Artificial Intelligence Assisted Clinical Decision Support and Referral Pathways from an Oral Health Perspective

Abstract

Despite the availability of published clinical guidelines, their use at the point of care remains inconsistent across medical and surgical fields. Variability in clinician adherence can lead to inconsistent outcomes, delayed referrals, and suboptimal care. Clinical decision support systems (CDSSs), particularly those built on rule-based, interpretable architectures, offer a scalable method to embed speciality guidelines into clinical workflows. These systems can prompt appropriate actions, flag deviations, and support diagnostic reasoning, serving as a bridge between published best practices and real-world decision-making. Such rule-based CDSS models are increasingly relevant across disciplines, including cardiology, oncology, gastroenterology, and rheumatology, and align with ongoing efforts to use artificial intelligence (AI) to enhance, rather than replace, clinician judgment.

This perspective describes an AI-CDSS developed for endodontic case assessment and referral. The system integrates structured data, radiographic interpretation, and complexity scoring. A proof-of-concept evaluation across 60 cases demonstrated high concordance with expert judgment and reinforced consistency in referral communication. While illustrated in the context of oral health, the architecture offers a transferable template for other specialities seeking to operationalize guidelines in a clinician-facing, explainable format. The approach highlights a promising strategy for promoting diagnostic consistency, interdisciplinary coordination, and adherence to evidence-based care across the healthcare ecosystem. The proof-of-concept application for endodontic case evaluation can be accessed on rootcanalai.vercel.app and rootcanalai.in.

Keywords:
Artificial Intelligence; Clinical Decision Support System; Referral Workflow; Diagnosis; Case Difficulty; Treatment Planning; Endodontics.

Introduction

Introduction

Clinical practice guidelines serve as structured, evidence-based tools designed to standardize and improve clinical decision-making. The translation of evidence-based guidelines consistently into routine clinical practice is one of the enduring challenges of modern healthcare due to barriers such as time constraints, fragmented workflows, and limited integration into clinical systems across specialities such as cardiology, oncology, rheumatology, and dentistry.1,2. While speciality societies produce rigorous consensus statements to standardize diagnosis and treatment, these documents often remain passive reference materials, underutilized at the point of care. In the high-pressure environment of

daily practice, clinicians often rely on heuristics rather than standardized protocols, leading to unwarranted variation in diagnosis, risk assessment, and referral patterns.3

This challenge is vividly illustrated in oral healthcare. Orofacial pain and pulpal disease represent one of the most common drivers of emergency visits, opioid prescription, outpatient procedure volume, and referral pathways in the healthcare system, with substantial interprofessional interaction involving general dentistry, endodontics, emergency medicine, primary care, and otolaryngology. Diagnostic variability in this setting impacts antibiotic use, opioid exposure, and timely referral2 Clinician-supervised clinical decision support systems (CDSSs) have emerged as a potential bridge between established speciality guidelines and real-world clinical practice. They can help ensure timely, standardized, and accurate clinical decisions. These systems can flag inconsistencies with best practices, prompt appropriate diagnostic or therapeutic actions, and ensure compliance with referral pathways, thereby reducing diagnostic variation and enhancing coordination among healthcare providers.1,3,4

While CDSSs have shown promise in various medical domains, uptake remains uneven in cardiology, oncology and other fields of medicine and surgery.3,5 These tools are not universally adopted due to issues related to clinician trust, alert fatigue, lack of transparency in AI logic, and difficulty with technical implementation.6,7 Figure 1 illustrates the conceptual workflow by which an AI-enhanced CDSS ingests published resources and patient data to generate editable recommendations across all domains.

Oral diseases affect more than 3.5 billion people globally.8,9 In endodontics, the diagnostic process involves the interpretation of radiographs, patient symptoms, and test results that are well-suited to algorithmic support. American Association of Endodontists (AAE) and the European Society of Endodontology (ESE) have developed comprehensive diagnostic terminologies and treatment guidelines.10-12 Figure 2 illustrates the envisioned referral network in oral health, where decision support may help to route patients through interprofessional care. An AI-assisted CDSS can help by embedding speciality recommendations into clinical workflows via rule-based logic. Importantly, the CDSS does not replace clinician judgment but augments it with transparent, guideline-backed decision support.1 CDSSs can also be used to embed complexity assessment tools to generate a structured referral amongst clinicians containing relevant data and initial interpretation, ensuring bidirectional flow of information.13,14

An effective CDSS must also be human-centred: usable, explainable, and adaptable over time. Clinician adoption improves when systems include clear references to guideline clauses, provide rationale for recommendations, and are integrated into existing workflows without disrupting patient care.6,7,15 While barriers to implementation include poor user interface design, lack of clinician engagement during development, and insufficient training, uptake also tends to diminish over time without ongoing support and system refinement. 4,6,16

The experience of building and piloting a CDSS prototype in endodontics offers lessons for broader application. First, decision pathways must be role-specific, distinguishing between general physicians/ dental practitioners and specialists. Second, hybrid approaches that

combine rule-based logic with AI-driven image analysis can offer a balance between explainability and diagnostic accuracy. Third, inclusion of structured output improves communication and facilitates clinical decision-making.

Beyond oral health, the principles demonstrated in this prototype are readily transferable. Most medical specialties already maintain structured guidelines that lend themselves to rule encoding. For instance, Rheumatology-for the diagnosis of early rheumatoid arthritis,17 Gastroenterology, to improve colorectal cancer screening adherence,18 cardiology, for acute coronary syndrome triage and post-discharge therapy adherence.5 These systems rely on the same architecture as the endodontic prototype: structured inputs, encoded decision thresholds, explainable logic, and integration into existing workflows (Figure 3). The comprehensive diagnostic and treatment guidelines can be operationalized on a CDSS for diagnostic reasoning, referral guidance, and treatment planning. Outputs are reviewed and editable by supervising clinicians. This structure illustrates a scalable model for reducing variability and improving evidence adherence across specialities, aligning with national initiatives on AI in healthcare and transparency in decision support.

Regulatory and ethical concerns remain important. Transparency in decision logic, citation of guideline sources, and human override mechanisms are all essential to clinician trust and regulatory compliance. CDSSs that generate treatment recommendations require evidence of safety and efficacy.15

For CDSS to become mainstream tools in clinical care, systems must be built to be interoperable, evidence-backed, and centered on clinical workflow. Open-access repositories of guideline-based rule sets and CDSS templates could accelerate cross-speciality adoption and promote standardization.

Therefore, integrating speciality guidelines into point-of-care clinical decision support systems offers a practical and scalable approach to improving diagnostic consistency and referral quality across multiple fields. The oral health prototype described here illustrates both the feasibility and the broader applicability of this approach. By combining structured knowledge with transparent AI, CDSSs can augment, not replace, clinical judgment, supporting the healthcare community's ongoing commitment to evidence-based, patient-centered care.

Methodology

This article describes the development and early evaluation of a decision support tool created to assist with diagnosing and referring dental cases, particularly in endodontics. The tool is presented here not just as a dental application, but as an example of how clinical guidelines can be turned into practical systems that help clinicians make consistent decisions. The approach used here could apply to many medical fields.

