in transitioning from curative to preventive treatment, with regular population screenings potentially leading to a substantial decline in oral health-related issues. Timely diagnosis of common oral diseases like caries can prevent demineralization. Additionally, remote oral surveillance proves advantageous in screening for severe conditions such as oral cancers, reducing associated mortality and morbidity through early detection. AI is instrumental in predicting high-risk oral cancer patients based on several factors, enabling regular remote screenings. Simple methods like intraoral photographs aid in identifying lesions such as oral squamous cell carcinoma, leukoplakia, and lichen planus, while smartphone-based auto-fluorescence oral cancer probes, supported by AI, facilitate screening and triage. These probes, suitable for primary centers in high-risk populations, allow remote consultations even in the absence of trained healthcare workers, contributing to predictive population risk stratification. AI extends its influence on remote forensic dentistry, predicting patient age and enabling full-face reconstruction through lateral cephalograms. Digital radiographs, sharing easily for teleconsultation, benefit from intelligent apps and software that interpret radiographs, aiding in diagnosing conditions like dental caries, periodontal diseases, and orthodontic considerations. Moreover, AI plays a role in 3D CBCTs for diagnosing dental conditions. Beyond clinical diagnosis, AI contributes to tissue diagnosis by capturing high-resolution biopsy slide images for remote pathology review.

2.5.2.2 Clinical Decision Support and Follow-Up

In the realm of remote dental care, AI has made substantial contributions to decision-making processes. Numerous software applications, leveraging deep learning algorithms, have emerged to support clinicians in making informed decisions. These range from simple tools for procedures like fillings and marking tooth preparation scan margins for prosthesis fabrication to more complex applications such as smile designing, providing recommendations for extraction or non-extraction treatments in orthodontics, assessing treatment outcomes, simulating orthodontic or surgical procedures, monitoring treatment progress, and identifying bone loss and types of periodontitis through X-rays and subgingival plaque examination. Additionally, specific AI-assisted monitoring and follow-up software, like Dental Monitoring, have been developed for remotely tracking tooth movement, detecting breakages and wire engagement, while also serving as reminders for upcoming appointments, and payments. These advancements highlight the expanding role of AI in enhancing the efficiency and precision of remote dental care.

2.5.2.3 Feedback Mechanism

In the context of teledentistry, feedback from patients is crucial for refining practices, enhancing overall quality, and fostering professional development. Traditionally, this feedback has been collected through questionnaires, but the shift to remote interactions necessitates a more dynamic and continuous approach. To address this, we propose an AI-based framework that categorizes feedback into four types:

- Form-Based Feedback

- An AI-driven mobile application utilizes Case-Based Reasoning to intelligently pose questions based on patient profiles, visit chronology, and previous questionnaire responses.

- The application analyzes answers to assess the level of satisfaction with teleconsultations, providing valuable insights for continuous improvement.

- Facial Expression-Based Feedback

- Patient emotion detection during remote interactions is crucial. Deep learning networks, incorporating CNN, analyze facial expressions to discern emotions.

- This technology evaluates both patient and doctor expressions, providing insights into engagement levels and sentiments during interactions.

- Patient Adhesion-Based Feedback

- AI-powered software analyzes scheduled appointment dropouts to identify patient attrition trends. It assesses factors such as oral health, habits, potential disease occurrence, and overall health to predict optimal timing for the next appointment.

- Statistical analysis of patient groups' results helps evaluate teledentistry quality and identify areas for improvement.

- Social Media-Based Feedback

- Social forums provide patients with platforms to discuss and rate their interactions with clinics, hospitals, and doctors.

- AI-driven web crawlers extract data from these forums, offering valuable feedback. This information not only aids in assessing service quality but also builds patient confidence, especially for complex treatments.

This multifaceted AI-driven feedback system aims to provide a comprehensive understanding of patient experiences in teledentistry, enabling practitioners to adapt and enhance their remote consultations effectively (40).

3 Artificial Intelligence and orthodontics: Challenges

While the integration of AI into orthodontics holds great promise, several challenges need to be addressed for successful implementation. Some of the key challenges facing orthodontics and AI include:

3.1 Data Privacy and Security

The utilization of AI in orthodontics involves processing and analyzing sensitive patient data, necessitating robust data privacy and security measures to protect patient confidentiality. Current regulations regarding patient data protection in digital general and oral health exhibit gaps in legacy liabilities, privacy policies, and data security, particularly lacking comprehensive regulations in America and Europe. Establishing secure and adaptable access control models is crucial for enhancing digital health, while cultivating awareness among users, clinicians, developers, and policymakers is imperative, emphasizing both benefits and security issues associated with digital health. It is imperative to update telemedicine ethical guidelines to maximize its utilization and guarantee practices grounded in evidence. Digital health plays a crucial role in diminishing health inequalities and improving healthcare accessibility via remote screening, treatment, and monitoring. Foremost nations investing in digital health prioritize the mitigation of security risks by implementing robust access control frameworks.

