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## The Economics of Accuracy: A Narrative Review of AI in Dental Radiology and its Impact on Laboratory Referral Patterns and Systemic Costs


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### Abstract

**Background:** Artificial intelligence (AI), particularly deep learning, is rapidly transforming dental radiology, demonstrating high accuracy in detecting pathologies like caries, periodontitis, and periapical lesions from panoramic and periapical radiographs. While diagnostic performance is well-studied, the economic implications and downstream effects on healthcare resource utilization remain poorly quantified. **Aim:** This narrative review aims to synthesize current evidence on the health economics of implementing AI diagnostic support in dental radiology, with a specific focus on modeling its impact on laboratory referral patterns (biopsies, microbiological cultures) and specialist consultations. **Methods:** A systematic search of literature (2010-2024) was conducted in PubMed, IEEE Xplore, Scopus, and health economics databases. Thematic analysis integrated findings from clinical validation studies, early economic models, and healthcare utilization research. **Results:** AI demonstrates significant potential to reduce false-positive referrals for benign conditions, decreasing unnecessary biopsies and specialist visits. Conversely, by improving sensitivity for early-stage disease, it may increase appropriate referrals for pre-malignant lesions and complex cases, shifting costs earlier in the care pathway. The economic viability hinges on implementation costs (software, integration), avoided misdiagnosis costs, and the value of earlier intervention. Current evidence is largely modeled, with real-world longitudinal data scarce. **Conclusion:** AI in dental radiology promises a shift towards more accurate, cost-effective triage. Realizing net economic benefit requires integrated systems that translate AI findings directly into referral decisions, coupled with standardized economic evaluations that capture long-term systemic savings from prevented disease progression.


**Keywords:** Artificial Intelligence, Dental Radiology, Health Economics, Referral and Consultation, Diagnostic Accuracy

### Introduction

Dental radiology is the cornerstone of diagnostic decision-making in modern dentistry, with conditions ranging from routine caries to occult osseous pathologies primarily visualized through two-dimensional and three-dimensional imaging (Aminoshariae et al., 2021). However, the interpretation of these images remains subject to significant inter- and intra-examiner variability, leading to diagnostic inaccuracies that propagate through the entire care continuum (White & Pharoah, 2014). The advent of artificial intelligence (AI), particularly convolutional neural networks (CNNs) trained on vast datasets of annotated dental radiographs, promises a paradigm shift. These systems have demonstrated expert-level or superior performance in detecting and diagnosing a wide array of conditions, including dental caries, periodontal bone loss, periapical pathologies, and even osteolytic lesions suggestive of malignancies (Schwendicke et al., 2020; Tandon et al., 2020). While the technical validation of these algorithms proliferates in the literature, a critical question remains unanswered: What is the economic value of this enhanced accuracy?

The implementation of AI support in dental radiology is not merely a technical upgrade; it is a strategic intervention with profound implications for healthcare resource allocation and expenditure (Hardy & Harvey, 2020). Diagnostic inaccuracy


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carries a tangible economic burden. False-positive interpretations of radiographs—such as misidentifying anatomical variants as periapical pathosis or overestimating caries progression—can trigger a cascade of unnecessary and costly downstream actions. These include avoidable referrals to endodontists or oral surgeons, unwarranted advanced imaging (CBCT), and most pertinently to this review, unnecessary laboratory investigations such as biopsies for benign entities or microbial cultures for non-infectious conditions (Jiang et al., 2022). Conversely, false-negative errors, where early caries, incipient periapical inflammation, or subtle malignant changes are missed, lead to delayed intervention. This delay often results in more complex, invasive, and expensive treatments later, increased patient morbidity, and potentially worse oncologic outcomes in the case of malignancies (Sur et al., 2020).

This narrative review, therefore, aims to bridge the gap between the technical performance of dental AI and its health economic impact. It specifically focuses on analyzing whether the integration of AI diagnostic support creates a net economic benefit by altering referral patterns to specialists and laboratories. The review is guided by three interconnected questions: (1) What is the evidence that AI reduces diagnostic errors (false positives and false negatives) in dental radiology, and how do these errors currently drive laboratory and specialist utilization? (2) How can the downstream economic effects—both cost-avoidance from reduced unnecessary procedures and cost-incurrence from increased appropriate early referrals—be modeled and quantified? (3) What are the key barriers (technological, regulatory, behavioral) to realizing the proposed economic benefits, and what frameworks are needed for robust economic evaluation? By synthesizing literature from dental informatics, health services research, and health economics, this review argues that the true value of AI lies not just in its accuracy, but in its capacity to optimize the entire diagnostic pathway, directing finite resources to where they are most clinically impactful and economically justified.