Turning Guidelines into Decision Rules

The tool was based on official recommendations from professional dental organizations. It draws inspiration from the recommendations of the American Association of Endodontists

(AAE) and the European Society of Endodontology (ESE).[9-11] These guidelines were translated into clear if-then rules. For example, if a patient had a specific set of symptoms and test results, the system would recommend a likely diagnosis and suggest whether a referral was appropriate. These rules were made easy to understand and were linked directly to the guideline sources so that users could verify the sources of recommendations.

All of the information needed for the tool was organized into categories, including patient symptoms, clinical tests like cold or percussion sensitivity, and radiographic findings.

Designing a Clinician-Friendly Interface (Figure 4,5)

To make sure the tool was easy to use, its design was tested and improved based on feedback from general dentists, dental specialists, and physicians familiar with decision support systems. The goal was to avoid overwhelming the user. Data was entered through drop-down menus and checkboxes, with built-in guidance on what information was needed.

Rather than making automatic decisions, the system provided suggestions that the clinician could review, modify, or override. This preserved the clinician's role while offering a consistent way to apply professional guidelines.

Testing with Real Cases

The tool was tested using 60 anonymized patient cases. Some were entered by specialists, others by general dental practitioners. The system's recommendations were then compared to those of experts. This helped evaluate how well the tool matched expert thinking and whether it improved consistency. The tool also helped sort cases into mild, moderate, or complex, which assisted with referral decisions.

Improving Referral Communication

The system also aimed to improve referrals by creating structured referral documents when specialist care was needed. These included key findings, reasoning behind the referral, and any relevant images or test results (Figure 6). This made it easier for specialists to understand the case and improved communication between providers.

Generalizing the Approach to Other Specialties

The tool was designed to be adaptable to other areas of medicine. A general framework is outlined to show how similar systems could be built for other specialties such as cardiology, oncology, rheumatology, and gastroenterology (Figure 3). The basic components needed for each specialty include:

1. Access to existing clinical guidelines
2. A list of relevant patient data points
3. A user-friendly interface for clinicians
4. Clear logic for producing recommendations
5. A component for producing structured referral summaries

“Glass-Box" vs. "Black-Box"

Trust is enhanced when clinicians can "see" what the AI sees. Techniques like LIME (Local Interpretable Model-agnostic Explanations) and SHAP (SHapley Additive exPlanation) provide this visibility.

Highlighting Evidence: LIME focuses on "local fidelity," meaning it explains a specific prediction by highlighting the exact regions (super-pixels) or symptoms that influenced the decision.

Radiographic Annotation: In the context of the endodontic CDSS, this is realized through bounding boxes. The system allows clinicians to manually annotate periapical radiolucency, defective restoration, secondary caries, missed canals and faulty root canal obturation using specific pen, box or circle tools. The AI receives the clinician’s annotations and focuses its analysis on the marked areas providing enhanced diagnostic detail, differential diagnoses and verification of the suspected pathology while also identifying any overlooked findings. When the AI identifies a periapical lesion, it places a visual box around the radiolucency. This provides immediate visual feedback, allowing the clinician to confirm that the AI is looking at the correct anatomical structure and not an artifact.

Application Architecture

The application was built using React (version 18.2.0) and TypeScript using Gemini 3.0 Pro with a fallback mechanism. Tailwind CSS was used for styling, enabling rapid development of a responsive, user-friendly interface. All core functions run on the client side. Local storage simulates data persistence, allowing users to save cases and referrals without needing a backend server. The application was implemented as a client-side web-based system to support proof-of-concept validation while minimising risks related to storage of patient-identifiable data. All case data used were anonymised before entry, and no identifiable clinical information was retained beyond the duration of individual assessment sessions. This design choice allowed functional evaluation of the system while maintaining data privacy and avoiding integration with external electronic health record systems at this stage of development.

Data Use and Ethical Oversight

Sixty anonymised simulated endodontic cases were included during the early evaluation phase. Cases were selected to represent a range of pulpal and periapical diagnoses, anatomical variations, and procedural complexity levels. Users of the platform were required to confirm that informed patient consent had been obtained for AI-assisted analysis of clinical data and radiographs.

Study Design

This investigation followed an exploratory framework aimed at evaluating a proof-of-concept clinical decision support system (CDSS) developed to assist in endodontic diagnosis, case difficulty assessment and referral planning. The system emulates a complete clinical workflow by guiding practitioners through structured data entry, radiographic interpretation and guideline-aligned reasoning. Because the purpose of this initial study was to determine whether the platform could generate assessments consistent with specialist judgement, the evaluation relied on testing using anonymised patient-derived clinical data.

Computation Translation

Each pathway is triggered through a conditional IF-THEN mapping structure:

Example-

IF pulpal_status = necrotic
AND apical_status = symptomatic_apical_periodontitis
AND tooth_restorable = TRUE
THEN treatment = non_surgical_root_canal_treatment

Complexity indicators such as severe root curvature, calcified canals, retreatment status, and limited mouth opening are encoded as Boolean or graded variables. These feed into a difficulty stratification model that classifies cases into minimal, moderate, or high complexity.

The logic schema was independently coded and does not replicate the layout, scoring blocks, or formatting of any proprietary forms. It represents an original computational translation of published diagnostic guidelines.

Results

The early evaluation of the endodontic prototype CDSS focused on two primary outcomes: diagnostic agreement with expert judgment and consistency in referral categorization. A total of 60 anonymized endodontic case summaries were selected from a validated clinical database.

Beta Testing Outcomes

Among cases entered by the endodontist, both blinded reviewers agreed with the system output in 29 of 30 cases, corresponding to an agreement proportion of 0.97. In contrast, for cases entered by general dental practitioners, agreement was observed in 25 of 30 cases for one reviewer and 26 of 30 cases for the other, yielding agreement proportions ranging from 0.83 to 0.87.

Five disagreement cases occurred within the general dental practitioner group, while one disagreement case occurred within the endodontist group. Disagreement cases within the GDP group were associated with incomplete or ambiguous clinical information, particularly relating to history of present illness and diagnostic testing.

Diagnostic Agreement

Agreement between the AI-assisted system and the blinded reviewers was high for pulpal diagnosis. Agreement with reviewer 1 was 90.0% ($\kappa = 0.87$; 95% CI: 0.80–0.95), while agreement with reviewer 2 was 91.7% ($\kappa = 0.89$; 95% CI: 0.82–0.96).

For apical diagnosis, complete agreement was observed between the system and both reviewers, with 100% harmony ($\kappa = 1.00$; 95% CI: 0.94–1.00).

Case Difficulty Classification and Referral Decisions

Case difficulty classification demonstrated substantial to near-perfect agreement. Agreement between the system and reviewer 1 was 91.7% ($\kappa = 0.87$; 95% CI: 0.82–0.96), while agreement with reviewer 2 reached 95.0% ($\kappa = 0.92$; 95% CI: 0.86–0.98).

Referral recommendations showed complete agreement between the system and both reviewers, with 100% agreement ($\kappa = 1.00$), indicating consistent alignment in decisions regarding specialist referral.

Inter-Operator Reliability

Inter-operator agreement between the two blinded endodontists was observed in 57 of 60 cases, corresponding to a proportion agreement of 0.95 with a Wilson 95% confidence interval of 0.86–0.98. This high level of agreement supports the internal consistency of the expert reference standard used in the study.

Paired Comparison Analysis

McNemar's tests demonstrated no statistically significant systematic disagreement between system-generated assessments and expert judgements across diagnostic and decision-making domains ($P > 0.05$ for all comparisons). This indicates that the observed discrepancies were not directionally biased.

