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Scoping Review

Algorithms at the Apex: A Scoping Review of Artificial Intelligence across the Endodontic Workflow, from Diagnosis to Prognosis and Education

Running title: Artificial intelligence in endodontics: a scoping review

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ABSTRACT

Introduction: Artificial intelligence (AI), particularly convolutional and artificial neural networks, is being applied to image interpretation, decision support and outcome prediction in endodontics. Since the scoping review by Asgary in 2024, the literature has expanded to include large language models, microrobotics and the first meta-analysis in the field. This scoping review aimed to map the current evidence on AI in endodontics across the clinical workflow and to identify gaps that limit clinical translation.

Materials and Methods: The review followed the Arksey and O'Malley framework, Joanna Briggs Institute guidance and the PRISMA-ScR checklist. Sources published between 2021 and 2026 addressing any application of AI in endodontics or closely related restorative fields were eligible. Data were charted on source type, scope, AI approach, clinical task and reported performance, and synthesised thematically.

Results: Twenty sources were included, 16 (80%) published from 2024 onward. Nineteen were secondary sources: ten narrative reviews, five structured literature reviews, one scoping review, one umbrella review, one systematic review with meta-analysis and one perspective. Only one was a primary study. AI applications clustered in diagnosis (periapical lesions, vertical root fractures, caries, root canal morphology), treatment (working length, case difficulty, retreatment decisions), prognosis (postoperative pain, retreatment success) and education. Reported accuracy exceeded 90% for periapical lesion detection and reached 95.6% for postoperative pain prediction. The only meta-analysis found higher odds of correct working-length determination with AI than with expert assessment, but it was based on five laboratory studies and the certainty of evidence was low. Large language models answered 25% to 72% of restorative and endodontic examination questions correctly, and performed worst on endodontics. Recurrent barriers were small and unrepresentative datasets, limited external validation, poor interpretability, cost, and ethical and privacy concerns.

Conclusions: AI shows high reported accuracy for image-based endodontic tasks, but the evidence base is dominated by reviews that repeatedly summarise a limited pool of internally validated, largely laboratory-based studies. Prospective, multicentre clinical validation, standardised reporting and ethical and regulatory frameworks are needed before routine clinical use.

Keywords: Artificial Intelligence; Convolutional Neural Networks; Deep Learning; Endodontics; Large Language Models; Machine Learning

INTRODUCTION

Endodontics is concerned with diseases of the pulp and periradicular tissues. Its clinicians must interpret two- and three-dimensional radiographs, integrate varied symptoms into complex diagnoses and deliver technically demanding

treatment [1]. Intra- and interobserver agreement in radiographic interpretation is low, and non-standardised techniques contribute to variation in outcomes, creating an unmet need for automated image analysis, decision support and assistance during treatment [1]. Artificial intelligence (AI) offers the capacity to replicate aspects of human intelligence in prediction and complex decision making, and its presence in dentistry, especially endodontics, has grown steadily [2].

AI in this context covers machine learning, deep learning and neural network architectures. Computer vision methods analyse images, while natural language processing extracts information from text [3]. More recently, large language models, large vision models and multimodal models have begun to reshape tasks ranging from clinical documentation to treatment planning across dental specialties [4]. In endodontics, convolutional neural networks (CNNs) and artificial neural networks (ANNs) have been used to study root canal anatomy, detect periapical lesions and root fractures, determine working length and predict treatment outcomes [2,5].

In 2024, Asgary published a scoping review of AI in endodontics that mapped these applications, highlighted the ability of AI to recognise landmarks and lesions on cone-beam computed tomography (CBCT) with high precision, and drew attention to ethical concerns including patient privacy, data security and bias [6]. The literature has since expanded rapidly. Structured literature reviews have reported the diagnostic and prognostic accuracy of AI across dozens of primary studies [7–9], and workflow-oriented reviews have examined how AI might be embedded in everyday practice [10]. The first quantitative synthesis in the field has examined AI for working-length determination [11], large language models have been tested against dental examination questions [12], and microrobotics has emerged as a related frontier for root canal disinfection [13,14].