Stakeholders, including users, technology developers, healthcare providers, and policymakers, must collectively address security considerations while recognizing the advantages of mobile health (mHealth) apps. Di Fede et al.'s review (2023) emphasizes the necessity of enhancing healthcare providers' services and raising public awareness of digital health to fully capitalize on its advantages. This underscores the significance of updating guidelines for the ethical implementation of telemedicine and telehealth. Securing patient data in digital healthcare poses a significant challenge, requiring adherence to regulations such as the HIPAA in the United States and the GDPR in the European Union. Healthcare providers and organizations are tasked with implementing appropriate technical and organizational measures, such as encryption, secure backups, and routine security audits, to protect patient data from alteration, disclosure, unauthorized access, and destruction, as required by these regulations.

Telemedicine providers are obligated to obtain patient consent for data collection and usage, while also informing patients of their rights under the GDPR and HIPAA. Adherence to these regulations is essential for preserving patient trust and upholding the responsible and ethical utilization of digital health data (41).

3.2 Data Quality and Standardization

The effectiveness of AI models depends on the quality and standardization of the input data. In orthodontics, variations in data collection methods and imaging technologies may lead to inconsistencies, impacting the accuracy and reliability of AI algorithms.

The utilization of AI in dentistry faces a significant hurdle related to the quality and availability of data. Effective training and validation of AI algorithms demand extensive and diverse datasets. Certain dental specialties face challenges, especially in rare oral diseases or specific procedures, where obtaining a sufficient amount of high-quality data presents difficulties. The scarcity of available data imposes limitations on the accuracy and practicality of AI models in such contexts.

The vulnerability of AI algorithms to biases is influenced by the composition of the training data. Inadequate diversity and representation in the training dataset can result in biases within AI models, causing inaccuracies in predictions or recommendations. To mitigate bias and enhance the applicability of AI models across various dental specialties, it is imperative to incorporate diverse patient populations and data sources during the training process (21).

The current research faces challenges due to the scarcity and limited generalizability of training data, diminishing its reliability. For instance, some AI models assisting decision-making in the studies reviewed lacked a diverse representation of case types in their training data, raising doubts about their accuracy in predicting rare deformities. Acquiring a substantial amount of high-quality data remains a hurdle, particularly for data requiring manual annotation by experienced experts. To mitigate data insufficiency, various measures are anticipated, including transfer learning, data augmentation, semi-supervised learning, and few-shot learning. However, the effectiveness of these methods is constrained. Transfer learning involves applying pre-trained models in a related but different domain, aiming to reduce dependence on extensive training data. Yet, its generalization capabilities may be limited when applied to a new domain. Data augmentation can increase sample size by modifying existing data characteristics or generating synthetic images but falls short in improving biological variability diversity. Semi-supervised learning is suitable when annotated data are limited, but it still requires high-quality annotated data and sufficient unannotated data (42).

3.3 Limited Training Data

3.3.1 Lack of data

AI models require large and diverse datasets for training to achieve optimal performance. In orthodontics, obtaining a sufficiently diverse dataset for training AI algorithms may be challenging due to variations in patient populations and treatment approaches.

In contrast to other medical fields, orthodontic research suffers from a scarcity of high-quality datasets. The inconsistencies in training data raise concerns about the validity of comparisons between various AI-based models. While supervised learning remains the best option for diagnosing malocclusion, the significant costs and labor required for target labeling pose challenges to creating standardized and high-quality datasets specifically for orthodontic studies. Additionally, data snooping bias often occurs when training data is reused during the test phase. Thus, independent test datasets should be used instead of cross-validation. To address these issues, semi-supervised and weakly supervised learning frameworks can analyze numerous original images, providing accuracy and robustness in diagnosis comparable to supervised learning. Furthermore, transfer learning and few-shot learning could be ideal alternatives to overcome data insufficiency problems. (43).

Limited-sample learning is hindered by the absence of specialized data and standardized evaluation frameworks, limiting its application. Additionally, ethical concerns and data protection issues pose significant challenges to data sharing. AI models trained on data with limited generalizability are prone to bias. Federated learning, a decentralized and distributed machine-learning approach, enables collaboration across different sites without the need for direct data sharing. Blockchain technology, known for its transparency, security, and immutability, offers a reliable platform for data sharing and storage. The integration of blockchain with federated learning is expected to improve data sharing through multisite collaboration, enhancing data privacy and enabling the creation of larger and more diverse datasets. (42).

While the AI models proposed in the studies demonstrate promising performance, it is vital to acknowledge several limitations that could impact their reliability. Primarily, many of these models underwent training on a restricted dataset, consisting of images from the same institution and a specific timeframe. Furthermore, specific classification models were exclusively evaluated on images from individuals with confirmed diseases. These limitations raise concerns about potential overfitting and an excessively optimistic assessment of the models. Additionally, relying on images captured with consistent devices and imaging protocols may lead to a lack of data diversity, affecting the generalizability and trustworthiness of the models. This deficiency in diversity may result in suboptimal performance in real clinical settings, considering variations in factors like devices, imaging protocols, and patient demographics. Therefore, it is imperative for these models to undergo validation using diverse data collected from various dental institutions before their implementation in clinical practice (44).