Subgroup and Sensitivity Analyses

Agreement was higher for cases entered by the endodontist (97%) than for those entered by general dental practitioners (83–87%), highlighting the influence of data completeness and precision on system performance. However, this difference did not reach statistical significance (Fisher's exact test, $p = 0.112$), suggesting that while data quality may influence system performance, the sample size was insufficient to confirm a systematic disparity.

In sensitivity analyses excluding cases with incomplete clinical information, agreement between the system and expert reviewers exceeded 95% across diagnostic, difficulty classification, and referral outcomes. Details are given in Figure 8.

These summaries consistently included essential diagnostic information, radiographic interpretations, and rationale for referral, improving communication and reducing follow-up clarification requests.

Clinicians using the system reported that it reduced decision-making time, improved confidence in referrals, and encouraged greater alignment with specialty guidelines. Importantly, no users reported feeling that the system restricted their clinical autonomy. Instead, most described it as a "safety net" that helped standardize care without replacing human judgment.

These results suggest that embedding specialty guidelines into a transparent, clinician-facing CDSS can enhance diagnostic consistency and referral quality. While this initial study focused on endodontics, the system architecture and workflow are designed for broader applicability across specialties with well-defined practice guidelines.

Discussion

The study illustrates how embedding specialty clinical guidelines into CDSS enhances clinical consistency and referral decisions, using endodontics as a test case. The broader goal was to explore whether such a model could serve as a foundation for cross-disciplinary adoption of structured, transparent, and clinically meaningful support tools. Results from the study showed high levels of diagnostic agreement and improved referral consistency, particularly when used by non-specialists. This section expands on these findings by comparing them to trends in other medical specialties and drawing lessons from interdisciplinary research.

In many fields of medicine, variability in clinical decisions has been attributed to inconsistent use of evidence-based guidelines. In cardiology, for instance, the GRACE (Global Registry for Acute Coronary Events) and TIMI (Thrombolysis in Myocardial Infarction) scores help stratify patients with chest pain, but studies have found wide variation in how they are used across settings.[19] In oncology, clinical pathways have been formalized in large institutions, yet even within the same centre, physician adherence may differ based on experience or speciality.[20] CDSS platforms have been proposed and tested in these settings to bridge the gap between written guidelines and bedside application. In a recent study, oncology-focused CDSS showed upto 90% concordance with tumor board recommendations, especially in early-stage cancers.[21] These findings align with the current study's observation that structured decision support enhances consistency, particularly in standard or guideline-defined cases.

Another relevant parallel comes from rheumatology. Early diagnosis of rheumatoid arthritis (RA) is crucial to prevent joint damage, but referral delays are common. A study found that AI based CDSS tools that flagged flare risk prediction in RA cases based on lab markers and joint symptoms significantly reduced flare risk prediction and prompted timely specialist input.[22] This mirrors the impact observed in the current study, where general dentists using the CDSS were more likely to identify complex cases warranting referral, reducing misclassification and unnecessary delays.

From a systems perspective, the structured referral component embedded in the CDSS represents an important contribution. Lack of electronic referral formats, integrated into CDSS tools, is a known factor that decreases clinician satisfaction and hinders streamlined

care coordination.[23] The auto-generated, structured referral summaries tested in this study received positive feedback, reinforcing the value of information completeness and clarity in lines with the current AI based CDSS recommendations. [24]

The integration of clinician oversight into the CDSS aligns with findings from health informatics and user-experience studies. Fully autonomous decision systems have faced pushback from clinicians due to concerns about safety, transparency, and loss of control. In contrast, tools that retain clinician authority while offering real-time, evidence-based suggestions tend to enjoy higher adoption and trust.[23] The CDSS in this study allowed users to review, modify, and override suggestions, contributing to favorable feedback and high usability. These insights are consistent with a human-in-the-loop design philosophy increasingly embraced across specialties.[3,24]

Another factor contributing to the success of decision support systems is the alignment of the user interface with clinical workflow. Studies in emergency medicine and hospital-based care have shown that when CDSS tools are poorly integrated or disrupt workflow, they are more likely to be bypassed.[25] In contrast, when tools mirror the clinical logic and decision sequence familiar to providers, uptake improves.[25] The design choices in the present study—structured inputs, drop-down menus, and visual feedback—reflected these best practices and likely contributed to the system's usability across clinician types.

The implications of this work extend beyond dental practice. The framework of the CDSS—built on converting clinical guidelines into simple, traceable rules—is transferable to any specialty that maintains a robust guideline infrastructure. Cardiology, oncology, rheumatology, and gastroenterology are all fertile ground for such applications. Indeed, recent studies suggest that the main barrier to wider CDSS adoption is not a lack of algorithms, but rather the difficulty of integrating them into diverse, real-world clinical settings.[25-27] This highlights the importance of generalizable system design, as demonstrated in the endodontic prototype. (Figure 3,4,5)

Equity considerations also deserve attention. Clinical algorithms, especially those involving machine learning, have faced criticism for replicating or exacerbating healthcare disparities when trained on non-representative data.[28] While the current study used rule-based logic to ensure transparency and reduce bias, future adaptations should incorporate representative data and involve diverse clinical settings. For example, dental pain is a leading cause of emergency visits among underserved populations, and a CDSS that helps general practitioners make timely referrals could reduce disparities in access to specialty care.[29] Similar opportunities exist in chronic disease management, where structured support can guide non-specialists in initiating evidence-based care.

Regulatory oversight and validation standards remain critical for CDSS tools that provide actionable recommendations. While the current system offers assistive rather than prescriptive guidance, the boundary between suggestion and automation is becoming increasingly blurred in clinical AI. The U.S. Food and Drug Administration (FDA) and similar bodies are actively developing frameworks to evaluate safety, explainability, and effectiveness. Tools like the one described here may eventually require certification,

especially as they scale into new specialities or integrate with live electronic health record systems.[30]

Finally, sustainability is key. Many CDSS pilots fail to scale due to a lack of ongoing maintenance, clinician training, or system updates.[7] There is a need for long-term support structures, such as governance committees, regular updates to reflect guideline changes, and feedback mechanisms to refine system logic. Institutional commitment, policy incentives, and interdisciplinary collaboration will be crucial for ensuring the longevity and evolution of such tools.

Recent advancements in AI-enhanced clinical decision-making reinforce the value of clinician-supervised support systems across diverse specialties emphasizing the need for accuracy, explainability, and real-world safety.[31] In ophthalmology, Paredes et al. highlight AI's role in structuring referral processes and standardizing diagnostics, mirroring the structured communication goals of the current CDSS.[32] Similarly, Yu et al. describe improved diagnostic reasoning among nurse practitioners using transparent, AI-assisted systems—underscoring how guideline-based decision frameworks can extend beyond physician-only settings.[33] Notably, the Clinician Turing Test described by Gazola et al. for evaluating sepsis and ARDS CDSS tools shares core design principles with the present study: clinician oversight, decision traceability, and real-world validation.[34] Xu et al. further demonstrate that AI models integrating medical domain knowledge can assist with targeted interventions, such as nutrition in traumatic brain injury, reflecting the adaptability of rule-based systems to condition-specific needs.[35]

Collectively, these advancements support the broader applicability of the current model and validate its design principles across specialties. It also demonstrates that a transparent, guideline-informed CDSS, even when developed for a speciality such as endodontics, represents a scalable model. The shared emphasis on structured clinical logic, interdisciplinary relevance, and clinician validation highlights a converging vision across specialties: to use AI not as a replacement for clinical expertise, but as a scaffold for more consistent, efficient, and coordinated care. As healthcare systems seek to translate static clinical guidelines into active point-of-care tools, this perspective offers an example of how that translation can be responsibly designed, evaluated, and adapted for broader clinical use.