Despite this growth, clinical application remains limited [1], and a knowledge gap persists among endodontists regarding the fundamentals and limitations of AI [3,5]. An updated map of the evidence is therefore needed. Following the structure and thematic areas of the review by Asgary [6], this scoping review aimed to (i) characterise recent literature on AI in endodontics by source type and scope; (ii) map AI applications across diagnosis, treatment, prognosis and education, together with their reported performance; (iii) summarise the barriers to clinical implementation; and (iv) identify gaps and priorities for future research.

MATERIALS AND METHODS

Framework and reporting

This scoping review followed the five-stage framework of Arksey and O'Malley [15], as refined in the Joanna Briggs Institute (JBI) methodological guidance [16], and is reported according to the PRISMA extension for scoping reviews (PRISMA-ScR) [17]. The thematic structure of the synthesis was adapted from the earlier scoping review by Asgary [6], so that the present findings can be read as an update to that map. [Protocol registration: state the OSF registration number, or state that no protocol was registered.]

Review question

The guiding question was: *What is the nature and extent of the recent evidence on artificial intelligence in endodontics, which clinical tasks has it addressed, and what limits its translation into practice?*

Eligibility criteria

Eligibility was defined using the Population–Concept–Context (PCC) framework.

- **Population:** patients, teeth, radiographic or CBCT images, clinical data, or dental students and clinicians, in the context of endodontic diagnosis, treatment or education.
- **Concept:** any AI approach, including machine learning, deep learning, CNNs, ANNs, natural language processing, large language models and AI-assisted robotic systems, applied to an endodontic task. Sources covering restorative dentistry or dentistry as a whole were included when they reported endodontic applications or endodontically relevant tasks such as caries detection.
- **Context:** any clinical, laboratory or educational setting; published 2021–2026; English language.
- **Source types:** primary studies, narrative, structured, scoping and umbrella reviews, systematic reviews with or without meta-analysis, and perspectives.

Conference abstracts, editorials and sources without full text were excluded.

Information sources and search

Sources were identified through an electronic search of [PubMed/MEDLINE; add other databases searched] using combinations of the terms *artificial intelligence*, *machine learning*, *deep learning*, *neural networks*, *convolutional neural network*, *large language model*, *ChatGPT*, *robotics* and *endodontics*, supplemented by hand-searching of reference lists. The final search was run on [date]. Records were managed in Zotero. [Insert the full search string as Supplementary File 1.]

Selection of sources
Two reviewers (M.M.K. and R.K.) independently screened titles and abstracts and then full texts against the eligibility criteria. Disagreements were resolved by discussion, with the remaining authors (N.B. and A.M.) consulted when needed. [Insert the number of records identified, duplicates removed, records screened, full texts assessed and reasons for exclusion, for the PRISMA-ScR flow diagram, Figure S1.] Twenty sources were included.

Data charting and synthesis
A standardised charting form recorded first author, year, journal, source type, scope (endodontics-specific or broader), number of included studies where reported, AI approach, clinical task, reported performance metrics and stated limitations. Charting was performed by one reviewer and verified by a second. Consistent with scoping-review methodology, individual sources were not formally appraised [16]; however, risk-of-bias and certainty judgements reported within included systematic reviews were extracted. Findings were synthesised narratively under six themes adapted from Asgary [6]: AI fundamentals, diagnosis and detection, treatment planning and execution, prognosis, education, and barriers and ethics. An evidence-gap map was then constructed by cross-tabulating clinical tasks against the highest level of evidence identified.

RESULTS

Characteristics of the included sources
Twenty sources published between 2021 and 2026 were included (Table 1, Figure 1). Sixteen (80%) appeared from 2024 onward, and 2024 was the peak year with eight sources. Nineteen of the 20 were secondary sources. Narrative reviews formed the largest group (n = 10) [1–5,10,14,18–20], followed by structured literature reviews that reported a database search and a count of included studies (n = 5) [7–9,21,22]. There was one scoping review [6], one umbrella review [23], one systematic review with meta-analysis [11] and one perspective article [13]. The only primary study was a cross-sectional evaluation of large language models [12].

