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Review article

Artificial intelligence for orthodontic diagnosis and treatment planning: A scoping review

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ABSTRACT

Objectives: To provide an overview of artificial intelligence (AI) applications in orthodontic diagnosis and treatment planning, and to evaluate whether AI improves accuracy, reliability, and time efficiency compared to expert-based manual approaches, while highlighting its current limitations.
Data: This review follows the Preferred Reporting Items for Systematic Reviews and Meta-Analyses extension for Scoping Reviews (PRISMA-ScR) Checklist.
Sources: An electronic search was performed on PubMed, Web of Science, and Embase electronic databases. Additional studies were identified from Google Scholar and by hand searching through included studies. The search was carried out until June 2023 without restriction of language and publication year.
Study selection: After applying the selection criteria, 71 articles were included in the review. The main research areas were classified into three domains based on the purpose of AI: diagnostics ($n = 29$), landmark identification ($n = 20$) and treatment planning ($n = 22$).
Conclusion: This scoping review shows that AI can be used in various orthodontic diagnosis and treatment planning applications, with anatomical landmark detection being the most studied domain. While AI shows potential in improving time efficiency and reducing operator variability, the accuracy and reliability have not yet consistently surpassed those of expert clinicians. At all moments, human supervision remains essential. Further advances and optimizations are necessary to strive towards automated patient-specific treatment planning.
Clinical significance: AI in orthodontics has shown its ability to serve as a decision-support system, thereby enhancing the efficiency of diagnostics and treatment planning within orthodontics digital workflow."

1. Introduction

In recent years, technological advancements have paved the way for digitalization in orthodontics, which has largely improved and simplified diagnostic and treatment planning workflows. The main highlights towards achieving a computer-based digital workflow in orthodontics have been the incorporation of three-dimensional (3D) imaging devices, computer-aided design and manufacturing platforms (CAD/CAM) and 3D printing. Such technologies offer faster, more precise and predictable treatment with less patient discomfort. Although such an approach has multiple advantages over traditional manual workflows, its implementation in clinical practice is still limited, possibly due to two main reasons: a lack of technical knowledge and the high costs associated with the equipment [1].

Specifically, some areas with room for improvement are time efficiency and observer variability. For instance, orthodontists still have to rely on their knowledge to identify cephalometric landmarks, which is time consuming, prone to human error and carries a high risk of observer variability. Another example is the decision-making process during treatment planning, which varies depending on the clinician's

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experience [2,3].

To overcome such limitations, incorporating artificial intelligence (AI)-based networks aims to automate some of these processes with high reliability and accuracy. This automation mainly depends on AI-driven machine learning (ML) or deep learning (DL) algorithms. While ML majorly relies on structured datasets for training and consists of simple and more linear algorithms, DL is a subset of ML that employs neural networks resembling human brain neurons for analysing complex and unstructured datasets. DL networks can efficiently deal with high dimensional data having multiple predictor variables. Amongst several DL-based artificial neural networks (ANNs), convolutional neural networks (CNNs), which have one or more layers of convolution units, have demonstrated the most optimal performance in the field of image analysis and are commonly being applied in the majority of dento-maxillofacial workflows for diagnostics, treatment planning and prognosis prediction [4].

Orthodontic procedures encompass a range of intricate tasks, including the identification of cephalometric landmarks and the making of treatment planning decisions, both of which necessitate precision and efficiency. Furthermore, the diagnosis of malocclusion and the interpretation of imaging data are vital for effective treatment planning. AI technologies have the potential to aid in meeting these orthodontic needs by automating tasks, enhancing accuracy, and minimizing variability. A number of studies have already utilized AI automation for manual orthodontic diagnostic tasks such as landmark detection, cephalometric analysis, and malocclusion diagnosis using both two-dimensional (2D) and three-dimensional (3D) imaging [5,6]. Other research has applied AI to orthodontic treatment planning and in aiding clinical decision-making processes, such as determining whether a tooth extraction is necessary or if orthognathic surgery should be considered [7,8]. However, there is still a need for a comprehensive review and mapping of the existing literature on the application of AI for various orthodontic tasks, taking into account their performance, reliability, and time efficiency.

Although several scoping reviews have previously explored this topic [9–14], the field of AI research in orthodontics has experienced rapid growth. In the last three years, there has been an exponential increase in studies focusing on AI applications in orthodontics, driven by advancements in ML and DL [14]. This surge in publications has revealed a range of new applications, methodologies, and insights that were either insufficiently addressed or overlooked in earlier reviews [15–18]. Consequently, this scoping review aims to bridge these gaps by consolidating more evidence and examining advancements in AI applications for orthodontic diagnosis and treatment planning, and evaluating whether AI improves accuracy, reliability, and time efficiency compared to expert-based manual methods, while also highlighting current limitations.

2. Materials and methods

2.1. Protocol and registration

This scoping review was conducted in accordance with the Preferred Reporting Items for Systematic Reviews and Meta-Analyses extension for Scoping Reviews (PRISMA-ScR) Checklist [19]. The study protocol was registered on the Open Science Framework platform and is available at the following link: https://osf.io/wd5nm.

2.2. Review question

The research was designed according to Population, Intervention, Comparison, and Outcome (PICO) framework as follows:

Patients (P): orthodontic patients

Intervention (I): AI-based algorithms for orthodontic diagnosis and treatment planning,

Comparison (C): conventional manual diagnosis and treatment planning by experts,

Outcome (O): accuracy, reliability and time-efficiency

Review question: Does the application of AI (I) offer improved accuracy, reliability, and time-efficiency (O) for diagnosis and treatment planning in orthodontic patients (P) compared to an expert-based manual approach (C)?

2.3. Eligibility criteria

The review was limited to articles published in the last ten years and in English. For an article to be included in the scoping review, the following criteria needed to be met: (1) focusing on orthodontic diagnosis and treatment planning; (2) assessing quantitative data (accuracy, validity or time-efficiency); (3) application of AI algorithms (ML, DL). Studies with ambiguous information, narrative or systematic reviews, case reports, letters, editorials, commentaries, and non-English articles were excluded.

2.4. Information sources and search strategy

An electronic search was undertaken on the electronic databases of PubMed, Web of Science and Embase. The search strategy consisted of two concepts (orthodontics and artificial intelligence) combined with the 'AND' operator. Each concept consisted of keywords and MeSH terms as shown in Supplementary Table 1.

A grey literature search was performed on Google Scholar and by hand searching through included studies to identify any additional studies that were not obtained from the selected electronic databases. The retrieved articles were imported to EndNote 20 (Thomson Reuters, Philadelphia, PA, USA) for the elimination of duplicates and further selection.

2.5. Selection of sources of evidence

Following the primary search, duplicates were removed using EndNote X8 software (Clarivate Analytics, Philadelphia, PA). Two reviewers (NW and MV) examined the titles and abstracts of all remaining articles to determine which studies were relevant for further evaluation through a full-text review. Afterward, the articles selected for a full-text review were evaluated by both reviewers based on the inclusion criteria to determine their eligibility. Study selection was conducted independently by both reviewers, and any disagreement was reconciled through discussion with a third reviewer (RJ).