In summary, this study contributes to a growing body of evidence that structured, guideline-driven decision support tools can improve diagnostic consistency, enhance referral quality, and complement clinician judgment. The use of endodontics as a prototype highlights both the specific value in oral health and the broader relevance of such tools across medical disciplines. The next steps should include formal validation in larger clinical settings, integration with health information systems, and cross-specialty partnerships to co-develop tailored CDSS models. As healthcare systems increasingly prioritize standardization, coordination, and evidence-based care, tools like this offer a practical path forward.

Limitations

Although, these results indicate that structured digital assessment may support consistency in diagnosis and treatment planning, future studies should incorporate larger, more diverse datasets and assess performance across specific diagnostic categories. With appropriate validation, the system has the potential to contribute meaningfully to guideline-based practice, referral decision-making and educational support for clinicians.

Future Directions

Future work should explore integration with imaging modalities such as CT, CBCT and structured EHR data to support real-world deployment. A unified CDSS framework spanning multiple specialties could support shared decision-making and referral coordination across care settings

Conclusion

This perspective underscores the potential of clinical decision support systems (CDSS) to translate specialty guidelines into actionable support at the point of care. When designed with clinician supervision and grounded in established protocols, CDSS tools can reduce diagnostic variability, enhance referral quality, and support more coordinated care delivery. Although this prototype was developed within an oral health context, its rule-based, transparent architecture presents a replicable framework for other medical and surgical specialties.

Future development should prioritize interdisciplinary collaboration to design unified, adaptable workflows capable of integrating multiple specialty guidelines within a single CDSS platform. Such efforts would promote continuity of care, support general physicians, dental practitioners and specialists in decision-making, and advance the responsible adoption of AI in clinical environments. As health systems embrace digital transformation, clinician-centred CDSS will be instrumental in ensuring that evidence-based practices are consistently applied across care settings. To realize this vision, clinical societies, informatics teams, and health systems will need to collaborate on standardizing guideline encoding and cross-specialty CDSS workflows.

Conflict of Interest

The authors declare no conflict of interest.

Notes

The prototype software **Endodontic Case Assessment with AI** is available as a proof-of-concept and can be accessed on https://rootcanalai.vercel.app.

Views expressed in the paper are those of the author and do not represent views of the Indian Armed Forces.

References

Declaration of Generative AI and AI-Assisted Technologies in Manuscript Preparation

During the preparation of this work the author(s) used Notebooklm in order to assist with language refinement and structural organisation of the manuscript. After using this tool, the author(s) reviewed and edited the content as needed and take full responsibility for the content of the published article

1. Derksen C, Walter FM, Akbar AB, et al. The implementation challenge of computerised clinical decision support systems for the detection of disease in primary care: systematic review and recommendations. *Implement Sci*. 2025;20(1):33. Published 2025 Jul 17. doi:10.1186/s13012-025-01445-4

2. Peres MA, Macpherson LMD, Weyant RJ, et al. Oral diseases: a global public health challenge. *Lancet*. 2019;394(10194):249-260. doi:10.1016/S0140-6736(19)31146-8

3. Sutton RT, Pincock D, Baumgart DC et al. An overview of clinical decision support systems: benefits, risks, and strategies for success. *NPJ Digit Med*. 2020;3:17. Published 2020 Feb 6. doi:10.1038/s41746-020-0221-y

4. Newton N, Bamgboje-Ayodele A, Forsyth R et al. A systematic review of clinicians' acceptance and use of clinical decision support systems over time. *NPJ Digit Med*. 2025;8(1):309. Published 2025 May 26. doi:10.1038/s41746-025-01662-7

5. Vani A, Kan K, Iturrate E, et al. Leveraging clinical decision support tools to improve guideline-directed medical therapy in patients with atherosclerotic cardiovascular disease at hospital discharge. *Cardiol J*. 2022;29(5):791-797. doi:10.5603/CJ.a2020.0126

6. Camacho J, Zanoletti-Mannello M, Landis-Lewis Z et al . A Conceptual Framework to Study the Implementation of Clinical Decision Support Systems (BEAR): Literature Review and Concept Mapping. *J Med Internet Res*. 2020;22(8):e18388. Published 2020 Aug 6. doi:10.2196/18388

7. Roshanov PS, Fernandes N, Wilczynski NL, et al. Features of effective computerised clinical decision support systems: meta-regression of 162 randomised trials. BMJ. 2011;346:f657.

8. Glick M, Williams DM, Kleinman DV et al. A new definition for oral health developed by the FDI World Dental Federation opens the door to a universal definition of oral health. *J Am Dent Assoc*. 2016;147(12):915-917. doi:10.1016/j.adaj.2016.10.001

9. Watt RG, Daly B, Allison P, et al. Ending the neglect of global oral health: time for radical action. *Lancet*. 2019;394(10194):261-272. doi:10.1016/S0140-6736(19)31133-X

10. American Association of Endodontists-Endodontic Case Difficulty Assessment Form and Guidelines Patient Information. Accessed January 21, 2026. https://www.aae.org/specialty/wp-content/uploads/sites/2/2022/01/CaseDifficultyAssessmentFormFINAL2022.pdf

11. American Association of Endodontists- AAE Consensus Conference Recommended Diagnostic Terminology. Accessed January 21, 2026. https://www.aae.org/specialty/wp-content/uploads/sites/2/2017/07/aaeconsensusconferencerecommendeddiagnosticterminology.pdf

12. Duncan HF, Kirkevang LL, Peters OA, et al. Treatment of pulpal and apical disease: The European Society of Endodontology (ESE) S3-level clinical practice guideline. *Int Endod J*. 2023;56 Suppl 3:238-295. doi:10.1111/iej.13974

13. Chen W, Howard K, Gorham G, et al. Design, effectiveness, and economic outcomes of contemporary chronic disease clinical decision support systems: a systematic review and meta-analysis. *J Am Med Inform Assoc*. 2022;29(10):1757-1772. doi:10.1093/jamia/ocac110

14. Bright TJ, Wong A, Dhurjati R, et al. Effect of clinical decision-support systems: a systematic review. *Ann Intern Med*. 2012;157(1):29-43. doi:10.7326/0003-4819-157-1-201207030-00450

15. Kwan JL, Lo L, Ferguson J, et al. Computerised clinical decision support systems and absolute improvements in care: meta-analysis of controlled clinical trials. *BMJ*. 2020;370:m3216. Published 2020 Sep 17. doi:10.1136/bmj.m3216

16. Baysari MT, Del Gigante J, Moran M, et al. Redesign of computerized decision support to improve antimicrobial prescribing. A controlled before-and-after study. *Appl Clin Inform*. 2017;8(3):949-963. Published 2017 Sep 13. doi:10.4338/ACI2017040069

17. Van Onna M, Boonen A. The challenging interplay between rheumatoid arthritis, ageing and comorbidities. *BMC Musculoskelet Disord*. 2016;17:184. Published 2016 Apr 26. doi:10.1186/s12891-016-1038-3

