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Review article

Applications of artificial intelligence in tooth extraction: A systematic review

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Review

Abstract *Background/purpose:* Tooth extraction is a common procedure in dental treatment. In recent years, with the advancement of artificial intelligence (AI) technology, research on tooth extraction using AI has been increasing. In the present study, we consider the applicability of AI to tooth extraction through a literature review.
Materials and methods: The PubMed, Scopus, and Web of Science databases were searched for ("tooth extraction") AND ("artificial intelligence" OR "machine learning" OR "deep learning") in June 2024.
Results: Thirty-five articles matched the eligibility criteria and were extracted for this review. The most widely covered topics were "relationship between the root of the tooth and the inferior alveolar nerve" and "tooth extraction decision-making" with 10 and 8 articles, respectively. These two topics are considered to be important factors that determine risk and treatment options in clinical decision-making. Next, there were six articles about tooth extraction difficulty, preparation, and time, and four articles about maxillary sinus evaluation. Furthermore, there were three articles about predictive models for osteonecrosis and osteomyelitis of the jaw, and two articles each about post-extraction complications and the use of ChatGPT, which were the fewest in number.
Conclusion: Findings from these papers will contribute to improving decision-making processes, treatment strategies, and preventive measures in dental care and are expected to

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serve as a foundation for future research. Furthermore, the diversity of each topic reflects the complexity and evolution of dental care and suggests that further exploration is warranted in future research.

Introduction

Tooth extractions may be necessary for a variety of reasons, including caries, fracture of teeth weakened by caries or endodontics, periodontal diseases, third molars, prosthetic reasons, orthodontics, and trauma.[1,2] Tooth extraction is one of the most commonly performed surgical procedures in dentistry. Various complications have been reported during tooth extraction, including bleeding, inferior alveolar nerve damage, oroantral communication, incomplete root removal, inflammatory bowel disease, alveolitis, delayed healing, postoperative infection, infected subperiosteal hematoma, pain, swelling, bony spicule, bony sequestrum, and alveolar osteitis.[3,4]

Artificial intelligence (AI) was first defined in 1956 by John McCarthy as "a computer program which seemingly exhibit intelligence".[5] This revolutionary definition became the foundation of AI research and has had a profound impact on subsequent technological advances.[5] AI-based machine learning and deep learning systems automatically learn models from data to make better decisions.[6] There are three approaches to AI-based machine learning and deep learning: supervised learning, unsupervised learning, and reinforcement learning.[6] Supervised learning uses labeled data to build predictive models, while unsupervised learning extracts hidden patterns from unlabeled data.[6] Semi-supervised learning is effective when labeled data is scarce.[6] Reinforcement learning seeks optimal performance through rewards and punishments.[6]

In the medical field, advanced algorithms based on supervised learning and classification models are being actively used in a variety of application areas, including endoscopic diagnosis support, radiological diagnosis support, and pathological diagnosis support, and the results are rapidly being reflected in actual clinical practice.[7–9] Applications of AI technology in the dental field are diverse, and active research is being conducted in various dental fields, including detection and diagnosis of cavities, vertical root fractures, periapical lesions, salivary gland diseases, maxillary sinusitis, maxillofacial cysts, cervical lymph node metastasis, osteoporosis, cancerous lesions, alveolar bone loss, prediction of orthodontic tooth extraction and the need for orthodontic treatment, head shadow analysis, and age and gender determination.[10] In recent years, with the rapid advancement of AI technology, research into the use of AI in tooth extraction in the field of oral surgery has been increasing rapidly, and its range of applications is expanding.

Although several studies on the use of AI in tooth extraction have been conducted in recent years, these studies are limited in scope, and comprehensive discussion of the potential benefits and challenges of introducing AI is still lacking. This systematic review aimed to evaluate the current applications and potential of AI in the field of tooth extraction, with a particular focus on image-based analysis and clinical decision. By synthesizing recent studies involving AI tools, such as deep learning and machine learning applied to panoramic radiographs and CBCT imaging, this review sought to clarify how AI contributes to diagnostic accuracy, prediction of extraction difficulty, risk assessment, decision-making support, evaluation of postoperative outcomes, and the emerging role of generative AI. Through this synthesis, we aimed to identify the clinical utility, limitations, and future directions for AI integration in tooth extraction procedures.