Fifteen sources addressed endodontics specifically; five took a broader view of dentistry [4], restorative dentistry [21], conservative dentistry [20], restorative and endodontic education [12] or caries diagnosis [23]. The *International Endodontic Journal* contributed three sources [3,5,13] and *BMC Oral Health* two [10,21]. Where reported, the structured reviews included between 11 and 88 primary studies [7–9,21,22], and the earliest primary work they covered dated from 1980 [8].

Fundamentals of AI relevant to endodontics
Most included sources described AI in terms of machine learning, in which algorithms learn patterns from data, and deep learning, in which multilayered neural networks learn representations directly from images or text [3,5]. CNNs were the dominant architecture for image-based tasks, and ANNs were used for tasks such as working-length estimation and outcome prediction [2,6]. Ourang and colleagues set out a development workflow running from data collection and annotation through model training and validation to clinical integration [3]. Mohammad-Rahimi and colleagues added the technical and ethical requirements of data preparation, and the evaluation metrics needed to judge a model, including accuracy, sensitivity, specificity and area under the curve [5]. Beyond imaging, natural language processing can extract information from clinical records, and generative adversarial networks can create synthetic images to enlarge training datasets [20]. At the frontier, large language models, large vision models and multimodal models are extending AI from single image tasks to documentation, patient communication and integrated treatment planning [4].

Diagnosis and detection
Diagnosis was the most extensively studied domain (Table 2).

Periapical lesions. Detection of periapical radiolucencies was the most common application [5,7,8]. CNN-based models, including the commercial platform Diagnocat, achieved accuracy above 90% for detecting periapical lesions on both periapical radiographs and CBCT [9]. Asgary highlighted the potential for early lesion detection and for recognising anatomical landmarks and lesions on CBCT with consistently high precision [6].

Root fractures and resorption. AI algorithms identified vertical root fractures with high precision on CBCT images [9], and fracture detection featured in most reviews [2,6,8]. Setzer and colleagues additionally noted applications for detecting resorptive defects [1].

Caries and pulpal inflammation. An umbrella review of seven systematic reviews, identified from 1,249 records, found that CNN-based models achieved high sensitivity, specificity and area under the curve for caries detection, segmentation and classification, with better accuracy on periapical and panoramic radiographs [23]. A structured review of restorative dentistry reported up to 95% accuracy for caries detection [21]. AI was also reported to identify pulpal inflammation [6].

Root canal morphology. Deep learning models detected C-shaped canals and other anatomical variations with high accuracy [9], and analysis of root canal anatomy was among the earliest described applications [2,5,6].

Treatment planning and execution

Working-length determination. Working length was the only task for which a quantitative synthesis was available. Neural network-based algorithms were reported to outperform conventional electronic apex locators [9]. A systematic review and meta-analysis identified five in vitro and ex vivo studies covering more than 1,765 teeth or radiographic images, and found higher odds of correct working-length determination with AI-based methods than with expert assessment [11]. However, the risk of bias was moderate to high, largely because of internal validation and laboratory designs, and the certainty of evidence was rated low [11]. Earlier reviews had already identified working length as a promising application [2,6,8].

Case assessment, treatment planning and second opinions. Deep learning models were reported to predict case complexity and improve treatment planning [9]. A structured review of 11 primary studies, selected from 785 records, concluded that AI can help identify apical lesions, classify and number teeth, support referral decisions and plan treatment with greater accuracy [22]. AI has also been proposed to offer second opinions for non-surgical root canal treatment [6] and to support decisions on retreatment [7]. Workflow-oriented reviews framed these applications as steps in a digital pathway from imaging and diagnosis to treatment and review [10], and restorative applications such as shade determination were reported to reduce chair time [20,21].