18. Wiest IC, Bhat M, Clusmann J, Schneider CV, Jiang X, Kather JN. Large language models for clinical decision support in gastroenterology and hepatology. *Nat Rev Gastroenterol Hepatol*. 2025;22(11):773-787. doi:10.1038/s41575-025-01108-1

19. Subherwal S, Bach RG, Chen AY, et al. Baseline risk of major bleeding in non-ST-segment-elevation myocardial infarction: the CRUSADE (Can Rapid risk stratification of Unstable angina patients Suppress ADverse outcomes with Early implementation of the ACC/AHA Guidelines) Bleeding Score. *Circulation*. 2009;119(14):1873-1882. doi:10.1161/CIRCULATIONAHA.108.828541

20. Forrester M, Breitenfeld L, Castelo-Branco M, Aperta J. Identification of an oncological clinical pathway through questionnaires to health professionals. *BMC Health Serv Res*. 2023;23(1):1011. Published 2023 Sep 20. doi:10.1186/s12913-023-09964-w

21. Oehring R, Ramasetti N, Ng S, et al. Use and accuracy of decision support systems using artificial intelligence for tumor diseases: a systematic review and meta-analysis. *Front Oncol*. 2023;13:1224347. Published 2023 Oct 4. doi:10.3389/fonc.2023.1224347

22. Labinsky H, Ukalovic D, Hartmann F, et al. An AI-Powered Clinical Decision Support System to Predict Flares in Rheumatoid Arthritis: A Pilot Study. *Diagnostics (Basel)*. 2023;13(1):148. Published 2023 Jan 1. doi:10.3390/diagnostics13010148

23. Viitanen J, Hyppönen H, Lääveri T, Vänskä J, Reponen J, Winblad I. National questionnaire study on clinical ICT systems proofs: physicians suffer from poor usability. *Int J Med Inform*. 2011;80(10):708-725. doi:10.1016/j.ijmedinf.2011.06.010

24. Shortliffe EH, Sepúlveda MJ. Clinical Decision Support in the Era of Artificial Intelligence. *JAMA*. 2018;320(21):2199-2200. doi:10.1001/jama.2018.17163

25. Liberati EG, Ruggiero F, Galuppo L, et al. What hinders the uptake of computerized decision support systems in hospitals? A qualitative study and framework for implementation. *Implement Sci*. 2017;12(1):113. Published 2017 Sep 15. doi:10.1186/s13012-017-0644-2

26. Carayon P, Wooldridge A, Hose BZ et al. Challenges And Opportunities For Improving Patient Safety Through Human Factors And Systems Engineering. *Health Aff (Millwood)*. 2018;37(11):1862-1869. doi:10.1377/hlthaff.2018.0723

27. Khairat S, Marc D, Crosby W et al. Reasons For Physicians Not Adopting Clinical Decision Support Systems: Critical Analysis. *JMIR Med Inform*. 2018;6(2):e24. Published 2018 Apr 18. doi:10.2196/medinform.8912

28. Obermeyer Z, Powers B, Vogeli C, Mullainathan S. Dissecting racial bias in an algorithm used to manage the health of populations. *Science*. 2019;366(6464):447-453. doi:10.1126/science.aax2342

29. Okunseri C, Okunseri E, Thorpe JM, Xiang Q, Szabo A. Medications prescribed in emergency departments for nontraumatic dental condition visits in the United States. *Med Care*. 2012;50(6):508-512. doi:10.1097/MLR.0b013e318245a575

30. U.S. Food and Drug Administration. Artificial Intelligence and Machine Learning in Software as a Medical Device. Accessed January 21, 2026. https://www.fda.gov/medical-devices/software-medical-device-samd/artificial-intelligence-and-machine-learning-software-medical-device

31. Ye J. Beyond binary diagnosis: Key questions on AI accuracy, real-world applicability, and safety in clinical decision support. *Int J Med Inform*. Published online January 17, 2026. doi:10.1016/j.ijmedinf.2026.106292 30.

32. Paredes AA, Banoub RG, Gill GS, et al. A Review of Recent Developments in Artificial Intelligence and Big Data Technologies for Ophthalmology Referrals and Clinical Practice. *Med Sci Monit.* 2026;32:e950686. Published 2026 Jan 15. doi:10.12659/MSM.950686 31.

33. Yu SY, Lin HP, Kung YM, Chen SC. Artificial intelligence-enhanced clinical reasoning in nurse practitioners: A systematic review. *Nurse Educ Pract*. Published online January 13, 2026. doi:10.1016/j.nepr.2026.104724

34. Angeli Gazola A, Bishop NS, Schmid BE, et al. Evaluating AI-based comprehensive clinical decision support for sepsis and ARDS: protocol for a Clinician Turing Test. *BMJ Open*. 2025;15(12):e106757. Published 2025 Dec 24. doi:10.1136/bmjopen-2025-106757

35. Xu R, Xia Y, Zhang L, Xu W, Wen J, Jiang L. Medical domain knowledge-enhanced automatic decision support for traumatic brain injury: protein nutrition intervention for traumatic brain injury. *Arch Physiol Biochem*. Published online December 22, 2025. doi:10.1080/13813455.2025.2600337