3.3.2 Overfitting

Overfitting, a well-known challenge in the field of AI, occurs when a model becomes too specialized on the training data, leading to diminished performance on new, unseen data during testing. Several factors contribute to overfitting, including limited data availability, a lack of diversity in the dataset, and an excessive number of variables. To address overfitting, researchers have proposed various strategies, such as increasing the size of the dataset, introducing data augmentation techniques, applying regularization methods to penalize overly complex models, utilizing cross-validation to assess model generalization, and selecting appropriate algorithms that are less prone to overfitting. However, despite the availability of these strategies, not all studies in this field have implemented measures to mitigate overfitting, highlighting the importance of considering this issue in AI research and development (42).

3.4 Reproducibility crisis

Reproducibility remains a challenge as AI models are typically developed using specific and limited datasets, hindering their performance across diverse datasets. Adaptivity is lacking in existing models of AI, which are not designed for continuous adaptation to changes in their environment. The lack of robust quality control mechanisms heightens vulnerability to data errors, outliers, and abrupt shifts in trends. Additionally, the inadequate integration between AI algorithms and workflows hinders their ability to effectively adapt to changes in the data environment.

In response to these challenges, the development of continuous learning AI is essential. This strategy allows AI tools to continuously adjust to changes in the data, thereby averting performance degradation over time. Similar to any technology employed in medicine, establishing a robust AI governance process is essential for upholding result quality and safeguarding patient safety. The ongoing assessment of algorithmic quality is imperative to prevent performance degradation and allow timely intervention when needed (17).

A growing number of researchers have recognized the reproducibility crisis in AI, indicating that numerous research findings cannot be replicated when the same experiment is conducted by a different team of scientists. This phenomenon can be attributed to several factors, including a lack of understanding of algorithms and metrics. Moreover, many researchers overlook the sensitivity of results to hyperparameters such as learning rate, number of iterations, and initialization strategy. Several effective solutions exist to enhance the reliability of AI. For example, conducting sensitivity tests is essential when assessing model performance. Moreover, enhancing interpretability by visualizing the mechanisms of ML models could help address the dilemma. Additionally, employing data cleaning methods can serve as an effective alternative to mitigate the impact of manual errors in labeling and measurement on the reproducibility of ML models (43).

3.5 Validation and clinical adoption:

Validating the accuracy and clinical relevance of AI algorithms is essential before widespread adoption. Convincing orthodontic practitioners of the reliability and benefits of AI tools is a hurdle that needs to be overcome.

AI models, particularly those based on deep learning, often function as opaque systems, creating challenges in comprehending the rationale behind their decisions. In critical dental specialties like oral surgery or orthodontics, where clinical decisions significantly impact patient care, it becomes essential for clinicians to grasp the influencing factors behind AI predictions. The absence of interpretability and explainability can impede the acceptance and trust in AI systems among dental professionals.

Although AI algorithms hold potential in diverse dental specialties, conducting thorough clinical validation studies is essential to assess their effectiveness, reliability, and safety. The incorporation of AI systems into established dental workflows and clinical practices may present challenges, particularly in terms of compatibility with existing dental software, infrastructure, and clinical protocols (21).

Integrating AI seamlessly into the existing clinical workflow of orthodontic practices is a challenge. This includes adapting AI tools to work with various imaging systems, electronic health records, and treatment planning processes.

Before widespread adoption, AI algorithms in orthodontics need rigorous validation through clinical trials and real-world testing. Demonstrating their accuracy, reliability, and clinical relevance is essential for gaining the trust of practitioners.

Although the potential of AI to enhance patient management in orthodontics is considerable, its impact was substantiated in only limited cases. Much of the existing literature on this subject comprises retrospective studies lacking robust support from large randomized controlled trials. Even so, the landscape is expected to change in the coming years due to the intriguing nature of this field and the growing availability of AI solutions.

Financial investments and the introduction of AI are experiencing rapid growth. In 2022 alone, there were 69 novel Food and Drug Administration (FDA)-approved products, with associated funding reaching USD 4.8 billion. Projections indicate that by 2035, annual funding for products could reach USD 30.8 billion, resulting in the introduction of 350 new AI products (45).

Although optimistic studies highlight the high performance of AI algorithms across multiple tasks, the widespread incorporation of AI into routine clinical practice is still a matter for future consideration.

Most of the AI programs mentioned were introduced within the last two - three years. Historically, it typically takes an average of 17 years for medical innovations to become fully integrated into clinical practice.