2.6. Data charting and data items

Two reviewers (NW and RSG) independently extracted data from eligible studies and resolved discrepancies through discussion. The data charting was performed on a standardized data abstraction form prepared in advance using a Microsoft Excel spreadsheet. The extracted information included general information (title, author and journal name, publication year), study characteristics (area of application, sample size, intervention type, outcome) and type of AI algorithm used (ML/DL).

3. Results

3.1. Search results

The search yielded 943 articles from the three databases, from which 576 remained after removing the duplicates. Based on the title and abstract screening, 122 articles were selected for further assessment. Finally, 71 articles met the eligibility criteria and were included in the review following full-text screening. Fig. 1 shows the PRISMA-ScR flowchart of the study screening process. Tables 1–3 summarize the characteristics of the included studies based on their focus: diagnostic,

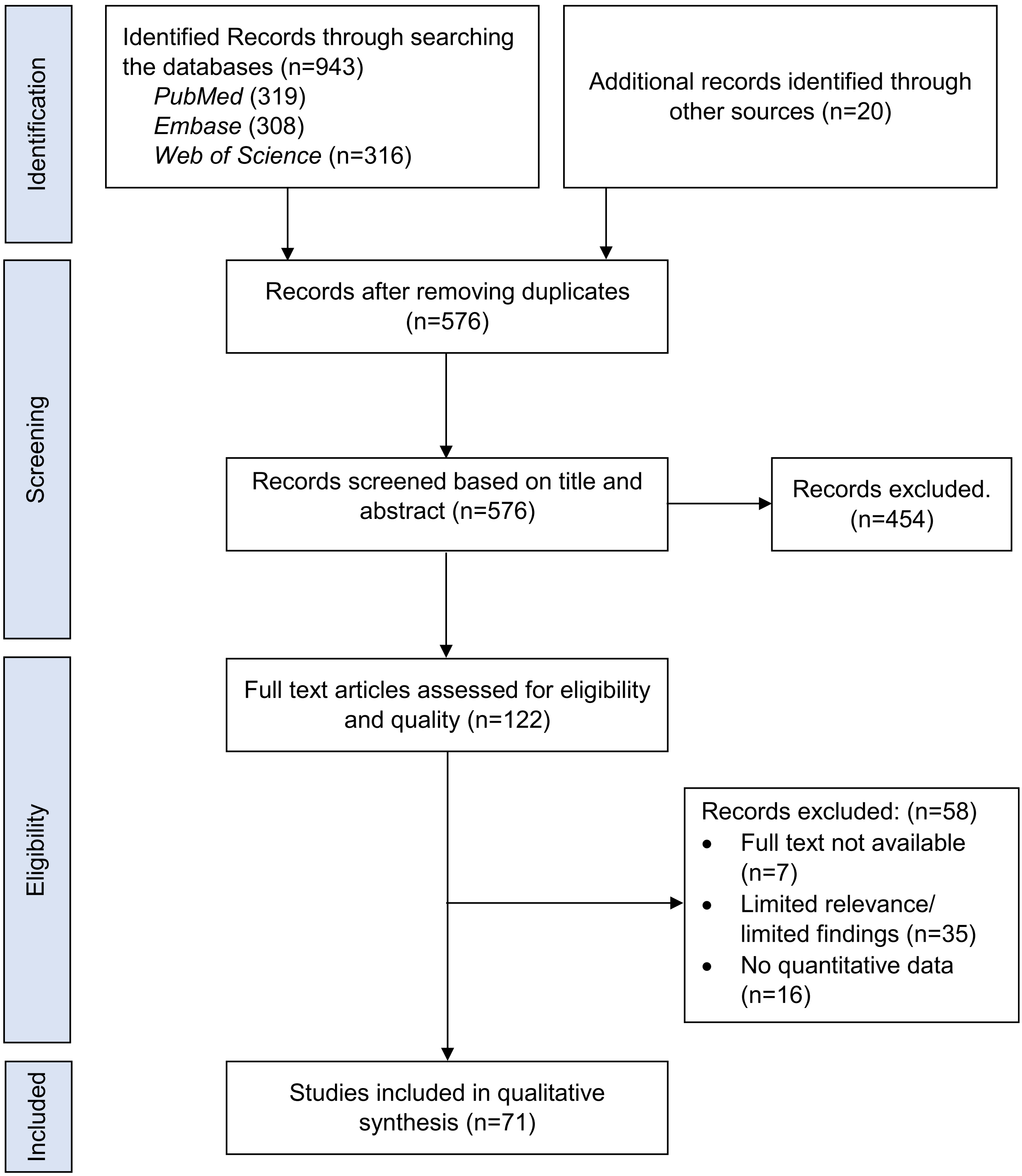

Fig. 1. Flowchart of article selection.

landmark detection and treatment planning tasks, with Supplementary Table 2 consisting of legend accompanying the tables.

Most studies were published between 2021 and 2023 ($n = 58$, 82 %), as illustrated in Fig. 2. The applications of AI in diagnostics included image indexing ($n = 2$), maturation determination ($n = 14$), diagnosis of occlusal traits ($n = 10$), and upper airway assessment ($n = 3$). Twenty studies (28 %) applied AI network for automated landmark detection, making this the most prevalent topic among the included studies (Fig. 2). In relation to treatment planning, 22 studies were identified, focusing on prediction of the need for tooth extraction ($n = 4$), general orthodontic planning ($n = 13$), and orthognathic surgery planning ($n = 5$).

3.2. Diagnostics

3.2.1. Image indexing and archiving

Two studies designed an AI-based algorithm to classify shuffled clinical and radiological images according to their respective categories: facial photos (front, smile), intraoral photos (front, upper, lower, buccal), lateral cephalograms and panoramic radiographs. Li et al. applied CNN to index clinical (intra- and extraoral) and radiological images (lateral cephalogram, panoramic radiograph) with an accuracy

Table 1
Overview on included studies in diagnostics domain.