Materials and methods

Protocol

A literature search was conducted based on PRISMA (preferred reporting items for systematic review and meta-analyses) guidelines in 3 databases (PubMed, Scopus, and Web of Science) in June 2024.[11] The following search terms were used in PubMed, Scopus, and Web of Science on June 17, 2024: ("tooth extraction") AND ("artificial intelligence" OR "machine learning" OR "deep learning").

Eligibility criteria

The following inclusion criteria were used to select publications: (1) studies published in English; (2) studies involving AI applications in tooth extraction, encompassing computational simulations, predictive modeling, or generative AI approaches; (3) studies that utilized AI in applications related to tooth extraction. We limited our review to English publications, as most high-quality AI studies are published in English, and this helps ensure consistency in interpretation. Major databases used also primarily index English literature.

The following exclusion criteria were applied: (1) review, comment, editorial, and case report; (2) studies for which references were not available; (3) studies written in languages other than English; and (4) studies that did not utilize AI in applications related to tooth extraction.

Study selection

One of the authors (M.H.) collected the studies using database, such as PubMed, Scopus, and Web of Science, and then he removed duplicates using EndNote X9 Clarivate

Analytics software (Clarivate Analytics, Toronto, Canada). A manual review was done to remove other duplicates not initially recognized by the software. Then two reviewers (M.H. and S.Y.) were independently screened the title and abstract of collected studies for relevant topics. Then, the same reviewers (M.H. and S.Y.) performed another screen for the full text of the included studies from the previous step. Disagreements between the reviewers (M.H. and S.Y.) were resolved by a discussion.

Results

Studies selection

The study selection process is summarized in Fig. 1. A total of 809 studies were retrieved in our initial search in the following databases: PubMed (n = 157, "tooth extraction" AND "artificial Intelligence" n = 78 OR "machine learning" n = 43 OR "deep learning" n = 36), Scopus (n = 402, "tooth extraction" AND "artificial Intelligence" n = 131 OR "machine learning" n = 132 OR "deep learning" n = 139), and Web of Science (n = 250, "tooth extraction" AND "artificial Intelligence" n = 85 OR "machine learning" n = 78 OR "deep learning" n = 87). After removing the duplicates, 356 studies were selected. Then, title/abstract screening and article type screening, such as review, comment, editorial, and case report, 46 studies were selected. 35 studies were selected for full-text eligibility assessments. Finally, considering the inclusion and exclusion criteria, 35 studies remained.

Relationship between the root of the tooth and the inferior alveolar nerve

In this study, the most commonly identified papers were those related to the relationship between the root of the tooth and the inferior alveolar nerve, with 10 relevant papers.[12—21] Many papers have used panoramic or cone-beam computed tomography (CBCT) images to evaluate the positional relationship between the mandibular third molar and the mandibular canal or the inferior alveolar nerve (IAN), and based on this, have compared the accuracy of AI with that of traditional human evaluations. These studies suggest that the diagnostic accuracy of AI may be comparable to or even surpass that of traditional methods. In addition to evaluating the positional relationship, Lee et al. built a model to automatically detect mandibular third molars using panoramic radiographic images and predict the difficulty of extraction and the risk of IAN injury.[17] Picoli et al. also investigated the risk of sensory loss based on surgical results using panoramic images and CBCT.[20] Apart from the study on positional relationship, On et al. investigated and compared the incidence of IAN injury based on the presence or absence of intraoperative IAN exposure during extraction of mandibular third molars, and reported that IAN exposure increases the risk of injury.[14]

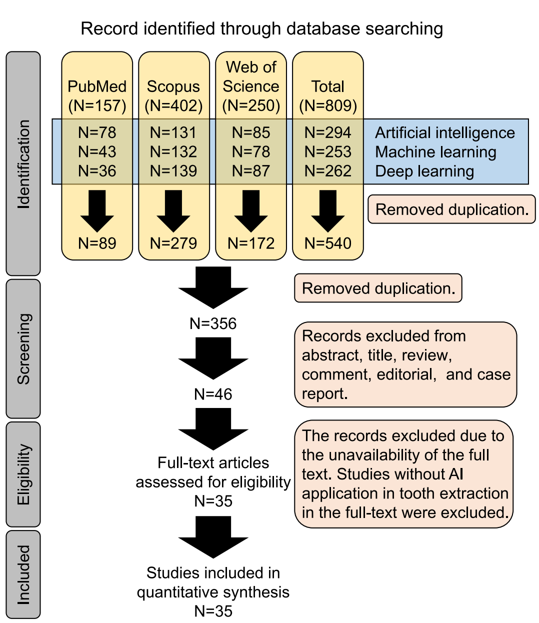

Figure 1 PRISMA flowchart of the literature review conducted.