Robotics and microrobotics. Augmented reality and robotics were identified as future directions for AI-assisted endodontic treatment [1], and robotic-assisted endodontic surgery has been proposed [2,18]. A distinct line of work concerns root canal disinfection. Multifunctional magnetic microrobots have been developed to disrupt, kill and retrieve biofilms in hard-to-reach areas of the root canal system [13]. Nanozyme-shelled microcapsules and advanced robotic systems enable precise navigation, biofilm removal and therapeutic delivery, but face challenges of biocompatibility, fabrication and clinical integration [14].

Prognosis and outcome prediction

AI models achieved 95.6% accuracy in predicting pain after root canal treatment [9], and prediction of postoperative pain was also reported in other reviews [5,7]. Prediction of the success of non-surgical retreatment recurred across the literature [2,8,9], as did prediction of dental pulp stem cell viability, a task relevant to regenerative endodontics [2,8,18]. A structured review of 88 articles, selected from 2,560 records published between 1980 and 2021, concluded that AI displayed accuracy in both diagnostic and prognostic evaluations and could raise the success rate of endodontic treatment by improving treatment planning [8]. Asgary likewise reported that AI appears effective in predicting treatment success [6].

Education and large language models

Several reviews anticipated that AI will reshape endodontic education and continuing professional development [1,3,5]. The only primary study in this review tested large language models on 151 multiple-choice questions from a restorative dentistry and endodontics question pool [12]. ChatGPT-4.0o answered 72% correctly, ChatGPT-4.0 62%, Gemini 1.0 44% and ChatGPT-3.5 25%, with significant differences between all models except the two GPT-4.0 versions. Performance was highest for direct restorations and caries and lowest for indirect restorations and endodontics. The authors concluded that only the ChatGPT-4 models could be used, with caution, to support the dental curriculum [12]. Other sources called for structured AI training programmes in dental education [21] and for AI-supported patient education [4].

Barriers to implementation and ethical considerations

The included sources agreed closely on the barriers to clinical use (Table 3). Data were the most frequently cited problem: endodontic datasets are small, often drawn from a single centre and seldom publicly available, which limits generalisability [1,9,10,20]. Larger multicentre datasets were repeatedly called for to give models external validity [7]. Interpretability was the second theme: opaque, “black box” algorithms may undermine clinician trust [5,10,20]. Cost and computational requirements restrict access, particularly in resource-constrained settings [9,20]. Ethical concerns centred on patient privacy, data security, algorithmic bias and over-reliance on AI [6,20,21,23]. Finally, several authors stressed that the reliability, applicability and cost-effectiveness of AI still need verification before routine use [2,19], and that evidence-based guidelines for implementation are lacking [22].

Evidence-gap map

Table 4 cross-tabulates each clinical task against the highest level of evidence identified among the included sources. Only two tasks had been examined through systematic evidence synthesis: working-length determination, through a meta-analysis of laboratory studies [11], and caries detection, through an umbrella review [23]. Every other application rested on narrative or structured literature reviews, and no task was supported by prospective clinical trials.

DISCUSSION

Principal findings

This scoping review mapped 20 recent sources on AI in endodontics. Four findings stand out. First, the literature has grown quickly, with 80% of sources published from 2024 onward, but almost all of it consists of reviews. Second, AI applications span the whole endodontic workflow, from detection of periapical lesions and fractures to working-length determination, outcome prediction and education. Third, reported accuracy for image-based tasks is consistently high, often above 90%. Fourth, the evidence behind these figures is weak: only one task has been meta-analysed, on laboratory data and with low certainty, and no task is supported by prospective clinical studies.

What has changed since the 2024 scoping review

The review by Asgary established the core map of AI in endodontics: anatomy, periapical lesions, working length, treatment success, caries, pulpal inflammation, vertical root fractures, second opinions and CBCT analysis [6]. The present review confirms that map and shows how it has shifted in three ways. The field has moved from describing individual tasks to embedding AI in a clinical workflow [3,10]. It has produced its first quantitative synthesis, for working length [11]. And it has expanded into generative AI [4,12] and microrobotics [13,14], two areas that barely featured in earlier reviews. The ethical concerns Asgary raised about privacy, data security and bias [6] remain unresolved and now recur in almost every source.