References	Purpose	Objective	Train datasets	Test datasets	Accuracy	Image type	2D/3D	Type AI	Conclusion
Li et al [15]		Develop automated classification of 14 orthodontic images	12,999	1,420	99%		2D		DL model improved accuracy, speed, and efficiency
Ryu et al [20]		Develop automated classification of 9 clinical orthodontic images	3,548	900	98%		2D		CNN model can classify intra- and extraoral images successfully
Guo et al [21]		Develop CNN-based method and compare with the manual method.	9,231	1026	92%-96%		2D		Compared to manual methods, the end-to-end CNN models perform better.
Amasya et al [22]		Develop ANN-based method and compare with manual method.	647	n.a.	58%		2D		In CVM analysis, the ANN model created, performed closed to human researchers.
Amasya et al [23]		Compare 5 AI machine learning models.	647	n.a.	93%		2D		ANN network showed the best result in predicting the cervical vertebrae morphology
Atici et al [24]		Compare 4 DL models with and without the use of directional filters.	761	257	75%		2D		Highest accuracy was obtained by the custommade CNN model with directional filters.
Kim et al [25]		Identify with ML-based method on cephalograms.	480	120	63%		2D		3-step based segmentation model had the highest accuracy
Kök et al [26]		Compare 7 AI algorithms.	300	n.a.	97%		2D		ANN network is preferred in determining the CMS.
Li et al [27]		Compare 4 CNN models.	4,253	914	67%		2D		RESNET5 achieved the highest accuracy.
Liao et al [28]		Develop a CNN model.	720	180	84%		2D		The model achieves a superior performance for staging the CVM.
Radwan et al [29]		Develop CNN and unsupervised learning model.	1,201	150	80%		2D		This CNN model is able to classifie the CVM stage with a good level of success
Seo et al [30]		Develop CNN-based method on LC.	480	120	94%		2D		DL models showed an accuracy of more than 90% in determining CVM stages.
Zhou et al [31]		Develop new AI-based method.	980	100	71%		2D		AI algorithm is accurate and useful for describing skeletal maturation and stages.
Atici et al [32]		Develop automated CVM stage detection and classification with pre-processing layer	823	189	82% (female), 75% (male)		2D		CNN with the pre-processing layer produce higher accuracy in CVM stages determination
Khazaei et al [33]		Develop CNN-based maturation stage classification	1,846	449	82% (3 class), 93% (2 class)		2D		CNN can classify CVM images with high accuracy
Mohammad-Rahimi et al [34]		Evaluate DL model CVM and growth spurt stage determination	692	99	62% (6 class) 83% (3 class)		2D		Current model had fair accuracy and needs more improvement
Aljabri et al [35]		Develop DL model to make a canine impaction classification	57	211	93%		2D		Efficient DL model with high accuracy was developed to assess canine impaction, shown that there is still too little automation in canine impaction assessment.
Vranckx et al [36]		Automatic third molar segmentation and predict eruption potential	588	250	Segment: 90% Angle: 80%		2D		The network can predict the third molar angulation with high accuracy
Talaat et al [6]		Assess malocclusions on intraoral scans using a CNN network model.	460	116	99%		2D		Deep CNN networks are valid to detect dental problems on intraoral scans. New AI technique can accurately locate malocclusions.
Aksoy et al [37]		Compare 3 ML algorithms for diagnosing skeletal class III malocclusion.	337	113	76%		2D		ML was the most effective method
Nan et al [38]		Develop DL-based method for automatic skeletal malocclusion classification	1,613	na	91% (cephalometric radiograph) 84% (Profile photographs)		2D		CNN successfully learns the discriminative representation of the lateral cephalograms and profile photographs
Yim et al [39]		Develop CNN to determine skeletal discrepancies with 1-step orthodontic diagnosis.	1,522	652	82%-89%		2D		Model created by the researchers on the basis of CNN network showed good results for clinical usability.
Yu et al [40]		Develop CNN-based skeletal diagnostics on lateral cephalograms	3,827	765	96%		2D		Study indicates that orthodontic diagnosis is easily possible automatically through RX inputs.
Zhang et al [41]		Develop DL model for mandibular growth prediction	256	40	85%		2D		DL model could predict the growth trend for children with anterior crossbite
Ali et al [42]		Develop neural network-based prediction to estimate the size of premolars and canines.	66	28	ICC 0.97-0.99		2D		Prediction of unerupted teeth (size) was accurately evaluated via a new neural network AI method.
Budiman [43]		Develop ANN networks to determine arch dimensions from pre-existing orthodontically treated malocclusion models.	114	76	76%		3D		ANN used to study the arch form, which can correctly capture the arch form.
Jeong et al [17]		Evaluate upper airway obstruction based on DL using lateral cephalograms	1099	120	F1 Score 0.88		2D		CNN model can detect upper airway obstruction with higher accuracy and more time-efficiency.
Shujaat et al [44]		Automatic segmentation of the pharyngeal airway space	48	25	DSC: 97%		3D		3D uNet model proposed an accurate and time-efficient automatic segmentation method
Dong et al [45]		Develop DL-based method for upper airway assessment on CBCT	700	170	F1 Score 0.90		3D		The proposed model showed good performance and faster detecting time for adenoid hypertrophy.

of 99 % in 0.08 min [15]. In another study, Ryu et al. designed a CNN model for classifying intra- and extraoral images with an overall success rate of 98 % [20].

3.2.2. Maturation determination

In one study, automated CNN-based age estimation was performed on panoramic radiographs by using Demirjian method. The network achieved a result in 0.3 s with an accuracy between 92 % and 96 %, which was 3 % higher than manual classification [21]. On the other hand, the remaining ten studies applied AI for cervical vertebrae maturation (CVM) staging on lateral cephalometric images [22–31]. Two studies found that ANN was the most stable and effective algorithm for automated CVM detection compared to other algorithms, such as random forest and decision tree [23,26]. In eleven studies, CNNs were used to automate CVM staging [24,25,27–34], where the study of Seo et al. [30] showed the highest accuracy of 90 % with an output below 0.1 s of staging time. Meanwhile, the lowest accuracy (61.62 %) was reported by Mohammad-Rahimi et al. [34], whose algorithm was used to classify six stages of CVM. Atici et al. [24] proposed a custom-designed CNN with tuneable directional filters, which provided an accuracy 75 % higher than the commonly used pre-trained network models without directional filters.

Table 2
Overview on included studies in landmark detection domain.