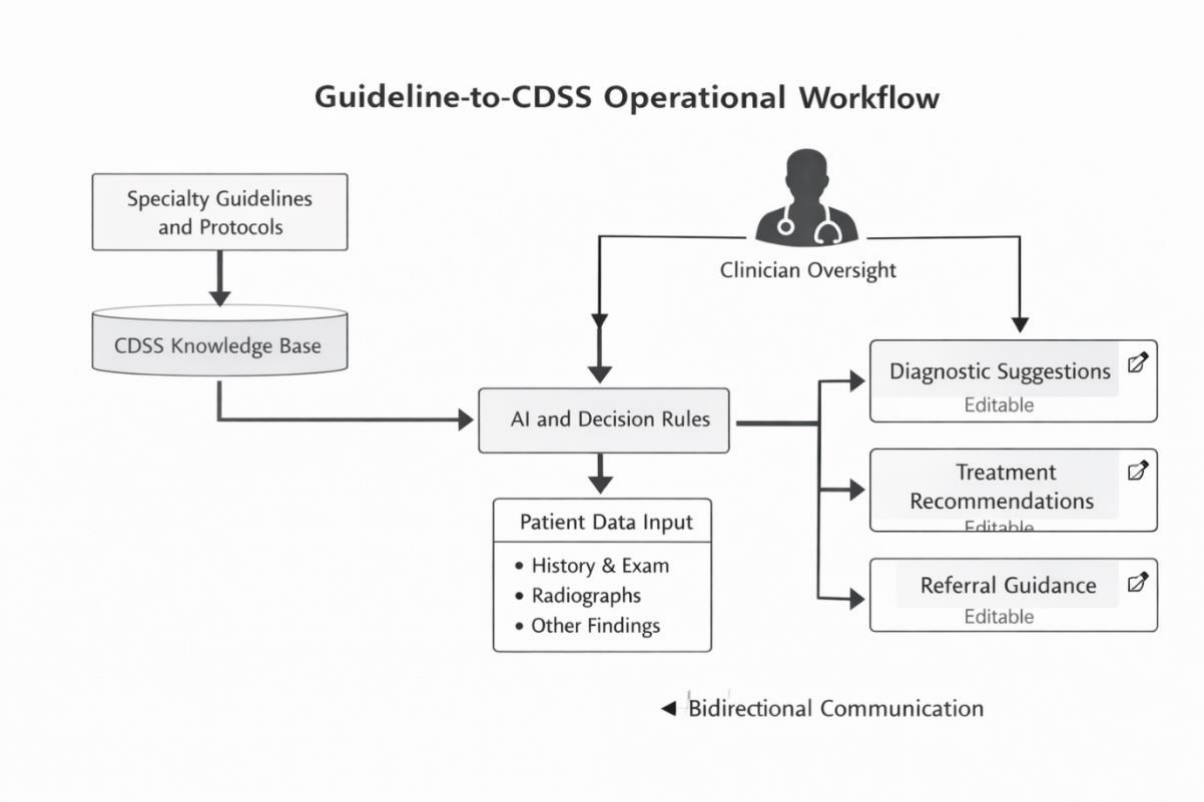


Figure 1. Guideline-to-CDSS Operational Workflow. Specialty clinical guidelines (e.g. diagnostic and treatment protocols from professional societies) are encoded into the CDSS knowledge base. Clinician-entered patient data (history, exam, imaging, investigations) are processed using these rules and AI models. The CDSS generates structured outputs—such as diagnostic suggestions, treatment plans, and referral recommendations—that align with guideline logic.

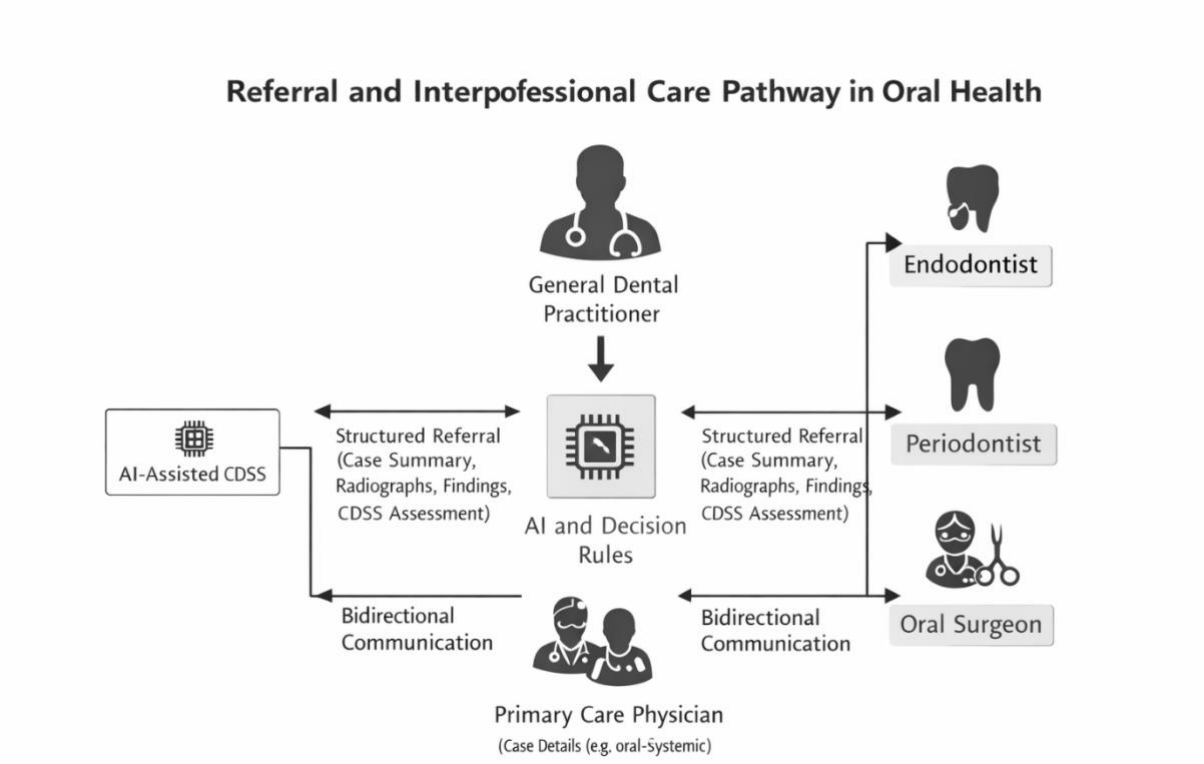


Figure 2. Referral and Interprofessional Care Pathway in Oral Health. A general dental practitioner (center) coordinates care with dental specialists (endodontist, periodontist, oral surgeon) and a primary care physician. An AI-assisted CDSS helps triage patients and generate structured referrals. Communication is bidirectional: generalists send cases to specialists (with relevant data and CDSS assessment), and specialists send reports back, enabling collaborative care.

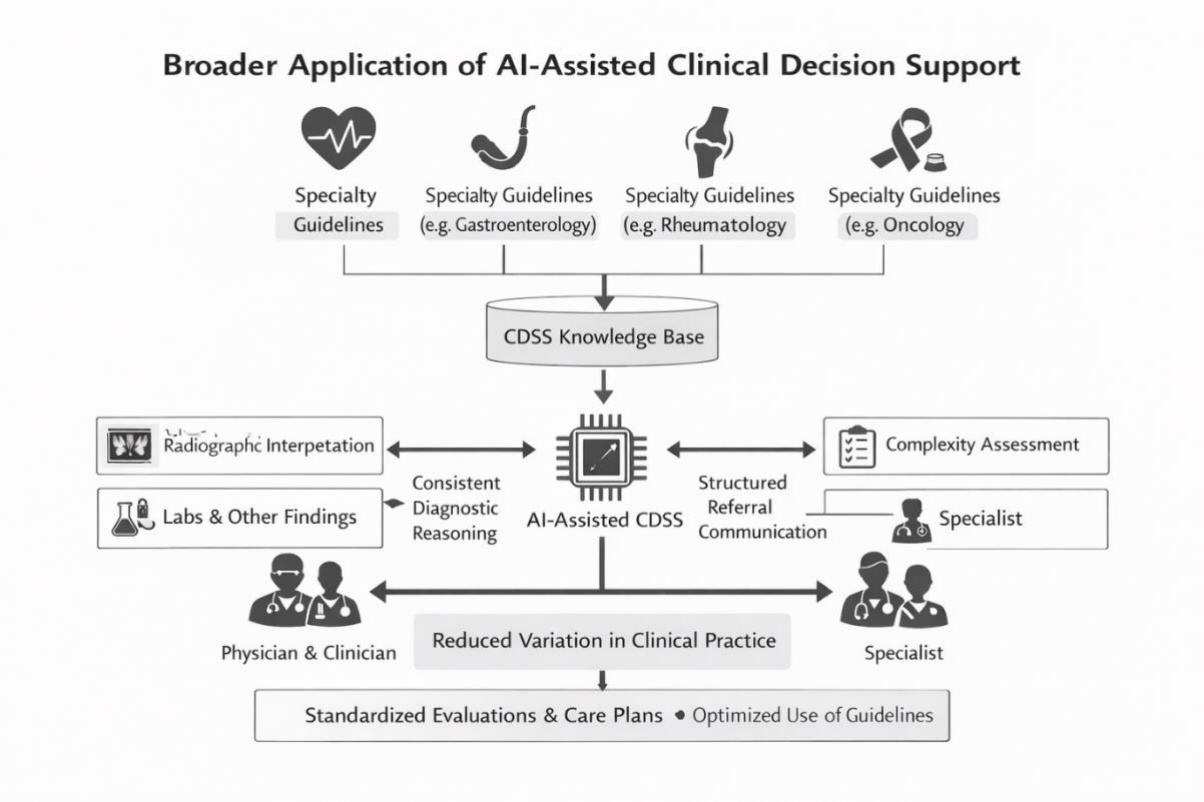


Figure 3. Cross-Speciality Implementation of Clinician-Supervised AI-Based Clinical Decision Support Systems (CDSS).