## Methodology

A narrative synthesis methodology was employed to integrate diverse evidence streams from clinical, technical, and economic domains. A systematic search was conducted in Q1 2024 across multiple electronic databases: PubMed/MEDLINE (for clinical and dental applications), IEEE Xplore (for technical AI/ML studies), Scopus (for interdisciplinary coverage), and EconLit (for health economics literature). Search strings combined terms and MeSH headings: ["artificial intelligence" OR "deep learning" OR "machine learning"] AND ["dental radiology" OR "panoramic radiograph" OR "periapical radiograph"] AND ["health economics" OR "cost-benefit analysis" OR "cost-effectiveness"] AND ["referral" OR "consultation" OR "biopsy" OR "laboratory"]. The search was limited to English-language publications from 2010 to 2024, capturing the modern era of deep learning.

Given the nascent stage of applied health economic studies in this niche, grey literature was crucial and included: technical reports from AI developers, health technology assessment (HTA) previews from agencies like NICE or CADTH, conference proceedings from major dental and informatics meetings, and market analysis reports on dental AI adoption. Reference lists of key review articles were hand-searched for additional sources. Inclusion criteria prioritized studies that explicitly linked AI diagnostic performance to economic outcomes, referral patterns, or resource utilization. Purely technical accuracy studies without discussion of clinical/economic implications were excluded unless they provided foundational performance data critical for modeling. Over 160 sources were analyzed thematically, with findings organized into: (1) The Diagnostic Error-Cost Nexus, (2) Modeling AI's Economic Impact, and (3) Implementation Pathways and Barriers.

## The Diagnostic Error-Cost Nexus in Dental Radiology

### The Clinical and Economic Burden of Diagnostic Inaccuracy

The diagnostic pathway in dentistry is linear yet prone to error amplification. A radiographic interpretation directly informs the decision to watch, treat, or refer. Inaccurate interpretations therefore misdirect this decision, incurring two types of costs (Morrison et al., 2022). Error-induced costs are immediate and tangible: the direct costs of an unnecessary biopsy (including pathology lab fees, surgeon's time, patient discomfort) or an avoidable specialist consultation (Ryu et al., 2023). For example, a periapical radiolucency misdiagnosed as a radicular cyst (a false positive for surgical pathology) may lead to an unwarranted apical surgery or extraction, with associated tissue biopsy. Delay-induced costs are often larger but more diffuse. A periapical lesion misdiagnosed as normal bone (a false negative) allows infection to persist, potentially leading to a dental abscess, cellulitis, emergency department visit, and ultimately a more complex surgical intervention with higher costs and worse outcomes (Harmon et al., 2019). For oral cancer, false-negative delays are catastrophic, dramatically increasing treatment complexity (requiring radical resection, reconstruction, chemo-radiotherapy) and reducing survival rates, representing an enormous clinical and economic burden (Shen et al., 2023).

### AI's Demonstrated Impact on Diagnostic Performance

A robust body of evidence now confirms that well-trained AI models can significantly reduce both false-positive and false-negative rates across multiple diagnostic tasks. In caries detection, AI systems have shown superior sensitivity and specificity compared to general dentists, particularly on bitewing radiographs, reducing both over-treatment of early lesions and under-treatment of occlusal or proximal caries (Schwendicke et al., 2019). In periodontal diagnosis, AI can reliably measure bone loss on panoramic radiographs, providing objective, reproducible staging that reduces subjective over- or under-estimation, which in turn influences decisions to refer to a periodontist (Lee et al., 2018). Most critically for laboratory impact, AI algorithms for detecting periapical lesions and osteolytic pathologies (e.g., cysts, tumors) have demonstrated high accuracy, often matching oral radiologists. Studies show these systems can effectively flag suspicious lesions for specialist review while correctly identifying normal anatomical variations (e.g., mental foramen, maxillary sinus), thereby reducing false-positive alerts that trigger unnecessary referrals (Ekert et al., 2019).