Tooth extraction decision-making

In this systematic review, AI-based tooth extraction decision-making was reported by Miladinović et al., in 2010.[22] Since then, various groups have reported on AI-based tooth extraction decision-making, and a total of 8 articles were found in this search.[22—28] Of the studies on this topic, most are related to orthodontic treatment, with four studies using artificial intelligence (AI) to examine the need for tooth extraction in orthodontic treatment.[23,25,27,28] All of the studies have produced positive results, suggesting the potential for AI to assist clinicians in making diagnoses and treatment plans.[8,10,12,13] On the other hand, Etemad et al. point out that in order to support clinical decision-making, it is important to resolve data discrepancies and apply more advanced artificial intelligence algorithms, and that these improvements are necessary in the future.[27] Outside of orthodontic treatment, Lee et al. demonstrated that a deep convolutional neural network algorithm is useful for assessing the diagnostic and predictive potential of periodontally compromised teeth.[24] Cui et al. stated that in decision-making regarding tooth extraction, a clinical decision support system achieved high performance by considering multiple factors and utilizing electronic dental records, prosthetic treatment, and relevant oral conditions.[26] Chopra et al. used AI to develop a model to predict the eruption of mandibular third molars and suggested that this could be a valuable adjunct tool to support clinicians in the decision-making process regarding mandibular third molar extraction.[29]

Tooth extraction difficulty, preparation, and time

A total of six papers have reported on the difficulty, preparation, and time required for tooth extraction.[30—35] Yoo et al. and Torul et al. conducted a study on tooth extraction difficulty.[30,35] Yoo et al. examined the difficulty of extracting impacted mandibular wisdom teeth by using panoramic images of C1 (depth), C2 (ramal relationship), and C3 (angulation).[30] Meanwhile, Torul et al. evaluated the difficulty of extracting impacted maxillary wisdom teeth by using panoramic images of depth (V), angulation (H), relation with maxillary sinus (S), and relation with ramus (R). They reported good results in all areas.[35] Sukegawa et al. and Lei et al. performed positioning classification using Pell and Gregory and Winter's classifications and reported good results.[33,34] Kwon et al. investigated extraction time by comparing the predicted extraction time with the actual extraction time, and reported that they obtained good results using clinical data such as age, sex, maximum mouth opening, weight, height, time from the start of incision to the start of suturing, and surgeon experience.[32] Badilla-Solórzano et al. conducted a study on surgical instrument detection by a robotic surgical scrub nurse and reported a reduction in labeling work in training a deep learning-based detection algorithm.[31]

Maxillary sinus evaluation

There are four studies evaluating the maxillary sinus, focusing on segmentation of the maxillary sinus, oroantral communication (OAC), and extraction of retention pseudocysts.[36–39] Choi et al. suggested that a deep learning-based method for fully automated segmentation of the maxillary sinus using CBCT images.[36] Vollmer et al. investigated OAC following maxillary molar extraction and showed that preoperative panoramic radiographs were poor predictors of OAC.[37,38] Ha et al. demonstrated that the proposed model for automatic classification of retention pseudocysts in the maxillary sinus using panoramic radiographs had excellent diagnostic performance.[39]

Predictive model for osteonecrosis and osteomyelitis of the jaw

There are three studies on "predictive models for osteonecrosis and osteomyelitis of the jaw," two of which are on bisphosphonate-related osteonecrosis of the jaw (BRONJ) or medication-related osteonecrosis of the jaw (MRONJ), and one is on osteoradionecrosis incidence in patients with head and neck cancer.[40–42] Kim et al. reported that machine learning methods performed better in predicting tooth extraction-related BRONJ compared with traditional statistical methods using drug holiday periods and serum CTX levels.[40] Kwack et al. showed that questionnaire data obtained at the first consultation was useful for predicting the occurrence of MRONJ after tooth extraction or implant surgery in osteoporosis patients.[42] Furthermore, Humbert-Vidan et al. proposed utilizing machine learning techniques to predict the incidence of mandibular osteoradionecrosis, suggesting a new approach to the toxicity of mandibular osteoradionecrosis by using a model to predict incidence on a case-by-case basis.[41]