References	Purpose	Objective	Train datasets	Test datasets	Accuracy	Image type	2D/3D	Type AI	Conclusion
Arik et al [5]		Develop fully automated quantitative cephalometry with CNN.	150	250	76%		2D		CNN model achieved high accuracy in the detection of anatomical landmarks
Hwang et al [39]		Compare with previous published AI method.	1,983	200	76%		2D		Latest AI algorithms work better than previous methods. Ceph. analysis has higher success rates than human research.
Hwang et al [40]		Compare the detection of 80 landmarks detection with manual method.	1,028	283	Mean error 1.46 mm		2D		AI identified ceph. landmarks = human researchers.
Kim et al [41]		Develop automated method by a trained 2-stage automated algorithm based on DL.	1,675	845	74%-84%		2D		Automatic ceph. analysis will be useful to save time and effort.
King et al [42]		Develop a 2-step algorithm method.	150	250	75%-86%		2D		The method used shows promising and effective results in automatically detecting ceph.landmarks.
Le et al [43]		Evaluate a human and AI collaboration on landmark detection.	1,193	100	73%		2D		Initial collaboration with AI was effective in the detection of ceph. landmarks.
Song et al [44]		Develop automated method using DL.	150	350	62%-86%		2D		Proposed method is practical for use, due to its accuracy and speed.
Yao et al [45]		Develop automated method based on CNN network.	312	100	97%		2D		Framework for ALD is high-speed and can detect landmarks with high accuracy.
Jiang et al [46]		Develop CephNet (CNN) for automatic cephalometric analysis	9,611	259	91.73%		2D		The algorithm showed high accuracy and applicability
Popova et al [47]		Evaluate whether growth structure and fixed appliances affect automated landmarks detection	430	460	84.73%		2D		The CNN model performance did not affected by the growth structures and fixed appliances
Hong et al [48]		Investigate the accuracy of CNN-based landmark identification in post orthognathic surgery	3,004	184	Mean error 1,17 mm		2D		CNN model can detect anatomical landmark despite the presence of bracket, plates, screws and bone remodelling changes
Tanikawa et al [49]		Evaluate the AI-based cephalometric landmarking on various patient groups	1,755	30	85%-91%		2D		AI systems can be applied for various patient conditions
Dot et al [50]		Evaluate of a DL-based method on 3D CT-scan.	160	38	90%		3D		DL provided high accuracy for 3D landmark detection on the test set.
Kim et al [51]		Evaluate the accuracy of automated method on PA-cephalograms generated form CBCT images.	345	85	61%		3D		Clinical low accuracy was achieved, but AI had a better consistency than manual landmark detection on the PA.
Kim et al [52]		Evaluate the accuracy of a CNN-based method on combined LC’s generated from CBCT images.	345	85	87%		3D		Studies need to verify the benefit of combining the two datasets.
Blum et al [53]		Evaluate the DL-based landmark detection on CBCT scan	931	114	Mean error 2.73 mm		3D		AI analysis is 2,12% better and 95% faster than the experts
Lu et al [54]		Develop CNN-based landmark identification on CBCT scans	75	75	Mean error 1.108 mm		3D		The algorithm has high accuracy, significant robustness, and time-efficient
Gil et al [55]		Evaluate the accuracy of CNN-based method on PA-cephalograms.	2,075	345	83%		2D		CNN for automatic identification of PA ceph. landmarks is a good alternative to manual identification.
Croquet et al [56]		Dental impressions used to search for a new DL method for automatic palate recognition.	732	104	68-93%		3D		Lower accuracy on large and small palatium’s was observed, but clinical applicability in the future is very useful.
Rao et al [57]		Identify automated facial landmarks on 2D facial images	1000	22	98% (5mm range)		2D		Facial landmark identification with the effective Yolo V3 algorithm gives a fast and reliable analysis.

3.2.3. Diagnosis of occlusal traits

All studies applied CNNs for dentoskeletal classification on either panoramic radiography [35,36], intraoral clinical images [6], profile photos [37,38] or lateral cephalometry [38–41]. Aljabri et al. [35] investigated automated classification of canine impaction and reported 93 % accuracy with balanced data of 268 images, equally split between the two impaction types. Vranckx et al. [36] developed automatic third molar segmentation and angulation measurements with 90 % and 80 % accuracy, respectively. Talaat et al. [6] showed an accuracy of 99 % for detecting and localizing malocclusion on intraoral images, such as crowding, spacing, overjet, crossbite, open bite and deep bite. Zhang et al. [41] trained CNN models to classify the mandibular growth of children with anterior crossbite using lateral cephalometry and achieved an accuracy of 85 %.

Two studies automated the diagnosis of sagittal and vertical skeletal malocclusions on lateral cephalometry [39,40], reporting an accuracy of 80 % and >90 %, respectively. Aksoy et al. automatically predicted skeletal class III malocclusion on profile photos with 76 % accuracy [37]. Nan et al. used both types of images, resulting in an accuracy of 90.33 % using lateral cephalometry and 83.39 % using profile photos [38].

Ali et al. [42] applied ANN to predict the mesiodistal dimensions of teeth on intra-oral photographs automatically and found a high correlation ($r = 0{,}91$) between the target and actual output. Budiman et al. [43] used an ANN-based software for predicting the dental arch form (oval, square or tapered) on two-dimensionally scanned dental casts and achieved an accuracy of 76.3 %.

3.2.4. Upper airway assessment

Three studies applied CNN-based models for the automated evaluation of the upper airway. Jeong et al. [17] implemented a deep-CNN to assess upper airway obstruction on lateral cephalogram and achieved an F1 score of 0.88. On the other hand, two studies employed CNN models with CBCT images. Shujaat et al. [44] introduced a method that segmented the pharyngeal airway space independently with a Dice Similarity Coefficient (DSC) of 97 %. Meanwhile, Dong et al. [45] used Hierarchical Masks U-Net (HMSAU-Net) for automated detection of adenoid hypertrophy on segmented CBCT images of the upper airway, obtaining an F1 score of 0.90.

3.2.5. Landmark detection

Twenty articles evaluated the use of AI for anatomical landmark detection, all of which applied a DL algorithm based on conventional neural networks (CNNs). Most articles trained and validated the AI network to automatically detect 19 anatomical landmarks on lateral cephalometric images using IEEE (Institute of Electrical and Electronics Engineers) ISBI (International Symposium on Biomedical Imaging) 2015 Challenge public datasets [5,46–52]. Other studies, on the other hand, used their own dataset of lateral cephalometric images with various patient conditions, including craniofacial deformities, images with orthodontic fixed appliances and post-orthognathic surgery patients [53–56]. Amongst the landmark detection studies, Yao et al. [52] reached the highest successful detection rate (SDR) within a 2 mm deviation range (97.30 %) and 37 landmarks were automatically detected in 3 s. The lowest SDR (67.68 %) was observed by Arik et al. [5] when using the IEEE ISBI 2015 Challenge dataset 2.

Furthermore, five studies automated landmark identification on 3D images [57–62]. Out of these, only three studies performed 3D landmark localization generated from CT [57] and CBCT [60,61], with Dot et al. achieving the highest SDR (90.4 %) and lowest mean error (1.0 mm)

Table 3
Overview on included studies in treatment planning domain.