Case Study

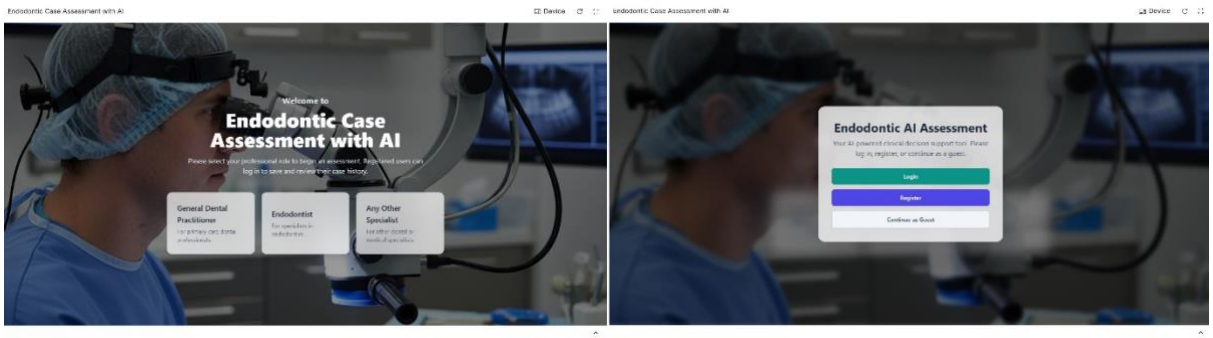


Figure 4: Demonstration- Endodontic case assessment with AI (Role Selection / Landing Page)

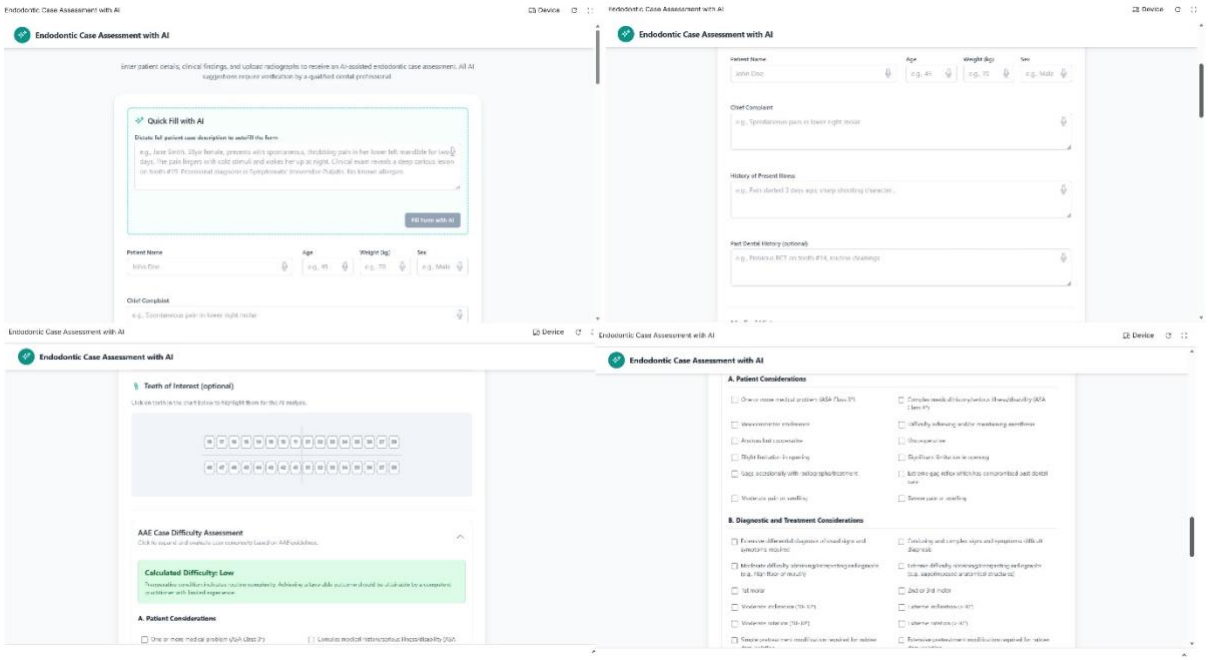


Figure 5: Application User Interface

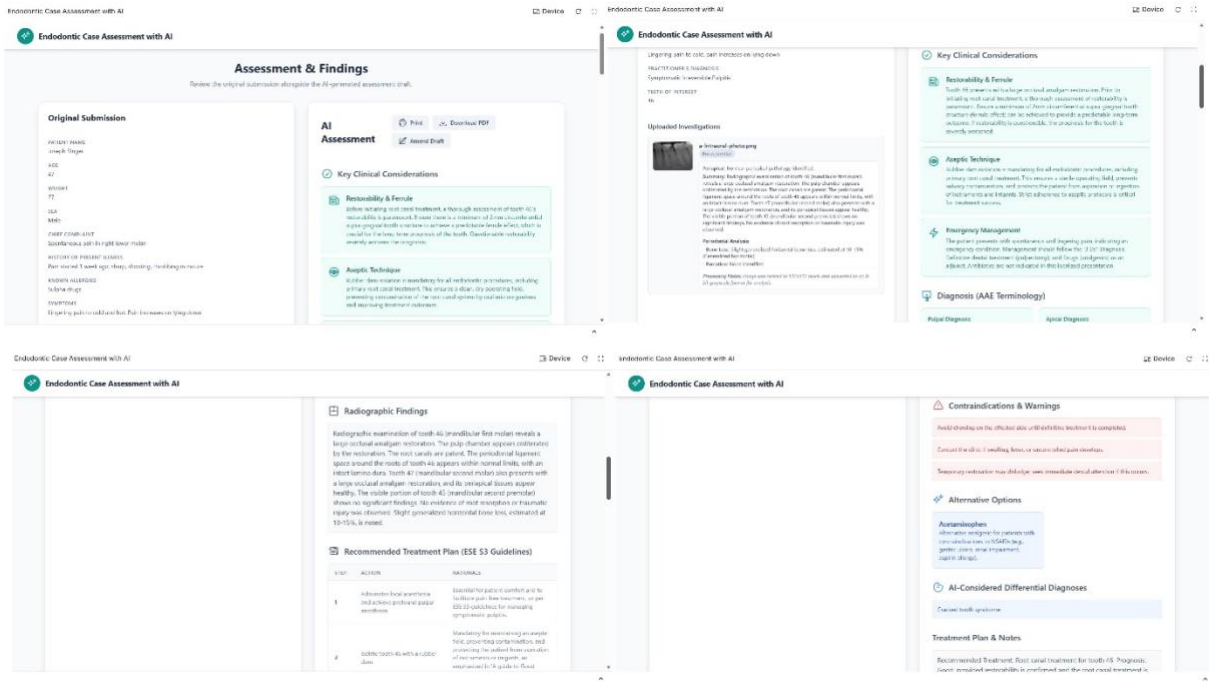


Figure 6: Case Assessment (Fully editable)