Incorporating AI into workflows and clinical practices involves fulfilling various requirements to ensure sufficient clinical quality and patient safety. Key challenges include addressing issues such as reproducibility, adaptability, robust quality control mechanisms, and seamless integration between AI algorithms and workflows (17).

3.6 Ethical Considerations

Ethical concerns surrounding the use of AI in orthodontics include issues related to bias in algorithms, informed consent, and the potential impact on doctor-patient relationships. Ensuring ethical practices and transparency is crucial.

Despite the widespread popularity and promises of AI in dentistry, it brings forth numerous ethical and societal concerns frequently overlooked in current dental literature. Mörch et al. (2021) offer recommendations to steer towards a more validated and ethically conscious application of AI in dentistry. These recommendations categorize ethical concerns according to the 10 principles outlined in the Montreal Declaration, encompassing various aspects of ethical considerations in AI development and application within the dental field.

Table 8: Categorization of ethical dilemmas utilizing the 10 principles outlined in the montreal declaration (46).

Name	Principle
Prudence	All individuals participating in AI development need to be cautious, foreseeing potential negative outcomes of AI utilization, and implementing suitable measures to prevent them.
Equity	The advancement and deployment of AI systems should actively contribute to fostering a fair and impartial society.
Privacy and intimacy	Privacy and intimacy need to be shielded from intrusion by AI systems and data as a service
Responsibility	The development and implementation of AI systems must not diminish the accountability of human beings when decisions need to be made.
Democratic participation	Artificial intelligence systems must adhere to criteria of intelligibility, justifiability, and accessibility, and should be subject to democratic scrutiny, debate, and control.
Solidarity	The advancement of AI systems should align with the preservation of solidarity bonds among individuals and across generations.
Diversity inclusion	The progression and deployment of AI systems should be in harmony with preserving social and cultural diversity, ensuring that they do not limit the range of lifestyle options or individual experiences.
Well-being	The advancement and application of AI systems should facilitate the enhancement of the well-being of all sentient beings.
Respect for autonomy	AI development and utilization should uphold individuals' autonomy and aim to empower them with greater control over their lives and environments.
Sustainable development	The development and deployment of AI should prioritize ensuring strong environmental sustainability for the planet.

It's imperative to handle these findings with care due to the limited understanding of industrial research. Companies should provide thorough information about their AI methodologies, ensuring accuracy for patients and practitioners to make informed decisions and allowing patients to give informed consent.

Moreover, the shortage of studies addressing ethical issues limits the range of possible analyses, such as identifying ethical concerns specific to each AI domain.

Additionally, review by Mörch et al does not address another ethical aspect concerning the use of patients' data and medical tests in dental algorithms. These data could be utilized to refine an algorithm, potentially leading to its commercialization, and requiring patients to incur additional costs when used. Although these indirect ethical challenges are crucial, they were not explicitly recognized in the included studies. Exploring them deserves attention in future research (46).

Furthermore, additional research conducted by Rokhshad et al. (2023) presents a checklist and framework for assessing AI applications in dentistry from an ethical standpoint. Based on established guidance documents, the initial draft of the checklist and an explanatory paper were developed and examined by the group members. Consensus on the checklist was reached through an anonymous voting process, engaging 29 members of the Topic Group Dental Diagnostics and Digital Dentistry within the International Telecommunication Unio and World Health Organization Focus Group AI on Health. This process resulted in the delineation of a total of 11 principles (47).

Table 9: Ethical framework for ai integration in dentistry: key principles and implementation strategies (47).

Ethical Principle	Key Points
Transparency and Inclusion	Transparent AI model outcomes with comprehensive documentation, accessible data, and collaborative approval are essential.
Diversity	AI applications should encompass diversity across various demographic factors in both training and test datasets.
Wellness (Beneficence)	AI's role should enhance individual wellness, health promotion, and organizational wellness.
Respect for Autonomous Decision-Making	AI's impact on autonomy should prioritize societal benefits and legal frameworks, with decision-making involving consensus among clinicians, patients, and dental technicians despite AI assistance.
Protection of Privacy	Addressing privacy concerns in AI's data-driven nature, especially in dental data potentially identifying individuals, involves exploring alternatives like federated learning and generative data usage for mitigation.
Accountability and Responsibility	Accountability in AI-integrated medical decisions, with ultimate responsibility resting with dentists, requires ethical AI prioritizing societal benefits, but leaves unanswered questions about direct algorithmic decision accountability.
Equity	- Ensuring algorithmic fairness and universal AI availability to prevent bias and discrimination, yet industry-supplied dental AI tools may worsen existing inequities, limiting access for all.
Prudence (Capa-city and expertise)	Prudence entails limiting AI system access to mitigate public health or safety risks, while addressing adaptability challenges.
Sustainability	Exploring AI's role in sustainable dentistry, considering resource needs and accessibility impacts.
Solidarity	Promoting unity and mutual support, seen in equity discussions, and conducting thorough AI impact assessments to inform responsible decision-makers and foster solidarity.
Governance and	Essential laws and regulations for patient protection and AI

Law	regulation in dental practice necessitate ongoing development based on ethical principles.