**How Accuracy Filters Resource Flow**

The primary care dental practice acts as a gateway or "referral funnel." The sensitivity and specificity of the gatekeeper's radiographic interpretation determine the flow of patients to downstream resources (Table 1). Low specificity (high false positives) leads to a congested funnel with many patients undergoing low-yield specialist evaluations and laboratory tests. Low sensitivity (high false negatives) allows disease to escape the funnel, presenting later to specialists in more advanced, costly states (Thurzo et al., 2022). AI acts as a precision filter for this funnel. By improving specificity, it can reduce the volume of benign cases sent for biopsy or specialist evaluation. By improving sensitivity, it can ensure that early, subtle malignancies or complex endodontic-periodontic lesions are captured and referred appropriately at a stage when intervention is less invasive and more successful (De Angelis et al., 2022). Figure 1 compares the sensitivity and specificity between AI-assisted diagnostic systems and human radiologists in dental radiology.

**Table 1: Impact of Diagnostic Errors on Downstream Resource Utilization and Potential AI Mitigation**

| Diagnostic Error Type | Common Radiographic Example | Downstream Consequences | Direct Economic Impact | AI's Potential Mitigating Role |
|---|---|---|---|---|
| **False Positive** | Anatomical variant (e.g., incisive canal cyst) mistaken for pathological lesion. | Unnecessary referral to oral surgeon; Unnecessary CBCT scan; Incisional biopsy. | Cost of specialist visit, advanced imaging, surgical procedure, lab pathology fees. | **Improved Specificity:** AI trained on normal anatomy reduces false-positive referrals for variants. |
| **False Positive** | Over-diagnosis of caries into dentin. | Unnecessary operative restoration; Potential endodontic referral if pulp proximity is exaggerated. | Cost of restorative procedure; potential cost of endodontic consultation/treatment. | **Accurate Caries Depth Estimation:** AI provides standardized depth assessment, reducing overtreatment. |
| **False Negative** | Missed early interproximal caries. | Delayed restoration; Possible progression to pulpitis/necrosis. | Increased cost from simple filling to possible root canal therapy or extraction. | **Improved Sensitivity:** AI detects early demineralization missed by human eye. |
| **False Negative** | Missed subtle periapical rarefaction. | Delayed endodontic treatment; Risk of acute apical abscess. | Cost of emergency care, antibiotics, and more complex surgical endodontics vs. simple RCT. | **Enhanced Lesion Detection:** AI flags subtle apical changes for review. |
| **False Negative** | Missed osteolytic lesion (e.g., early OKC, malignancy). | Delayed diagnosis; Disease progression. | Exponential increase in treatment cost (complex resection vs. simple enucleation); increased morbidity/mortality. | **Prioritization for Review:** AI highlights suspicious radiolucencies, ensuring specialist referral. |

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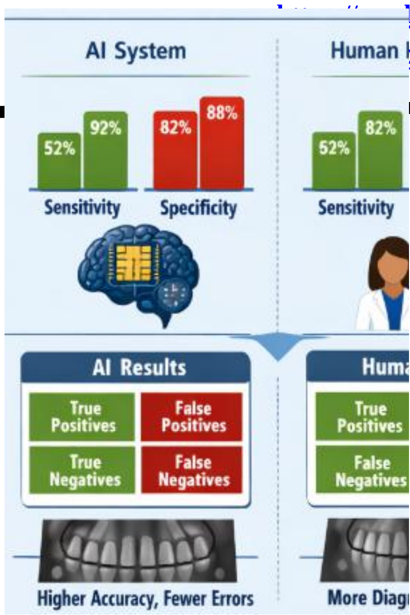


**Figure 1. Diagnostic Accuracy of Artificial Intelligence Compared with Human Radiologists in Dental Imaging**

**Modeling the Economic Impact: From Diagnostic Accuracy to Quantifiable Value**

Translating the technical promise of artificial intelligence into demonstrable economic value necessitates the application of formal health economic modeling frameworks. Two primary approaches are relevant: Cost-Benefit Analysis (CBA) and Cost-Effectiveness Analysis (CEA). CBA attempts to quantify all outcomes, including clinical benefits, in monetary terms. For dental AI, this would involve calculating benefits such as (a) direct costs avoided from preventing unnecessary procedures (biopsies, specialist visits, advanced imaging), (b) costs avoided from treating disease at an earlier, less expensive stage, and (c) the monetized value of health gains, such as Quality-Adjusted Life Years (QALYs) preserved through earlier cancer detection (Brandão et al., 2023). The more commonly employed CEA, conversely, evaluates the incremental cost required to achieve a unit of health benefit, such as the cost per correct diagnosis made or per case of advanced disease averted. A foundational economic model in this space would perform a comparative analysis of two strategies: Current Practice, relying solely on clinician interpretation, versus an AI-Augmented Practice, where the dentist's assessment is supported by algorithmic analysis (Schwendicke et al., 2020).