References	Purpose	Objective	Train datasets	Test datasets	Accuracy	Image type	2D/3D	Type AI	Conclusion
Jung et al [7]		Develop CNN model for orthodontics extraction decision making.	96	60	93%		2D		AI expert systems based on machine learning can make a very large contribution within orthodontics, both in planning and diagnosis.
Li et al [65]		Develop ANN for orthodontics extraction decision making.	181	120	94%		2D		Model offers several practical alternatives for doctors when making extraction decisions, increasing applicability.
Del Real et al [66]		Develop AI system to utilize need for extractions.	214	n.a.	94%		2D		Optimal extraction prediction can be obtained with combination of dental model and cephalometric data.
Leavitt at al [67]		Compare 3 ML algorithm to predict extraction pattern	256	110	82%		2D		RandomForest showed best accuracy for predicting upper and lower first premolar extraction
Prasad et al [68]		Develop 7 algorithms for taking multiple treatment decisions.	490	210	84%		2D		ML misses the ability of expert decision making, but can be useful in the future because of the fast progress.
Shimizu et al [69]		Develop and compare 2 AI systems to optimize treatment planning.	800	100	48%-65%		2D		The prioritized list by AI is clinical acceptable, the treatment plan has room for improvement. The system was non-significant to the worst specialist.
El-Dawlatly et al [71]		Evaluate of a newly assisted decision support system (DSS)for treatment planning of patients with a deep overbite.	51	n.a.	94%		2D		High level of agreement was found in mandibular buccal segment extrusion (94%), maxillary incisor proclination (98%), levelling of the curve of Spee (98%), mandibular incisor proclination (98%).
Leite et al [74]		Automated tooth detection and segmentation on panoramic radiographs	70	65	IoU >92%		2D		The DL algorithm showed an accurate and fast tooth detection and segmentation
Alqahtani et al [75]		Automated segmentation of teeth with orthodontics bracket from CBCT images	140	40	99%		3D		The CNN model could offer an accurate and efficient segmentation of teeth with bracket
Lahoud et al [76]		Automated tooth segmentation on CBCT	387	46	IoU 87%		3D		The CNN-based 3D tooth segmentation can improve the accuracy and efficiency in various dental procedures including orthodontics
Shaheen et al [77]		Automated tooth segmentation and classification from CBCT images	140	11	IoU 82%		3D		The cloud-based DL system could be useful for diagnostic and treatment planning digital workflow
Xing et al [73]		Construct AI-aided tool to predict lip prominence based on hard-tissue information input	1,160	389	root mean square 1.25, 1.49		2D		XGBoost-aided prediction model performed well in predicting lip prominence
Cai et al [70]		Assess intricate relationship between facial soft tissue and skeletal types in dental therapy for aesthetic improvement with AI-based modules	835	209	93%		2D		CNN model can accurately classify diverse sagittal skeletal classes based on facial traits
Cai et al [72]		Develop ANN-based prediction of facial aesthetic improvement induced by occlusal plane rotation	767	136	Regression score 0.92		2D		ANN model can provide a reference of occlusal plane change efficiency to aesthetic improvement
Xu et al [16]		Construct ANN-based prediction of patient experience of Invisalign treatment	152	44	88% (Pain) 93% (Anxiety) 92% (QoL)		-		AI systens developed has potential for clinical application to enhance patient compliance
Lee et al [78]		Evaluate DL-based integrated tooth models for 3D evaluation of root position	600	n.a.	Mean errors 0.07 mm (maxilla) 0.08 mm (mandible)		3D		DL automatic method for integrated tooth models show high accuracy and time efficiency
Hu et al [79]		Develop automated method for dynamic root position monitoring and evaluate semi-automatic root apical distance measurement procedure	412	n.a.	Mean errors 0.05 mm (maxilla) 0.06 mm (mandible		3D		Automated registration improves accuracy and efficiency of root position monitoring.
Chaiprasittikul at al [8]		Develop a standardized decision-making system for orthognathic surgery	484	54	96%		2D		Combining CNN and ANN shows high diagnostic agreement for orthognathic surgery screening
Cheng et al [80]		Investigate DL-based automatic method to predict reposition vectors in orthognathic surgery plan	383	49	Mean errors 1.41 mm		3D		The model can predict reposition vectors of orthognathic surgery plan with high accuracy and interpretability
Verhelst et al [81]		Automated 3D mandible segmentation from CBCT images	160	30	DSC: 98%		3D		The cloud-based AI platform is accessible and easy to use by the clinician to perform automated segmentation
Preda et al [18]		Automatic segmentation of maxillofacial complex bone	110	24	DSC: 93%		3D		CNN model provided a time-efficient, accurate, and consistent 3D maxillofacial complex automated segmentation
Nogueira-Reis et al [82]		Automatic maxillary virtual patient creation	40	n.a.	DSC: 99%		3D		Integrated CNN model proved to be fast, accurate, and consistent

[57].

Kim et al. [59] extracted conventional lateral and maximum intensity projection (MIP) lateral cephalograms from the CBCT images, achieving high reliability with both images. However, MIP yielded better soft tissue profiles with an SDR of 87.13 % within the 2 mm error range. In another study, Kim et al. [58] showed an SDR of 60.88 % within 2 mm range on posterior-anterior cephalograms generated from CBCT images. In contrast, Gil et al. [62] achieved an SDR of 83.3 % on directly acquired posterior-anterior cephalograms. Supplementary Fig. 1 illustrates the SDR values of the studies that applied automated AI-based landmark detection within the clinically acceptable range of 2 mm [46].

Only two studies performed landmark detection on non-radiological images i.e., dental casts [63] and facial photographs [64]. Croquet et al. [63] automated landmarking on the palatal region of the dental cast with an accuracy ranging between 68 and 93 % within a 2 mm error range. In addition, Rao et al. [64] automated the detection of photometric points on 2D facial photographs and found that 97.71 % of the landmarks fell between a 5 mm error range with a detection time of 0.00023 ms.

3.3. Treatment planning

3.3.1. Predicting the need for tooth extraction

Two studies applied neural networks to determine the need to extract teeth for orthodontic purposes, using measurements on lateral cephalometry and other model variables as input. Although the type and number of input variables were not equal, both networks showed almost similar accuracy of 93 % [7] and 94 % [65]. Furthermore, both studies also showed a similar accuracy (84 %) for determining four extraction patterns, which were upper and lower first premolar extractions, upper and lower second premolar extractions, upper first premolar and lower second premolar extractions, and upper first premolar extractions only [7,65]. Del Real et al. [66] achieved an accuracy of 93.9 % when automatically identifying the need for tooth extraction, while Leavitt et al. [67] used ML to detect tooth extraction patterns with an accuracy

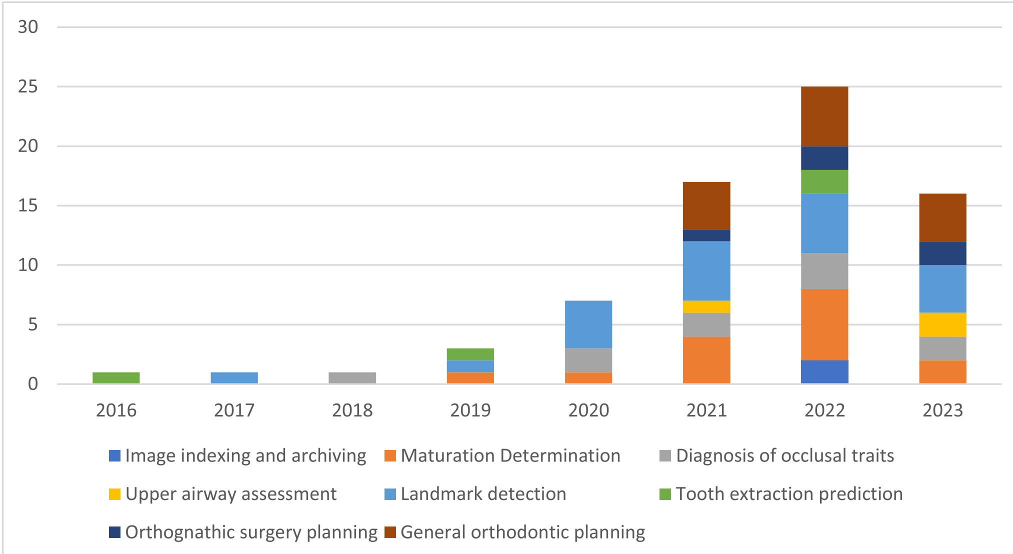

Fig. 2. Publication years of the included articles with the distribution of articles based on the purpose of AI network.

of 81.63 % for upper and lower first premolar extraction.