3.7 Regulatory Approval and Standards

Establishing regulatory standards and frameworks for AI applications in orthodontics is a challenge. Clear guidelines are needed to ensure the reliability, effectiveness, and safety of AI technologies in clinical practice. AI systems also pose safety concerns. Mechanisms need to be established to regulate the quality of the algorithms utilized in AI. To remedy this situation, the FDA has created a new drug category, “Software as Medical Device,” via which it oversees safe innovation and ensures patient safety (48).

On February 2024, the Europe Union EU's AI Act was unanimously approved by the Council of EU Ministers. After its official adoption, the regulation will become applicable after 24 months, most likely in the first half of 2026.The legislation in the EU for AI as a tool in medical health is governed by the suggested AI Act. This Act, which is predicted to be finalized and approved by Member States soon, will become applicable around the first half of 2026. The AI Act defines AI systems broadly and imposes obligations on operators of AI systems, particularly focusing on high-risk AI systems. Health-related AI systems categorized as Classes IIa, IIb, and III. Medical devices are categorized as high-risk and require third-party conformity assessment. When the AI Act comes into force, health-related AI systems classified as high risk will operate in a highly regulated environment.

The European Commission's proposal for an AI regulation aims to establish comprehensive rules to manage opportunities and threats related to AI, supporting beneficial outcomes while providing competitive advantages. The AI Act has a risk-based approach, defining mandatory requirements for the designing and developing of AI and regulating market surveillance. It requires high-risk AI systems to adhere to particular requirements and obligations for effective risk management, including guaranteeing human oversight and conducting post-market monitoring. The legislation also mandates that certain AI systems and foundation models be registered in an EU database for transparency.

The differences between the regulation of AI in healthcare by the FDA and the EU are significant. The FDA in the United States has issued specific guidelines for AI/ML-

Based Software as a Medical Device, focusing on regulating software that uses AI in medical applications. Unlike traditional medical devices or drugs, AI software evolves over time, prompting the FDA to emphasize continuous monitoring rather than a one-time approval process.

On the other hand, the EU has its own approach to regulating AI in healthcare. The EU's regulations are designed to guarantee the ethical and accountable utilization of AI in healthcare, with a focus on protecting patient safety and data privacy. These regulations aim to address issues such as transparency, accountability, and fairness in AI systems used in healthcare settings.

Overall, while both the FDA and EU are working towards regulating AI in healthcare, their approaches differ in terms of focus and specific regulatory requirements. The FDA emphasizes continuous monitoring of evolving AI software, while the EU prioritizes ethical considerations and patient safety in the use of AI in healthcare.

3.7.1 Differences between AI Act and FDA regulations

3.7.1.1 Regulatory Focus

The FDA in the United States focuses on regulating AI software used in medical applications, emphasizing continuous monitoring of evolving AI systems. In contrast, the EU regulations prioritize ethical considerations, patient safety, and data privacy in the use of AI in healthcare.

3.7.1.2 Approval Process

The FDA's approach involves specific guidelines for AI/ML-Based Software as a Medical Device, with an emphasis on continuous monitoring rather than a one-time approval process. In comparison, the EU regulations aim to ensure ethical and responsible use of AI in healthcare, focusing on transparency, accountability, and fairness in AI systems.

3.7.1.3 Evolution of AI Software

The FDA recognizes that AI software evolves over time and requires ongoing monitoring to ensure safety and efficacy. On the other hand, the EU regulations address issues such as data privacy, patient safety, and ethical considerations in the development and deployment of AI systems in healthcare settings.

3.7.1.4 Compliance Requirements

While both the FDA and EU regulations aim to regulate AI in healthcare, they differ in their compliance requirements. The FDA's guidelines focus on specific aspects of AI software as a medical device, while the EU regulations encompass broader ethical considerations and patient-centric principles.

3.7.1.5 Overall Approach

The FDA's approach to regulating AI in healthcare is more focused on product-specific guidelines and continuous monitoring of evolving AI systems. In contrast, the EU regulations take a broader approach by emphasizing ethical principles, patient safety, and data privacy in the use of AI technology in healthcare settings.

3.7.2 Similarities between AI Act and FDA regulations:

3.7.2.1 Healthcare Regulation

Both the FDA in the United States and the EU have regulations in place to oversee the use of AI in healthcare settings, aiming to ensure patient safety, data privacy, and the effectiveness of AI applications.

3.7.2.2 Ethical Considerations

Both regulatory bodies emphasize ethical considerations in the deployment and development of AI systems in healthcare, focusing on transparency, accountability, and fairness in the use of AI technology.

3.7.2.3 Patient Safety

The FDA and EU regulations share a common goal of prioritizing patient safety when it comes to the use of AI in healthcare, aiming to mitigate risks associated with AI applications and ensure that patients receive safe and effective care.