Post-extraction complications

Two studies on post-extraction complications have been reported, one on facial swelling and the other on postoperative pain.[43,44] In a study on facial swelling by Zhang et al., 15 parameters were used to predict postoperative facial swelling after extraction of impacted mandibular third molars.[43] These parameters include patient's age, gender, physique and oral hygiene as personal factors; relation of the third molars to the mandible ramus and second molar, relative depth of the third molars in bone, relationship of the long axis of the third molars in relation to the long axis of the second molar, relation of the third molars in mandibular dental arch, number of root as anatomy factors of third molars; and type of incision, location and quantity of bone removal, section into pieces or not, root fracture condition, fracture of lingual bone plate or not, surgical time. Their study reports the development of a new system that uses these parameters to accurately predict facial swelling after extraction of impacted mandibular third molars.[43] Yu et al. conducted a study aimed at identifying patients at high risk of postoperative pain after tooth extraction and reported that a machine learning-based postoperative pain risk prediction model was promising as a theoretical basis for better pain management to reduce postoperative pain after third molar extraction.[44]

Use of generative AI

Research on tooth extraction and the Chatbot Generative Pre-Trained Transformer (ChatGPT), an AI-based natural language, was first reported in 2024.[45,46] These studies asked generative AIs ChatGPT, Microsoft Bing, and Google Bard questions about tooth extraction to see if they could play a role in medical consulting. They were reported that the AIs performed well.

Discussion

In recent years, with the development of AI, research into tooth extraction, a common surgical procedure in the field of dentistry, has become more active. In this review of ("tooth extraction") AND ("artificial Intelligence" OR "machine learning" OR "deep learning"), and 35 papers were extracted. Among these studies, the most common ones involve the extraction of anatomical structures such as the mandibular canal and maxillary sinus, including the relationship between the tooth roots and the inferior alveolar nerve, as well as the evaluation of the maxillary sinus. These studies are mainly performed using panoramic X-rays and CBCT and play an important role in assessing the risk of complications, hypoesthesia in the chin area, and even perforation of the maxillary sinus. AI model shows promising accuracy in assessing mandibular third molar and IAN relationship via CBCT, supporting its potential role in surgical risk assessment. Of the three research methods, supervised learning, unsupervised learning, and reinforcement learning, the supervised learning method is used. In particular, it is important to use the data diagnosed by dentists as training data and have the system learn from them. In the papers extracted in this study, metrics such as dice-coefficient, accuracy, precision, recall, F1 score, and AUC were used to evaluate AI performance (Table 1). Since each of these metrics evaluates model performance from a different aspect, it is important to select an appropriate

Table 1 Application of AI in tooth extraction.