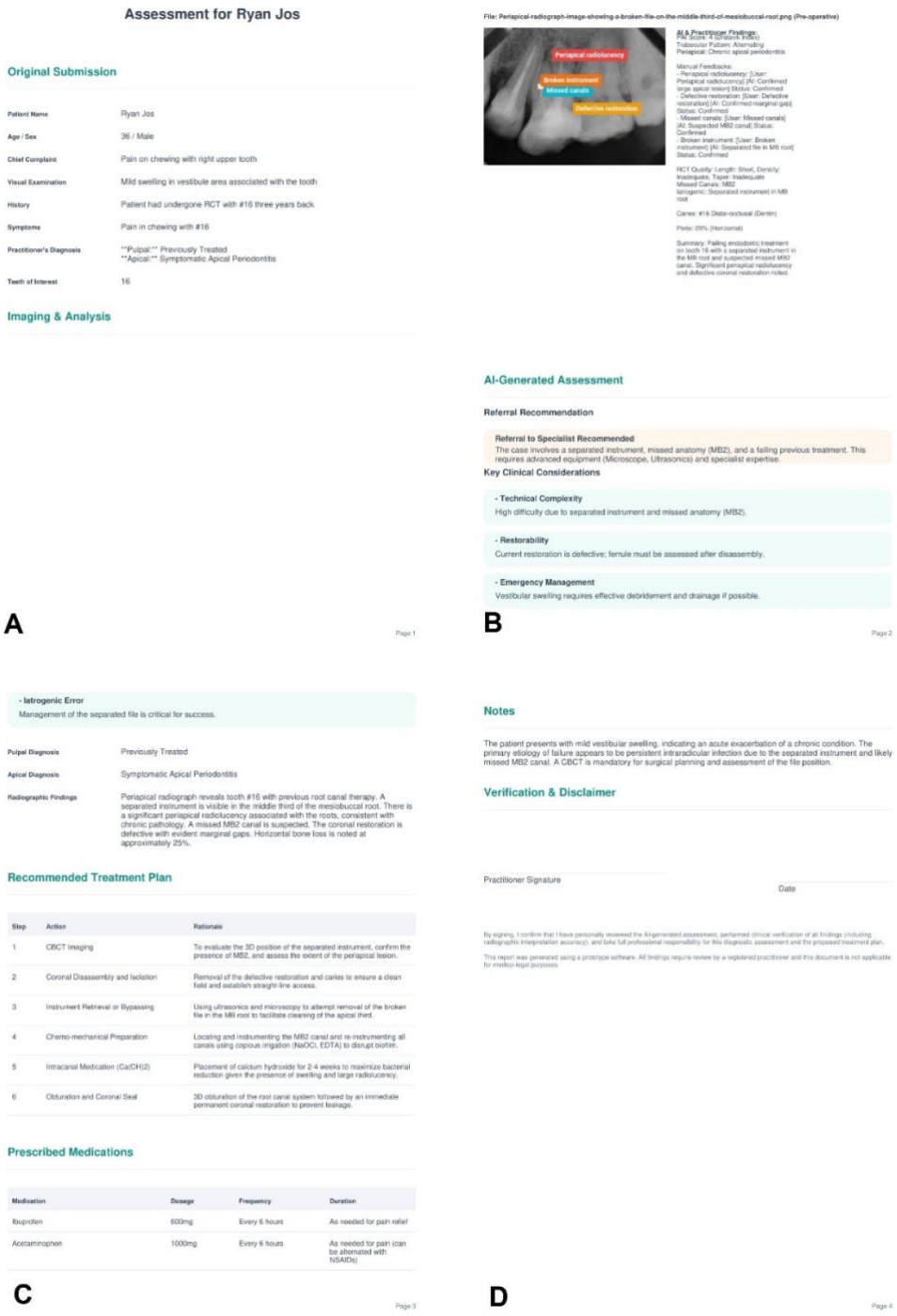


Figure 7. Standardised case report generated by the CDSS showing **A.** Clinician-entered submission data. **B.** Guideline-based assessment and referral recommendation. **C.** Treatment plan and medications. **D.** Documentation elements for referral and continuity of care.

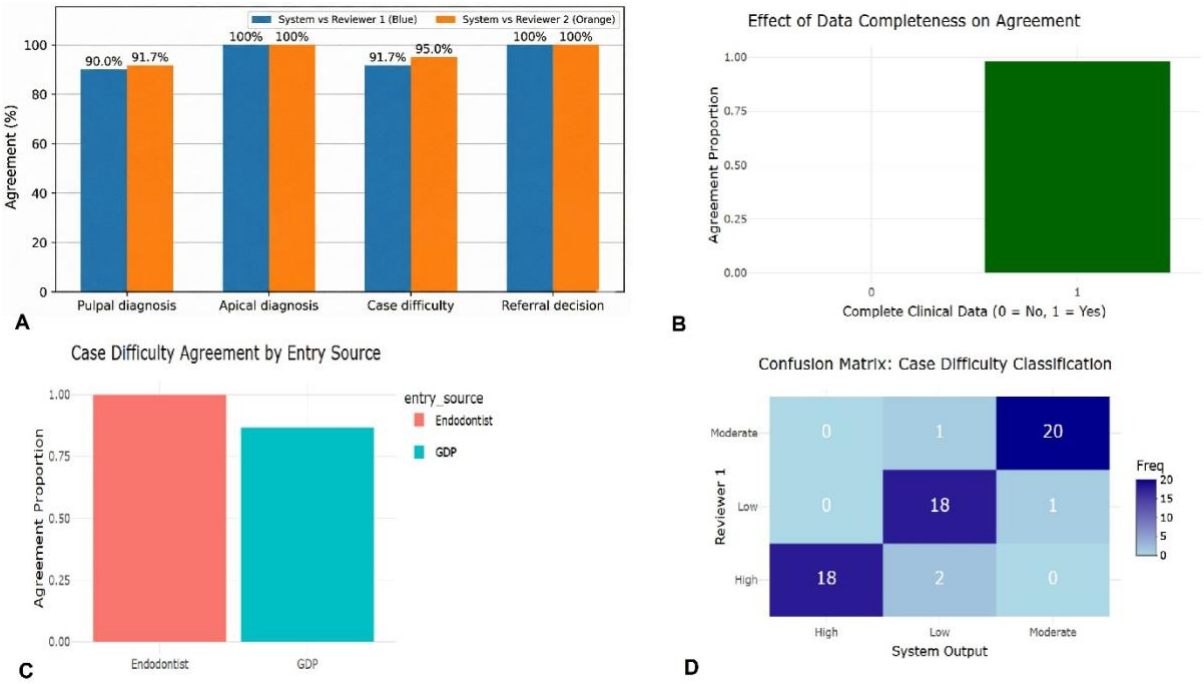


Figure 8. Agreement profiles between the CDSS and blinded expert endodontists across diagnostic and management domains. **A**. Percentage agreement between system and reviewers 1 & 2. **B.** Effect of data completeness on agreement proportion. **C.** Agreement proportion for endodontist-entered versus general dental practitioner-entered cases. **D.** Confusion matrix for case difficulty classification.