Review saturation and the evidence behind accuracy figures

Nineteen of the 20 sources were secondary. Many summarise overlapping primary studies, so the same accuracy figures are repeated from review to review. This creates an impression of maturity that the primary evidence does not support. The single meta-analysis illustrates the gap: its pooled result favoured AI, but it rested on five laboratory studies with moderate-to-high risk of bias, largely because models were validated only on data from the centre that developed them [11]. Summary statements such as “accuracy up to 90%” [7] or “accuracy greater than 90%” [9] combine different tasks, imaging modalities, reference standards and metrics, and so cannot show how a model would perform on a new population. Models trained on small, single-centre datasets are likely to perform worse on external data [1,10]. Readers should therefore treat headline accuracy figures as upper bounds from development settings, not as expected clinical performance.

From accuracy to clinical benefit

High diagnostic accuracy does not by itself show that patients benefit. None of the included sources reported a study showing that AI assistance changed treatment decisions, reduced errors or improved outcomes in practice. Reviews that proposed AI as a second opinion [6] or as a planning aid [9,22] described potential rather than demonstrated benefit. The next stage of research should therefore move from diagnostic accuracy studies to decision-impact studies and pragmatic trials that compare clinicians with and without AI support.

Large language models and education

Large language models are likely to reach students and clinicians faster than any image-analysis tool, because they are freely available and require no integration with practice software. The only primary study found wide variation between models and weakest performance in endodontics, with the best model answering 72% of questions correctly [12]. Because models change rapidly, these results will date quickly, but the underlying message holds: accuracy depends strongly on the model, and output must be checked. Structured AI literacy in the dental curriculum [21] would help students use these tools critically.

Interdisciplinary relevance

Several applications cross specialty boundaries. CBCT-based lesion and landmark detection [6,9] is shared with oral and maxillofacial surgery and radiology, periapical bone healing is of shared interest with periodontics, and caries detection sits at the interface with restorative dentistry [21,23]. The broader dental literature describes parallel AI applications in periodontics and oral and maxillofacial surgery [4]. Collaboration among clinicians, computer scientists and industry was repeatedly identified as essential for successful integration [3,4,10].

Research priorities

1. Prospective, multicentre clinical studies with external validation for periapical lesion detection, fracture detection and working length.
2. Standardised reporting of AI studies in endodontics, including dataset source, reference standard, validation strategy and complete performance metrics.
3. Public, annotated and demographically diverse endodontic imaging datasets.
4. Decision-impact studies and pragmatic trials comparing clinicians with and without AI support.
5. Interpretable models, together with evaluation of their effect on clinician trust and over-reliance.
6. Health-economic studies, particularly in resource-constrained settings.
7. Repeated, endodontics-specific evaluation of large language models as they evolve.
8. Biocompatibility and first-in-human studies of microrobotic disinfection.

Strengths and limitations
This review updates an existing scoping review using a transparent framework and maps AI applications across the full endodontic workflow, with an explicit evidence-gap map. Its limitations are those of the evidence it maps. Most included sources were reviews, so primary studies were represented indirectly and some may have been counted more than once. The review was limited to English-language sources published from 2021, and its completeness depends on the search. Individual sources were not critically appraised, and reported performance figures were charted as stated without re-analysis. Finally, because AI evolves quickly, some findings, particularly those on large language models, may soon be outdated.