AI application areas and their potential	Detail	Study	Country	Year	Number of patients	AI performance	Evaluation metrics
Relationship between the root of the tooth and the inferior alveolar nerve	Third molar extraction	Vinayahalingam et al.[12]	Netherlands	2019	81	Excellent-good	Dice-coefficient
	Third molar extraction	Kim et al.[13]	Korea	2021	300	Excellent	AUC
	Third molar extraction	On et al.[14]	Korea	2021	240	N/A	N/A
	Third molar extraction	Zhu et al.[15]	China	2021	503	Excellent-good	Precision, recall, F1 score
	Third molar extraction	Choi et al.[16]	Korea	2022	394	Good-needs improvement	Accuracy, precision, recall, F1 score
	Third molar extraction	Lee et al.[17]	Korea	2022	4903	Good	Accuracy
	Third molar extraction	Carvalho et al.[18]	Switzerland	2023	4516	Excellent-good	Accuracy
	Third molar extraction	Jeon et al.[19]	Korea	2023	518	Needs improvement	Accuracy
	Third molar extraction	Picoli et al.[20]	Belgium	2023	6010	Good-needs improvement	Precision, AUC
	Third molar extraction	Gong et al.[21]	Korea	2024	5374	Excellent-good	Dice-coefficient, accuracy
Tooth extraction decision-making	Reason for extraction	Miladinović et al.[22]	Kosovo	2010	10582	N/A	N/A
	Orthodontics	Jung et al.[23]	Korea	2016	156	Good	Precision
	Periodontal diseases	Lee et al.[24]	Korea	2018	651	Good-needs improvement	Accuracy
	Orthodontics	Suhail et al.[25]	USA	2020	287	N/A	N/A
	Clinical decision support	Cui et al.[26]	China	2021	3559	Excellent-good	Accuracy, precision, recall
	Orthodontics	Etemad et al.[27]	USA	2021	838	Excellent-good	Accuracy
	Orthodontics	Ryu et al.[28]	Korea	2023	1636	Excellent	Accuracy, AUC
	Prediction eruption	Chopra et al.[29]	Sweden	2024	771	N/A	N/A
Tooth extraction difficulty, preparation, and time	Extraction difficulty	Yoo et al.[30]	Korea	2021	600	Good	Accuracy
	Robotic scrub nurses	Badilla-Solórzano et al.[31]	Germany	2022	369	N/A	N/A
	Extraction time	Kwon et al.[32]	Korea	2022	724	N/A	N/A
	Positioning classification	Sukegawa et al.[33]	Japan	2022	1330	Excellent-good	Accuracy, precision, recall, F1 score, AUC
	Positioning classification	Lei et al.[34]	China	2023	1347	Excellent-good	Precision
	Extraction difficulty	Torul et al.[35]	Turkey	2024	708	Excellent	Precision, F1 score
Maxillary sinus evaluation	Maxillary sinus	Choi et al.[36]	Korea	2022	45	Excellent	Dice-coefficient
	Oroantral communication	Vollmer et al.[37]	Germany	2022	300	Needs improvement	AUC
	Oroantral communication	Vollmer et al.[38]	Germany	2022	357	Needs improvement	AUC
	Retention pseudocysts	Ha et al.[39]	Korea	2023	213	Excellent-good	Accuracy

(*continued on next page*)

Table 1 (*continued*)

AI application areas and their potential	Detail	Study	Country	Year	Number of patients	AI performance	Evaluation metrics
Predictive model for osteonecrosis and osteomyelitis of the jaw	BRNOJ	Kim et al.[40]	Korea	2018	125	Excellent	AUC
	Osteoradionecrosis	Humbert-Vidan et al.[41]	United Kingdom	2021	96	Needs improvement	Accuracy
	MRONJ	Kwack et al.[42]	Korea	2023	340	Good-needs improvement	AUC
Post-extraction complications	Facial swelling	Zhang et al.[43]	China	2018	400	Excellent	Accuracy
	Postoperative pain	Yu et al.[44]	China	2023	185	Good	AUC
Use of generative AI	Medical concierge	Acar et al.[45]	Turkey	2024	N/A	N/A	N/A
	Medical concierge	Aguiar de Sousa et al.[46]	Brazil	2024	N/A	N/A	N/A

AI Performance Evaluation Criteria;
Excellent: Dice-coefficient >0.85, or AUC >0.9, or accuracy >90 %, or precision >90 %, or recall >90 %, F1 score >0.85.
Good: Dice-coefficient 0.7–0.85, or AUC 0.8–0.9, or accuracy 80–90 %, or precision 75–90 %, or recall 75–90 %, F1 score 0.7–0.85.
Needs improvement: Dice-coefficient 0.7>, or AUC 0.8>, or accuracy 80 %>, or precision 75 %>, or recall 75 %>, F1 score 0.7>.
N/A: Not applicable.

metric according to the purpose of the evaluation and the characteristics of the data.

The decision to extract a tooth requires careful consideration. There are many reasons why a tooth may need to be extracted, including damage to a tooth weakened by decay or endodontic treatment, periodontal disease, problems with the third molar, the need for prosthetic treatment, orthodontic requirements, and trauma.[1,2] In our review of tooth extraction and AI, we found a total of eight studies related to the decision to extract teeth, with the most common being orthodontic extraction, accounting for four out of eight (50 %) studies. In these studies, the decision to extract or not extract teeth was made using data such as cephalometric variables, electronic medical records, and intraoral photographs.[23,25,27,28] Furthermore, AI was used to make decisions about tooth extraction in a wide range of fields other than orthodontic treatment, such as examining reasons for tooth extraction, predicting periodontally compromised teeth, determining whether or not to preserve teeth, and predicting the eruption of mandibular third molars.[22,24,26,29] In this way, it was confirmed that AI can be an important tool in decision-making related to tooth extraction. However, in order to put AI into practical use, it is necessary to collect more clinical data and improve its accuracy, and it is considered that future challenges will include examining how the introduction of AI will contribute to improving the quality of medical care in clinical settings.