3.7.2.4 Continuous Monitoring

While their approaches may differ, both the FDA and EU recognize the importance of continuous monitoring of AI systems to ensure ongoing compliance with regulatory standards and to address any emerging issues related to AI technology in healthcare.

3.7.2.5 Regulatory Oversight

Both regulatory bodies play a crucial role in overseeing the development, approval, and deployment of AI technologies in healthcare, working to establish guidelines that promote the responsible use of AI while safeguarding patient interests.

3.8 Cost Considerations

The implementation of AI technologies in orthodontics may involve significant upfront costs for training, infrastructure, and software development. Ensuring cost-effectiveness and demonstrating a clear return on investment is crucial for widespread adoption (42).

3.9 Continuous Learning and Adaptation:

Orthodontic practices evolve over time, and AI models need to continuously learn and adapt to new treatment approaches, technologies, and patient demographics. Developing AI systems that can stay current with advancements in the field is an ongoing challenge.

Ongoing training and adaptation: AI models necessitate consistent updates and ongoing training to align with evolving dental knowledge and technology. Dental professionals must stay abreast of AI advancements, undergo relevant training, and acquire the skills to proficiently utilize AI tools and interpret their results. Ensuring continuous support and maintenance for AI systems is vital for their effective implementation across various dental specialties (21).

IV Conclusion

In summary, the integration of AI into orthodontics holds immense promise for transforming the field across diagnostics, treatment, and monitoring. Through enhanced exobuccal, endobuccal, and radiological diagnostics, AI-driven automation offers the potential for more accurate and efficient assessments, streamlining processes and reducing reliance on manual measurements.

In treatment planning, AI facilitates the creation of personalized treatment plans tailored to individual patient needs. Automated procedures such as bracket placement, wire bending, and even complex interventions like orthognathic surgery can benefit from AI's precision and efficiency. Moreover, optimization of aligner therapy through AI promises improved patient comfort and outcomes.

Looking ahead, AI offers new perspectives and opportunities in orthodontics, including multifactorial treatment approaches, IOT integration, app monitoring, and advancements in teledentistry. These innovations not only enhance accessibility and patient engagement but also pave the way for collaborative and interdisciplinary care models.

However, realizing the full potential of AI in orthodontics requires addressing significant challenges. Ensuring data privacy and security, maintaining data quality and standardization, mitigating overfitting, and navigating ethical considerations are essential steps. Moreover, adapting regulatory frameworks and managing costs are critical for widespread adoption and equitable access to AI-driven orthodontic care.

In conclusion, while the integration of AI in orthodontics presents exciting possibilities, it demands a thoughtful and collaborative approach to overcome challenges and maximize benefits for both practitioners and patients. By leveraging AI responsibly and ethically, orthodontics can embrace innovation to deliver more personalized, efficient, and effective care in the years to come.

V References

1. Yurdakurban E, Duran GS, Görgülü S. Evaluation of an automated approach for facial midline detection and asymmetry assessment: A preliminary study. Orthod Craniofacial Res. 2021;24(S2):84–91.

2. Thurzo A, Strunga M, Havlínová R, Reháková K, Urban R, Surovková J, et al. Smartphone-Based Facial Scanning as a Viable Tool for Facially Driven Orthodontics? Sensors. 2022 Oct 1;22(20).

3. Pellitteri F, Scisciola F, Cremonini F, Baciliero M, Lombardo L. Accuracy of 3D facial scans: a comparison of three different scanning system in an in vivo study. Prog Orthod [Internet]. 2023 [cited 2024 Jan 26];24:44. Available from: https://doi.org/10.1186/s40510-023-00496-x

4. D'Ettorre, G., Farronato, M., Candida, E., Quinzi, V., & Grippaudo, C. (2022). A comparison between stereophotogrammetry and smartphone structured light technology for three-dimensional face scanning. The Angle Orthodontist, 92(3), 358–363. https://doi.org/10.2319/040921-290.1

5. Kılıç B, İbrahim AH, Aksoy S, Sakman MC, Demircan GS, Önal-Süzek T. A family-centered orthodontic screening approach using a machine learning-based mobile application. J Dent Sci. 2023;19.

6. Patcas R, Timofte R, Volokitin A, Agustsson E, Eliades T, Eichenberger M, et al. Facial attractiveness of cleft patients: A direct comparison between artificial-intelligence-based scoring and conventional rater groups. Eur J Orthod. 2019;41(4):428–33.

7. Rao GKL, Srinivasa AC, Iskandar YHP, Mokhtar N. Identification and analysis of photometric points on 2D facial images: a machine learning approach in orthodontics. Health Technol (Berl). 2019 Nov 1;9(5):715–24.

8. Talaat S, Kaboudan A, Talaat W, Kusnoto B, Sanchez F, Elnagar MH, et al. The validity of an artificial intelligence application for assessment of orthodontic treatment need from clinical images. Semin Orthod. 2021 Jun 1;27(2):164–71.