CONCLUSIONS

Artificial intelligence now touches every stage of the endodontic workflow. It shows high reported accuracy for detecting periapical lesions, vertical root fractures and caries, for analysing root canal morphology and determining working length, and for predicting postoperative pain and retreatment outcomes. Since the 2024 scoping review, the field has added a first meta-analysis, early evaluations of large language models and microrobotic approaches to disinfection. However, the evidence is dominated by reviews that repeatedly summarise a limited pool of internally validated, largely laboratory-based studies, and no application has yet been tested in prospective clinical trials. Before AI can move from promising tool to routine clinical aid, the field needs multicentre external validation, standardised reporting, diverse public datasets, demonstration of clinical benefit, and clear ethical and regulatory frameworks.

Declarations
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Ethical approval: Not required; this review synthesised published literature only.

Supplementary material: Figure S1, PRISMA-ScR flow diagram; File S1, full search strategy; File S2, completed PRISMA-ScR checklist.

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Tables

Table 1. Characteristics of the included sources (n = 20), in order of citation.

Ref.	First author, year	Source type	Scope and size	Principal finding relevant to this review
[1]	Setzer, 2024	Narrative (critical) review	Endodontics	Low observer agreement creates need for AI; steady rise in studies but limited clinical application; AR and robotics as future directions
[2]	Aminoshariae, 2021	Narrative review	Endodontics	CNNs/ANNs applied to anatomy, lesions, fractures, working length, DPSC viability and retreatment; reliability and cost-effectiveness unverified
[3]	Ourang, 2024	Narrative review	Endodontics	ML and DL fundamentals; development workflow from data collection to clinical integration; computer vision and NLP tasks
[4]	Samaranayake, 2025	Narrative review	Dentistry	LLMs, LVMs and multimodal models across specialties; need for validation and regulation
[5]	Mohammad-Rahimi, 2024	Comprehensive review	Endodontics	Data preparation, evaluation metrics and ethics; interpretability and generalisability limit adoption
[6]	Asgary, 2024	Scoping review	Endodontics	High precision on CBCT landmarks and lesions; second opinions for NSRCT; privacy, security and bias concerns
[7]	Ahmed, 2023	Structured	Endodontics; 56	Accuracy up to 90% across tasks;

Ref.	First author, year	Source type	Scope and size	Principal finding relevant to this review
		literature review	papers	larger multicentre datasets needed
[8]	Karobari, 2023	Structured literature review	Endodontics; 88 of 2,560 articles, 1980–2021	Most research on apical foramen, working length, periapical pathology, root morphology, retreatment and VRF
[9]	Kun, 2025	Structured literature review	Endodontics; 51 articles, 2016–2025	>90% accuracy for periapical lesions; outperformed EALs; 95.6% accuracy for postoperative pain
[10]	Huang, 2026	Narrative review	Endodontics; literature to July 2025	Clinical workflow framing; scarce public databases and poor interpretability limit use
[11]	Bansal, 2026	Systematic review with meta-analysis	Working length; 5 in vitro/ex vivo studies, >1,765 teeth or images	Higher odds of correct working length with AI vs expert; moderate-to-high risk of bias; low certainty
[12]	Künzle, 2024	Cross-sectional study	Restorative and endodontic assessment; 151 questions	ChatGPT-4.0o 72%, ChatGPT-4.0 62%, Gemini 1.0 44%, ChatGPT-3.5 25%; endodontics among weakest subcategories
[13]	Babeer, 2024	Perspective	Microrobotics	Magnetic microrobots can disrupt, kill and retrieve biofilms
[14]	Jaruchotiratanasakul, 2025	Narrative review	Robotics, microrobotics, nanozymes	Nanozyme-shelled microcapsules for biofilm removal; biocompatibility and fabrication challenges
[18]	Parinitha, 2024	Narrative review	Endodontics	Applications from anatomy to retreatment prediction; robotic surgery and scheduling as future uses
[19]	Kumar, 2025	Narrative review	Endodontics	High accuracy in detection and prediction; reliability and cost-effectiveness need validation
[20]	Bansal, 2025	Narrative review	Conservative dentistry and endodontics	NLP and GANs for data; opaque algorithms, cost and resource-limited settings as barriers
[21]	Najeeb, 2025	Structured literature review	Restorative dentistry; 63 publications, 2020–2025	Up to 95% caries detection accuracy; reduced chair time; need for AI training in dental education
[22]	Asiri, 2022	Structured (qualitative) review	Endodontic diagnosis and planning; 11 of 785 articles	AI aids apical lesion detection, tooth numbering, referral and treatment planning; guidelines lacking
[23]	Negi, 2024	Umbrella review	Caries; 7 SRs from 1,249 records	CNNs showed high sensitivity, specificity and AUC; best with periapical and panoramic radiographs