3.3.2. General orthodontic planning

One study constructed an ML algorithm to automate multiple decision-making tasks during orthodontic treatment planning, such as diagnosis of skeletal malocclusion, extraction vs. non-extraction and treatment modalities, reporting an accuracy of 84 % compared to planning by expert orthodontist [68].

Shimizu et al. [69] specifically used facial photographs to illustrate their importance in treatment planning. They designed an AI-based support vector machine that could automatically prioritize orthodontic problems based on a list and create a plan to address them. However, both prioritization and planning tasks showed low precision (65 % and 48 %) and recall (55 % and 48 %) to be used as an equivalent to an expert orthodontist. Cai et al. [70] employed facial photographs and lateral cephalograms as training data for CNN models. The authors automatically differentiated diverse sagittal skeletal classes based on facial traits with an accuracy of 93 %.

El-Dawlatly et al. [71] constructed a DL-based decision support system for automated treatment planning of patients with deep bite. The authors achieved precise decision-making with a very good agreement (94.4 %) between the plans proposed by the algorithm and the actual treatment plan.

Two studies formulated prediction models based on ANNs pertaining to treatment outcomes. Cai et al. [72] developed an ANN-based model to predict facial aesthetic enhancements resulting from occlusal plane rotation. This model achieved a regression score accuracy of 0.92 using cephalogram data. Meanwhile, Xu et al. [16] designed a prediction model for patient experience and perception of Invisalign treatment. This model achieved predictive success rates of 88 %, 93 %, and 92 % for pain, anxiety, and quality of life, respectively. These predictive models could assist clinicians in decision-making processes regarding treatment strategies to mitigate treatment compliance issues. One study employed ML to create a downloadable toolkit for predicting the prominence of the upper and lower lips. This was achieved by inputting 14 hard tissue cephalometric measurements and demographic data [73]. The AI model demonstrated superior performance, with root mean square error values of 1.25 and 1.49 for the upper lip and lower lip prominence, respectively.

Four studies developed CNN-based tooth detection and segmentation from 2D and 3D images. Leite et al. [74] reported an intersection over union (IoU) over 92 % for automatic tooth segmentation from panoramic images. The procedure was able to reduce working time by 67 % in comparison to manual segmentation. Three other studies used CBCT scan with Alqahtani et al. [75] showing the highest IoU of 99 %, followed by the study of Lahoud et al. [76] and Shaheen et al. [77], with respective IoU of 87 % and 82 %. Alqahtani et al. developed automatic tooth segmentation from CBCT scans of patients with orthodontic brackets [75].

Moreover, two studies focussed on the automated segmentation and integration of CBCT-scanned tooth root and intraoral-scanned tooth crown. This was performed to aid in the monitoring of tooth and root position during orthodontic treatment. Both studies achieved low mean errors, where Lee et al. [78] reported errors of 0.07 mm for the maxilla and 0.08 mm for the mandible. Meanwhile, Hu et al. [79] reported even mean errors of 0.05 mm and 0.06 mm for maxilla and mandible, respectively.

3.3.3. Orthognathic surgical planning

Two studies employed DL algorithm to assist with the planning of orthognathic surgery. Chaiprasittikul et al. [8] applied CNN and ANN to develop a decision-making system for determining the need for orthognathic surgery with a diagnostic agreement of 96.3 %. Cheng et al. [80] used CNN to predict reposition vectors as guidance for surgical planning with a mean error of 1.34 mm.

Four studies used CNN as the AI framework to explore automatic segmentation of anatomical structures from 3D scans relevant to orthognathic surgery planning. Verhelst et al. [81] developed an automatic mandibular segmentation with a DSC of 98 %. Another study by Preda et al. [18] achieved a DSC of 93 % for automatic maxillofacial complex segmentation from CBCT scans with metal artifacts from dental implants, restorations, and orthodontic brackets. Furthermore, Nogueira-Reis et al. [82] created a CNN-based maxillary virtual patient that integrates automatic segmentation of the maxillary complex, sinus and teeth with DSC of 99 % (Fig. 3).

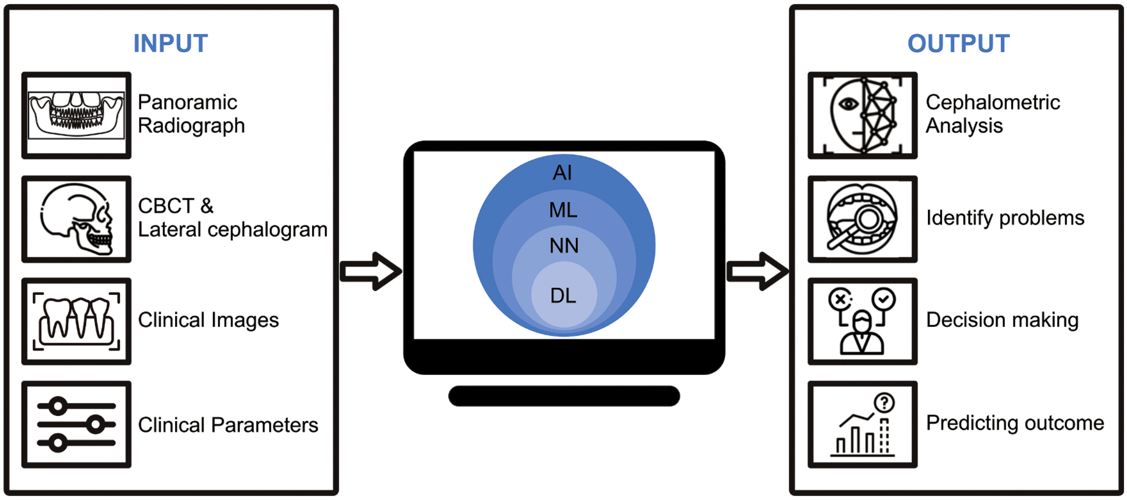

Fig. 3. Input and output of AI applications in orthodontics. AI: Artificial Intelligence; ML: Machine Learning; NN: Neural Networks; DL: Deep Learning.

4. Discussion

The following review provides a comprehensive and up-to-date coverage of AI applications in orthodontic diagnosis and treatment planning by evaluating the performance of AI-based systems in comparison to manual methods, without delving into comparisons between different AI algorithms or models. Prior reviews often concentrated on specific tasks or restricted their findings to particular AI algorithms [83,84], thus providing a fragmented perspective of the field. While some reviews have delivered valuable insights into the broader context of AI applications in orthodontics [10,11], the present review adopts a more targeted approach by conducting an in-depth examination of all essential domains. This approach highlights the unique challenges, opportunities, and direct relevance of AI technology in enhancing the efficiency and accuracy of orthodontic workflows. Moreover, a diverse range of orthodontic applications were included that have previously been unexplored or underexplored, such as image indexing, upper airway assessment, maxillary complex segmentation, and patient experience and perception [15–18]. By incorporating these various facets, this review offers a more cohesive perspective on the potential impact of AI in the field of orthodontics.