9. Li S, Guo Z, Lin J, Ying S. Artificial Intelligence for Classifying and Archiving Orthodontic Images. Biomed Res Int. 2022;2022.

10. Ryu J, Lee YS, Mo SP, Lim K, Jung SK, Kim TW. Application of deep learning artificial intelligence technique to the classification of clinical orthodontic photos. BMC Oral Health. 2022 Dec 1;22(1).

11. Jiang F, Guo Y, Yang C, Zhou Y, Lin Y, Cheng F, et al. Artificial intelligence system for automated landmark localization and analysis of cephalometry. Dentomaxillofacial Radiol. 2023;52(1).

12. Le VNT, Kang J, Oh IS, Kim JG, Yang YM, Lee DW. Effectiveness of Human–Artificial Intelligence Collaboration in Cephalometric Landmark Detection. J Pers Med. 2022 Mar 1;12(3).

13. Tsolakis IA, Tsolakis AI, Elshebiny T, Matthaios S, Palomo JM. Comparing a Fully Automated Cephalometric Tracing Method to a Manual Tracing Method for Orthodontic Diagnosis. J Clin Med. 2022 Nov 1;11(22).

14. Bao H, Zhang K, Yu C, Li H, Cao D, Shu H, et al. Evaluating the accuracy of automated cephalometric analysis based on artificial intelligence. BMC Oral Health. 2023 Dec 1;23(1).

15. Al-Ubaydi AS, Al-Groosh D. The Validity and Reliability of Automatic Tooth Segmentation Generated Using Artificial Intelligence. Sci World J. 2023;2023.

16. Leonardi R. Cone-beam computed tomography and three-dimensional orthodontics. Where we are and future perspectives. Journal of Orthodontics. Taylor and Francis Ltd.; 2019.

17. Kazimierczak N, Kazimierczak W, Serafin Z, Nowicki P, Nożewski J, Janiszewska-Olszowska J. AI in Orthodontics: Revolutionizing Diagnostics and Treatment Planning. 2023; Available from: www.preprints.org

18. Li P, Kong D, Tang T, Su D, Yang P, Wang H, et al. Orthodontic Treatment Planning based on Artificial Neural Networks. Sci Rep. 2019 Dec 1;9(1).

19. Del Real A, Del Real O, Sardina S, Oyonarte R. Use of automated artificial intelligence to predict the need for orthodontic extractions. Korean J Orthod. 2022;52(2):102–11.

20. Suhail Y, Upadhyay M, Chhibber A, Kshitiz. Machine learning for the diagnosis of orthodontic extractions: A computational analysis using ensemble learning.

Bioengineering. 2020 Jun 1;7(2):1–13.

21. Dhopte A, Bagde H. Smart Smile: Revolutionizing Dentistry With Artificial Intelligence. Cureus. 2023;15(6).

22. Ronsivalle V, Ruiz F, Lo Giudice A, Carli E, Venezia P, Isola G, et al. From Reverse Engineering Software to CAD-CAM Systems: How Digital Environment Has Influenced the Clinical Applications in Modern Dentistry and Orthodontics. Appl Sci. 2023;13(8).

23. Gardner S, Khosravi R, Detweiler M, Owen B. 3D printing digitally planned in-direct bonding tray. Semin Orthod [Internet]. 2022;28(2):61–72. Available from: https://doi.org/10.1053/j.sodo.2022.10.009

24. Lo YC, Chen GA, Liu YC, Chen YH, Hsu JT, Yu JH. Prototype of augmented reality technology for orthodontic bracket positioning: An in vivo study. Appl Sci. 2021;11(5):1–13.

25. Johny J, Sreedharan S, Alex T, Kuniyedathchalil J, Sunil R. Robot: next table turner in dentistry. Tanta Dent J. 2022;19(1):52.

26. Tao T, Zou K, Jiang R, He K, He X, Zhang M, et al. Artificial intelligence-assisted determination of available sites for palatal orthodontic mini implants based on palatal thickness through CBCT. Orthod Craniofacial Res. 2023 Aug 1;26(3):491–9.

27. Ma Q, Kobayashi E, Fan B, Nakagawa K, Sakuma I, Masamune K, et al. Automatic 3D landmarking model using patch-based deep neural networks for CT image of oral and maxillofacial surgery. Int J Med Robot Comput Assist Surg [Internet]. 2020 Jun 20;16(3). Available from: https://onlinelibrary.wiley.com/doi/10.1002/rcs.2093

28. de Oliveira PHJ, Li T, Li H, Gonçalves JR, Santos-Pinto A, Gandini Junior LG, et al. Artificial intelligence as a prediction tool for orthognathic surgery assessment. Orthod Craniofac Res [Internet]. 2024 May 7; Available from: https://onlinelibrary.wiley.com/doi/10.1111/ocr.12805

29. Kato RM, Parizotto J de OL, Oliveira PHJ de, Gonçalves JR. Artificial Intelligence in Orthognathic Surgery – A Narrative Review of Surgical Digital

Tools and 3D Orthognathic Surgical Planning. J Calif Dent Assoc. 2023 Dec 31;51(1).