Abbreviations: ANN, artificial neural network; AR, augmented reality; AUC, area under the curve; CBCT, cone-beam computed tomography; CNN, convolutional neural network; DL, deep learning; DPSC, dental pulp stem cell; EAL, electronic apex locator; GAN, generative adversarial network; LLM, large language model; LVM, large vision model; ML, machine learning; NLP, natural language processing; NSRCT, non-surgical root canal treatment; SR, systematic review; VRF, vertical root fracture. References 15–17 are methodological and are not included sources.

Table 2. Reported applications of artificial intelligence across the endodontic workflow

Domain	Clinical task	AI approach and input	Reported performance	Ref.
Diagnosis	Periapical lesion detection	CNNs (e.g. Diagnocat) on periapical radiographs and CBCT	Accuracy >90%	[5–9]
Diagnosis	Vertical root fracture detection	CNNs on CBCT and radiographs	High precision (metrics vary)	[2,6,8,9]
Diagnosis	Caries detection	CNNs, SVMs, multilayer perceptrons on radiographs and photographs	Up to 95% accuracy; high sensitivity, specificity and AUC	[21,23]
Diagnosis	Root canal morphology, C-shaped canals	Deep learning on CBCT and radiographs	High accuracy	[2,5,6,9]
Diagnosis	Pulpal inflammation, resorption	Deep learning on clinical and imaging data	Described; few metrics	[1,6]
Treatment	Working-length determination	ANNs; radiographic or impedance input	Outperformed EALs; higher odds of correct length than experts in vitro	[2,9,11]
Treatment	Case difficulty and treatment planning	Deep learning on clinical and radiographic data	Described as improved planning	[9,10,22]
Treatment	Retreatment decisions and second opinions	Neural networks	Described	[6,7]
Treatment	Canal disinfection	Magnetic microrobots, nanozyme microcapsules	Preclinical	[13,14]
Prognosis	Postoperative pain	Machine learning on clinical variables	Accuracy 95.6%	[9]
Prognosis	Retreatment success, DPSC viability	ANNs	Described	[2,8,18]
Education	Answering examination questions	LLMs (ChatGPT, Gemini)	25–72% correct; weakest in endodontics	[12]

Abbreviations: AUC, area under the curve; CBCT, cone-beam computed tomography; CNN, convolutional neural network; DPSC, dental pulp stem cell; EAL, electronic apex locator; LLM, large language model; SVM, support vector machine.

Table 3. Barriers to clinical implementation of artificial intelligence in endodontics and remedies proposed by the included sources.

Barrier	How it limits clinical use	Proposed remedy	Ref.
Limited, unrepresentative datasets	Models overfit to single-centre data and generalise poorly	Public, standardised, annotated imaging databases; data-sharing initiatives; synthetic data	[1,9,10,20]
Lack of external validation	Reported accuracy may not hold in new settings	Multicentre and prospective clinical validation	[7,10,11]
Poor interpretability	Clinicians cannot see why a model reached its output	Explainable, interpretable AI models	[5,10,20]
Cost and computational demand	Limits access, especially in resource-constrained settings	Efficient models; demonstration of cost-effectiveness	[2,9,19,20]
Privacy, security and bias	Risk to patient data and to fairness of decisions	Ethical and regulatory frameworks	[4,6,10,21,23]
Over-reliance and knowledge gaps	Uncritical use by clinicians unfamiliar with AI	AI literacy and structured training; clinician oversight	[3,5,20,21]
Absence of guidelines	No evidence-based pathway for adoption	Guidelines developed through interdisciplinary collaboration	[3,4,22]