In the present study, the number of studies was not only updated, yet also the respective content was further structured with more advanced tabulation of the involved AI tools. Indeed, more than 80 % of the papers included in the present scoping review were published between 2021 and 2023, which shows an exponential increase in research involving AI in orthodontics. Additionally, the present scoping review identifies previously unexplored applications of AI in orthodontics not mentioned in the aforementioned reviews, such as image indexing, diagnosis of occlusal traits, and automated virtual patient creation, illustrating the advancement of AI integration in orthodontics.

The findings of this review show that AI can aid in various areas, particularly when tasks are time-consuming or require advanced expertise. Fig. 3 illustrates the use of AI in orthodontics, where images and clinical parameters are typically used as input. The state-of-the-art ML approaches in the form of DL CNNs are increasingly becoming the backbone of orthodontic task automation. In recent years, there has been a surge in articles on the use of DL algorithms in orthodontics, with many studies highlighting the efficiency and accuracy of these techniques. AI has primarily relied on 2D radiographic images [26] and there is limited evidence supporting its use with clinical images [6] and facial photographs [38]. However, there has been an increase in the use of 3D radiographic images [44].

A key element in the field of orthodontics involves translating intricate orthodontic requirements into clearly defined AI tasks, which requires careful attention to detail and methodological clarity. For example, tasks like cephalometric analysis involve the transformation of the task into a computational one, which includes the annotation or labeling of landmarks on lateral cephalograms. Similarly, predicting treatment outcomes necessitates the segmentation of teeth. In addition, when deciding on the optimal treatment plan, clinical parameters are used as training data. The training phase is crucial in enhancing the performance of AI algorithms and heavily depends on the expertise of the professionals involved. Therefore, those responsible for creating training datasets should have significant experience in this field [68].

In the creation of an AI system, the testing phase is equally important as it allows for the evaluation of its performance using various metrics, offering vital insights into its effectiveness and precision. A variety of performance metrics have been employed to evaluate the performance of AI models in specific orthodontic tasks across the studies included in this review. While accuracy was the most commonly used metric, other metrics such as the F1 score, mean errors, dice coefficient, and root mean square were also used in some articles. A comprehensive explanation about performance metrics can be found in Supplementary Table 3.

The first part of orthodontic diagnosis is the indexing and classification of shuffled radiological and clinical images into their categories, which is time-consuming and has to be manually performed by an orthodontist. Therefore, AI models have been proposed to provide automated and efficient image indexing, aiming to enhance efficiency and reduce clinician workload. Although there is limited evidence related to automated classification, several studies have reported promising results, demonstrating that AI can achieve high accuracy and significantly improve time efficiency compared to manual methods. When considering a fully automated orthodontic diagnostic system, future studies should consider further reduction of the workload of orthodontists. Following image indexing, dental model analysis on conventional plaster or digital casts is another important task in the diagnostic process. It is generally performed manually and carries a high risk of observer variability. So far, limited studies are available implementing AI for automating model analysis, where studies have only automated the process of assessing mesiodistal dimensions of teeth and predicting arch form [42,43]. Hence, future studies should focus on developing AI models for automating study cast analysis.

Another important diagnostic task in orthodontics is CVM determination, which is vital for determining the skeletal maturation stage of a patient during growth. Identifying the most optimal time to initiate treatment and assessing the completion of active growth are crucial aspects of orthodontic treatment planning [24]. The findings of this review demonstrate that AI can determine CVM in just 0.1 s, presenting a remarkable contrast to the time-intensive manual evaluation conducted by clinicians [30]. However, while AI's performance is nearly comparable to that of expert manual assessments, its reliability remains insufficient for full trust without ongoing human validation [22]. Liao et al. made their datasets publicly available to ensure the consistency of images for comparing AI models in future studies [28].

Regarding the diagnosis of occlusal traits, AI algorithms were proposed for a one-step diagnosis approach on lateral cephalometric images with optimal accuracy, eliminating the need for landmark detection and its associated errors [39,40]. However, these types of algorithms have not yet been widely explored. Furthermore, applying such approaches using 3D images still needs to be investigated.

AI has also been applied to upper airway assessment, a critical component in orthodontic treatment due to its influence on craniofacial growth and development [44]. Certain conditions, such as adenoid hypertrophy, can result in airway obstruction, altering the breathing pattern and potentially leading to malocclusion [17]. AI methodologies provide a more rapid assessment of these structures compared to traditional manual techniques, although issues with model generalizability persist [45]. Many studies are constrained by the limited datasets they employ, which restricts their wider applicability. When these models are applied to public datasets, their performance often decline, highlighting the necessity for ongoing research to ensure the reliability of AI-based tools in orthodontic practice.

Although AI models demonstrate promising potential in automating some aspects of orthodontic diagnosis, current applications are still unable to make independent diagnoses. Their reliability is not yet sufficient to warrant complete trust, underscoring the need for continuous improvement and validation. Despite significant advancements in time efficiency compared to manual methods, AI's diagnostic capabilities serve as a supplement to expert clinical judgment. Future research should focus on improving the accuracy of AI algorithms, while recognizing the crucial role of clinician input and validation.

In the articles reviewed, the most researched AI application was automatic landmark detection, which is a crucial step for orthodontic diagnosis. The accuracy of AI algorithms varied in different studies due to the use of diverse datasets and landmarks. Consistency is a key requirement when comparing different AI methods. Some studies have overcome this challenge by using publicly available datasets to ensure consistency [5].

Interestingly, when compared to manual methods by expert clinician, AI has the ability to show better reproducibility, which overcomes the limitation of observer variability. However, its accuracy has not yet consistently surpassed that of human experts, indicating that while AI is less prone to variability, further improvements are needed to ensure that landmarks are placed as precisely as those identified by expert clinicians [40].

Most studies used landmark detection on lateral cephalometric images. However, it is important to acknowledge that a 2D projection could lead to an inaccurate representation of 3D anatomical structures due to certain limitations, such as distortion, superimposition and magnification. The increasing use of 3D imaging in managing orthodontic cases has created a greater need to explore 3D landmark detection [57]. Manual landmark localization on 3D images is time-consuming and demands a skilled operator, as it involves manual segmentation of anatomical structures and precise landmark positioning. Notably, only three studies investigated automated landmarking directly on CBCT and CT-derived 3D image. Although AI cannot replace clinicians in making diagnoses, its application in this field could markedly decrease the duration required for landmark identification, thereby conserving substantial time for clinicians. Such an automation is expected to optimise the workflow of orthodontists and significantly improve their productivity, ultimately leading to better patient care and treatment results.