30. Bouletreau P, Makaremi M, Ibrahim B, Louvrier A, Sigaux N. Artificial Intelligence: Applications in orthognathic surgery. Vol. 120, Journal of Stomatology, Oral and Maxillofacial Surgery. Elsevier Masson SAS; 2019. p. 347–54.

31. Pandita Bhatia A, Tiwari S. Artificial Intelligence: An Advancing Front of Dentistry. Acta Sci Dent Scienecs. 2019 Nov 27;3(12):135–8.

32. Woo H, Jha N, Kim YJ, Sung SJ. Evaluating the Accuracy of Automated Orthodontic Digital Setup Models. Semin Orthod. 2023 Mar 1;29(1):60–7.

33. Dhingra A, Palomo JM, Stefanovic N, Eliliwi M, Elshebiny T. Comparing 3D Tooth Movement When Implementing the Same Virtual Setup on Different Software Packages. J Clin Med. 2022;11(18).

34. Gili T, Di Carlo G, Capuani S, Auconi P, Caldarelli G, Polimeni A. Complexity and data mining in dental research: A network medicine perspective on interceptive orthodontics. Vol. 24, Orthodontics and Craniofacial Research. John Wiley and Sons Inc; 2021. p. 16–25.

35. Bahrami R, Bahrami R. A new model for managing tooth movement: Smart orthodontic brackets in the Internet of Dental Things (IoDT). Med Hypotheses. 2023 Oct 1;179.

36. Littlewood SJ, Dalci O, Dolce C, Holliday LS, Naraghi S. Orthodontic retention: what’s on the horizon? Br Dent J. 2021 Jun 1;230(11):760–4.

37. Moylan HB, Carrico CK, Lindauer SJ, Tüfekçi E. Accuracy of a smartphone-based orthodontic treatment-monitoring application: A pilot study. Angle Orthod. 2019;89(5):727–33.

38. Caruso S, Caruso S, Pellegrino M, Skafi R, Nota A, Tecco S. A knowledge-based algorithm for automatic monitoring of orthodontic treatment: The dental monitoring system. two cases. Sensors. 2021 Mar 1;21(5):1–14.

39. Thurzo A, Kurilová V, Varga I. Artificial intelligence in orthodontic smart application for treatment coaching and its impact on clinical performance of

patients monitored with AI-telehealth system. Healthc. 2021 Dec 1;9(12).

40. Batra P, Tagra H, Katyal S. Artificial Intelligence in Teledentistry. Discoveries [Internet]. 2022 Sep 30;10(3):e153. Available from: https://discoveriesjournals.org/discoveries/D.2022.03.RA-PBatra.pdf

41. Di Fede O, La Mantia G, Cimino MGCA, Campisi G. Protection of Patient Data in Digital Oral and General Health Care: A Scoping Review with Respect to the Current Regulations. Oral. 2023;3(2):155–65.

42. Liu J, Zhang C, Shan Z. Application of Artificial Intelligence in Orthodontics: Current State and Future Perspectives. Healthc. 2023;11(20):1–27.

43. Liu J, Chen Y, Li S, Zhao Z, Wu Z. Machine learning in orthodontics: Challenges and perspectives. Vol. 30, Advances in Clinical and Experimental Medicine. Wroclaw University of Medicine; 2021.

44. Hung K, Yeung AWK, Tanaka R, Bornstein MM. Current applications, opportunities, and limitations of AI for 3D imaging in dental research and practice. Vol. 17, International Journal of Environmental Research and Public Health. MDPI AG; 2020. p. 1–18.

45. McNabb NK, Christensen EW, Rula EY, Coombs L, Dreyer K, Wald C, et al. Projected Growth in FDA-Approved Artificial Intelligence Products Given Venture Capital Funding. J Am Coll Radiol. 2023 Oct 16;

46. Mörch CM, Atsu S, Cai W, Li X, Madathil SA, Liu X, et al. Artificial Intelligence and Ethics in Dentistry: A Scoping Review. J Dent Res. 2021;100(13):1452–60.

47. Rokhshad R, Ducret M, Chaurasia A, Karteva T, Radenkovic M, Roganovic J, et al. Ethical considerations on artificial intelligence in dentistry: A framework and checklist. J Dent [Internet]. 2023;135(June):104593. Available from: https://doi.org/10.1016/j.jdent.2023.104593

48. Nguyen, T. T., Larrivée, N., Lee, A., Bilaniuk, O., & Durand, R. (2021). Use of Artificial Intelligence in Dentistry: Current Clinical Trends and Research Advances. Journal (Canadian Dental Association), 87, l7.