Table 4. Evidence-gap map of artificial intelligence in endodontics derived from the included sources

Domain	Clinical task	Highest level of evidence identified	Principal gap	Ref.
Diagnosis	Periapical lesion detection	Structured literature reviews	Systematic review with meta-analysis; external clinical validation	[7–9]
Diagnosis	Vertical root fracture	Structured literature reviews	Standardised metrics; validation on clinical CBCT	[8,9]
Diagnosis	Caries detection	Umbrella review	Transfer to endodontic decision pathways	[23]
Diagnosis	Root canal morphology	Structured literature review	Diverse, multi-population datasets	[9]
Diagnosis	Pulpal inflammation, resorption	Narrative and scoping reviews	Primary studies with defined reference standards	[1,6]
Treatment	Working-length determination	Meta-analysis of 5 laboratory studies (low certainty)	Clinical studies; external validation	[11]
Treatment	Case difficulty, planning, retreatment decisions	Structured literature reviews	Prospective decision-impact studies	[9,22]
Treatment	Microrobotic disinfection	Perspective and narrative review	Biocompatibility testing; first-in-human studies	[13,14]
Prognosis	Postoperative pain, retreatment outcome	Structured literature reviews	Prospective, externally validated prediction models	[8,9]
Education	Large language models	Single cross-sectional study	Evaluation of newer models; endodontics-specific item banks	[12]
Implementation	Cost-effectiveness, ethics, regulation	Narrative reviews	Health-economic and implementation studies	[2,4,10]

Figure

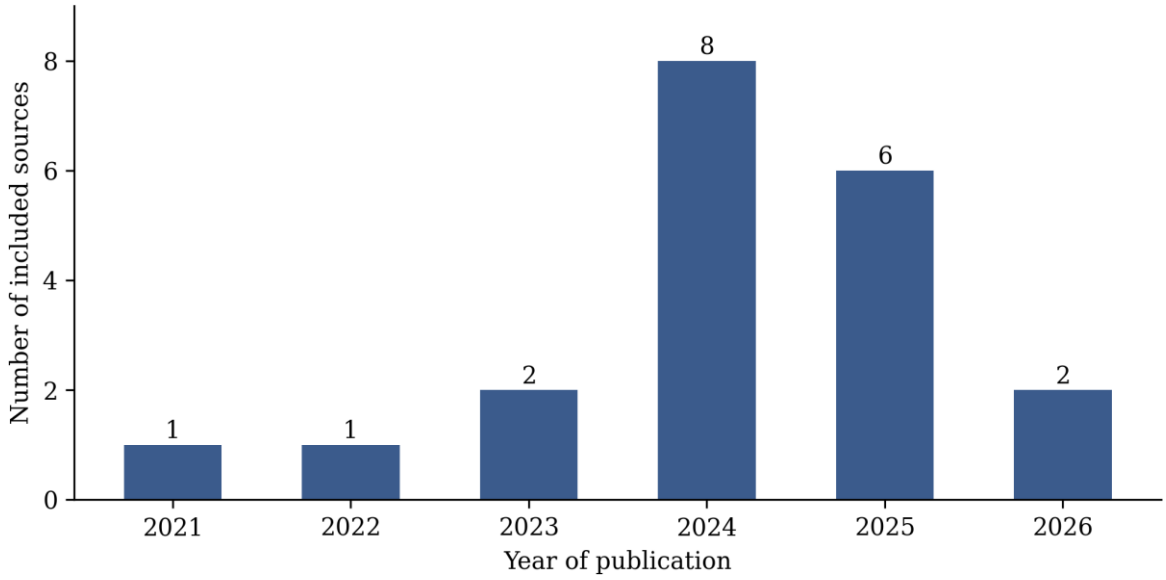


Figure 1. Distribution of the included sources by year of publication. Sixteen sources (80%) were published from 2024 onward.