AI was successfully implemented to predict the need for dental extraction and orthognathic surgery planning. However, the inclusion criteria of these studies were limited to non-complex malocclusions and patients with full dentitions [7,8,65]. However, further research is still needed to implement AI for treatment planning of complex and/or partially edentulous cases. The use of expert opinion as the gold standard is concerning due to the variety of treatment approaches. This diversity can lead to varying plans for the same patient, raising questions regarding the reliability of expert opinion as a reference point in AI-driven systems. Determining whether the opinion represents a consensus among orthodontists or individual practitioner viewpoints is essential. Thus, future research should evaluate the definition of the gold standard and its implications for clinical applicability. Nevertheless, the existing findings showed that AI could act as a useful adjunct by improving the clinical decision-making process of orthodontists during training or at the beginning of a clinical career to compensate for lack of experience. At the same instance, it is crucial to emphasize that AI is currently incapable of independently generating treatment plans. Human oversight remains essential to guide AI's recommendations and ensure that the proposed treatment plans align with clinical judgment and patient-specific needs.

Several studies have attempted to develop automatic segmentation of anatomical structures relevant to general orthodontics treatment planning [74–77] and orthognathic surgery planning [18,81,82], such as teeth and maxillofacial complex. The ability of AI to perform these tasks can significantly enhance time efficiency by automating traditionally labor-intensive processes, such as manual segmentation. The results of these studies are important for creating treatment planning simulations and depicting treatment outcomes. Furthermore, it is also an important step in digital workflow in orthodontics [82]. However, these studies showed limitations of sample heterogeneity. It is necessary to incorporate data from different imaging machines with different parameters to improve the generalizability of the AI model [82].

Beyond tooth segmentation, the application of AI in monitoring tooth movement is crucial for evaluating the results and efficacy of orthodontic treatment. Studies have focused on automating both the teeth segmentation and registration processes of intra-oral scans and CBCT image [78,79], which could allow clinicians to compare and predict tooth crown and root position during orthodontic treatment. These advancements represent a paradigm shift towards orthodontic care, heralding enhanced patient outcomes and more efficient clinical workflows.

While AI cannot independently generate treatment plans and requires continuous human intervention to ensure accuracy and reliability in clinical practice, it shows significant promise in enhancing time efficiency and automating tasks such as segmentation and treatment planning simulations. Consequently, AI can serve as a valuable adjunct for less experienced orthodontists, helping them develop more informed treatment plans.

There are certain limitations associated with this review. Firstly, data search was confined to articles written in English, which excluded studies published in other languages. Secondly, several studies might have been excluded based on eligibility criteria. Finally, a scoping review was conducted to evaluate the overall state of research in diagnosis and treatment planning in orthodontics and identify areas where further research is needed instead of performing a systematic review that focuses on assessing the reliability and quality of existing knowledge in a specific research area. When considering the robustness of such a review, Arksey and O'Malley argued that a scoping review enables to present an overview of existing literature where quality becomes irrelevant [85].

The incorporation of AI in orthodontics presents both opportunities and challenges. A significant hurdle is the scarcity of data, as the annotated datasets required for training AI models in orthodontics are often limited in size and diversity. Furthermore, the variability in clinical practices and patient populations necessitates robust model generalization to ensure applicability across diverse settings. It is essential to ensure the interpretability of AI models to foster trust and acceptance among clinicians, as the complexity of "black-box" algorithms may impede their adoption in clinical practice. Overcoming these challenges necessitates interdisciplinary collaboration among orthodontists, data scientists, and computer engineers to develop AI solutions that are both clinically relevant and technically robust. By addressing these technical aspects, we can gain valuable insights into the practical applications and future directions of AI-driven orthodontic care.

In the realm of AI model development, particularly in specialized fields such as orthodontics, the role of data annotation is indeed pivotal. The process of data labeling, which involves assigning meaningful and informative labels to raw data, is often subjective and requires a deep understanding of the domain. This is where the expertise of dental professionals becomes invaluable. Their nuanced understanding enables them to generate accurate and reliable data labels, which are critical for training robust AI models. By involving dental experts in the data labeling process, we can ensure that the AI models developed are not only technically sound but also contextually relevant and reliable. This underscores the indispensable role of domain expertise in the development of AI models, reinforcing the idea that technology and human expertise must go hand in hand for optimal outcomes.

While AI has made considerable strides in various facets of orthodontic practice, there remain several areas that are under-researched yet hold substantial promise for the discipline. One such area is the prediction of eruption patterns for impacted teeth, a critical factor for effective treatment planning. AI can also offer valuable insights into long-term treatment outcomes through facial growth simulation. Another potential application of AI lies in orthodontic indices, which assess treatment needs based on occlusal characteristics. This could streamline treatment planning and optimize resource distribution. The integration of AI into these processes could lead to more precise evaluations, potentially influencing policy decisions and healthcare economics.

AI is not designed to supplant the clinical judgement and expertise of clinicians. Rather, it aids in tasks such as image analysis, data interpretation for diagnosis, and the selection of optimal treatment plans. The human element remains indispensable for interpreting unique patient-specific factors and complexities. The integration of human expertise and AI-driven insights is crucial for efficient and precise patient-specific treatment planning. In this context, AI should be viewed as a decision-support system, not as a replacement for the orthodontist until clinically applicable models are established in future studies.

Moreover, as the use of AI systems to assist healthcare professionals in diagnosis and treatment planning increases, concerns regarding legal liability emerge. The incorporation of AI in medical decision-making introduces complex legal quandaries concerning responsibility and liability. These extend beyond individual practitioners and encompass broader aspects such as institutional liability, regulatory oversight, and the evolution of medical malpractice law [86]. To successfully navigate these legal complexities, it is vital to establish clear guidelines and mechanisms that prioritize patient safety, foster innovation, and ensure accountability.

5. Conclusion

Orthodontists are constantly seeking tools that improve the accuracy, reliability, and time efficiency of diagnostic and treatment planning workflows. AI has been shown to be a powerful tool for reducing operator variability, human error, and time consumption compared to expert manual methods. Despite these advances, the accuracy and reliability of AI have not yet consistently surpassed those of expert clinicians. Consequently, human supervision remains indispensable to ensure that AI-generated recommendations align with clinical judgment and patient-specific needs. The reliance on expert opinion as the gold standard for AI training introduces variability, further challenging the consistency and reliability of AI-driven models. Future research must focus on improving AI's generalizability and accuracy, particularly for more diverse patient populations and complex clinical scenarios. AI should be regarded as a decision-support tool that enhances, rather than replaces, the critical role of clinical judgment in orthodontic care.

CRediT authorship contribution statement

Rellyca Sola Gracea: Writing – review & editing, Methodology, Investigation. **Nicolas Winderickx:** Writing – original draft, Methodology, Investigation, Conceptualization. **Michiel Vanheers:** Writing – original draft, Methodology, Investigation, Conceptualization. **Julie Hendrickx:** Writing – original draft, Methodology, Investigation, Conceptualization. **Flavia Preda:** Writing – review & editing, Methodology. **Sohaib Shujaat:** Writing – review & editing, Supervision. **Maria Cadenas de Llano-Pérula:** Writing – review & editing, Supervision. **Reinhilde Jacobs:** Writing – review & editing, Supervision, Methodology, Investigation.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Supplementary materials

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