When performing tooth extraction, the preparation of instruments and the consultation time (chair time) are important factors. In this regard, Badilla-Solórzano et al. are researching the application of AI technology in instrument preparation as robotic scrub nurses.[31] Meanwhile, Kwon et al. are studying the time required for tooth extraction and classifying the difficulty of tooth extraction and the position of the tooth to evaluate the consultation time and difficulty related to tooth extraction, aiming to apply it to actual clinical practice.[32] These research results are expected to contribute to the management of consultation schedules and reduce the burden on dentists. In addition, important significance in actual clinical practice is recognized in terms of the appropriate allocation of medical resources according to the difficulty of tooth extraction and smoother advance explanation to patients, and it is expected to improve the quality of treatment and improve patient satisfaction.

Radiation-induced osteonecrosis is one of the most serious complications in patients with head and neck cancer undergoing radiotherapy.[41] In addition, MRONJ, previously known as BRONJ, can be caused by antiresorptive therapies such as bisphosphonates (BPs), denosumab (DMB), and romosozumab, which are administered orally or parenterally for the management of osteoporosis, cancer-related bone metastases, and metabolic bone disease.[40,42] This condition can cause necrosis of the jaw and significantly reduce the quality of life of patients, so early diagnosis and treatment are crucial. These problems have become important issues for dentists and require solutions.[40,42] Supervised learning, especially classification techniques, are considered to be very effective in disease prediction since they deal with discrete output variables.[42] All three papers extracted in the present study showed high accuracy, and by utilizing these results, it is possible that new approaches can be opened up for the individualization of radiation therapy based on the risks of head and neck cancer. Machine learning demonstrates potential in predicting MRONJ and osteoradionecrosis, which may aid in early risk detection and personalized care. Further research is expected to advance AI applications in this field.

There are various complications associated with tooth extraction, but one paper each has been reported on facial swelling and postoperative pain. Zhang et al. investigated facial swelling after wisdom tooth extraction and reported that the model had a 98.00 % predictive accuracy in predicting facial swelling after impacted mandibular wisdom tooth extraction.[43] Yu et al. also constructed a model to predict the risk of postoperative pain, suggesting that it may provide a theoretical basis for more effective pain management aimed at reducing postoperative pain after third molar extraction.[44] AI models for predicting post-operative complications such as facial swelling and pain have shown encouraging performance and may support individualized preoperative planning and postoperative care to improve clinical outcomes.

OpenAI launched its ChatGPT service in 2022 and quickly gained attention and widespread support as an innovative service available for free.[47] The application of ChatGPT in the dental field is gradually spreading to answer support for the National Dental Examination, medical assistance, and dental education.[48—51] In the present study, we conducted a systematic review of AI related to tooth extraction and extracted two related papers. These studies consider the use of AI as a medical concierge in tooth extraction. However, since ChatGPT has not been approved as a medical device, there is no guarantee of the accuracy of its answers, and it is unclear who is responsible if a problem occurs based on incorrect information. Currently, there are many issues that need to be resolved regarding these points. However, research on generative AI is progressing rapidly, and further research on tooth extraction is expected to be conducted. Indeed, even after the search period for this study ended, studies on tooth extraction and ChatGPT continued to be reported.[52,53] It is believed that these limitations will need to be fully taken into consideration in the future.

While some studies include large sample sizes, others have relatively small samples or lack external validation. Therefore, larger and multicenter research are still needed to support clinical application of AI in tooth extraction. Moreover, no formal risk of bias assessment was conducted, but we considered methodological factors such as study design and validation methods in our interpretation of the included studies. Variability in these aspects may influence the strength of the conclusion drawn. In conclusion, findings from these papers will contribute to improving decision-making processes, treatment strategies, and preventive measures in dental care and are expected to serve as a foundation for future research. Furthermore, the diversity of each topic reflects the complexity and evolution of dental care and suggests that further exploration is warranted in future research.

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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