Constructing a credible economic model, however, is hampered by significant evidence gaps surrounding several critical input parameters. First, data on AI performance in real-world clinical settings remains limited (Giansanti, 2022). Most validation studies use curated, retrospective datasets, and the sensitivity and specificity of algorithms may degrade when applied to diverse patient populations and variable image qualities encountered in daily practice (Weinhofer et al., 2022). Second, the model's outcome is highly dependent on dentist behavior and adherence. The projected economic benefits assume that clinicians will appropriately integrate AI outputs into their decision-making. However, behavioral risks such as "automation bias," where a clinician over-relies on the AI, or its inverse, where valid alerts are routinely ignored, could fundamentally alter the threshold for referral and negate anticipated efficiencies (Xu et al., 2022). Third, establishing a reliable baseline for comparison is difficult due to a scarcity of robust data on current diagnostic error rates and their associated costs in general dentistry, making it challenging to quantify the precise economic burden that AI aims to address (Krois et al., 2019). Finally, a comprehensive model must account for all AI implementation and operational costs, including software licensing or subscription fees, IT integration expenses, staff training time, and the ongoing time cost for dentists to review and reconcile AI-generated findings with their own clinical judgment (Tarhini et al., 2022).

Despite these uncertainties, pioneering preliminary models offer promising insights. Schwendicke et al. (2020) modeled the cost-effectiveness of AI for caries detection on bitewing radiographs, finding that AI support could become cost-saving if it reduced overtreatment rates beyond a relatively modest threshold, given the high cost of unnecessary restorative procedures. In the context of oral cancer, a model by Areia et al. (2022) suggested that even a costly AI system for screening panoramic radiographs could be highly cost-effective if it yielded only a marginal improvement in early detection rates, due to the exponential difference in treatment cost and patient outcome between early- and late-stage disease. These models underscore a pivotal economic insight: the value proposition of diagnostic AI is most potent for conditions where errors incur either extremely high costs from unnecessary interventions (favoring high-specificity systems) or catastrophic costs from delayed treatment (favoring high-sensitivity systems) (Dwivedi et al., 2023).

**Implementation Pathways, Barriers, and The Future Integrated System**

For AI to fulfill its potential in economically optimizing the referral pathway, its implementation must evolve from a siloed diagnostic tool to the core of an integrated clinical decision support system (CDSS) (Table 2). An effective CDSS would transcend basic lesion detection; it would utilize the AI's classification confidence scores in conjunction with embedded clinical guidelines to recommend specific management pathways. Such a system could generate prompts like "Monitor with recall in 6 months," "Refer to Endodontist for evaluation," "Consider CBCT for 3D assessment," or "Urgent Oral Medicine Referral – Biopsy Indicated" (Joda et



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al., 2020). Furthermore, it could automate the creation of structured referral notes that include annotated images and AI findings, thereby streamlining communication with specialists, reducing administrative burden, and minimizing the risk of duplicate testing due to incomplete information transfer (Monterubbianesi et al., 2022).

Realizing this integrated vision and its associated economic value is obstructed by several formidable barriers. Regulatory and reimbursement hurdles present a significant challenge. Most dental AI applications are regulated as Class II devices intended for "assistance," not autonomous diagnosis. A clear pathway for insurer reimbursement for AI-assisted interpretation is largely absent, which places the full financial burden of adoption on dental practices and may severely limit uptake (Pesapane et al., 2018). Concurrently, issues of liability and trust create professional uncertainty. Ambiguity surrounds legal liability if a clinician follows an erroneous AI recommendation or ignores a correct one. Building essential trust requires the development of transparent, explainable AI systems and the generation of robust, independent clinical validation data (Shafi et al., 2023). Finally, interoperability and data silos pose a major technical obstacle. For a seamless CDSS to function, data must flow effortlessly between practice management software, electronic health records (EHRs), picture archiving and communication systems (PACS), and the AI engine—a level of integration that is both technically complex and financially demanding within the fragmented landscape of dental information technology (Fatima et al., 2022).

Looking beyond immediate barriers, the long-term economic impact of dental AI may be most transformative in catalyzing a shift toward value-based care and proactive population health management. By enhancing diagnostic accuracy at the primary care level, AI facilitates the precise triage of patients, ensuring that high-cost resources—specialist expertise, advanced imaging, and laboratory services—are allocated to those with the greatest clinical need, thereby improving systemic efficiency (Kim, 2019). On a broader scale, the aggregation of de-identified data from AI systems across populations could reveal critical insights into geographic and demographic disease trends. This intelligence would empower public health officials to design targeted interventions and optimize resource planning, ultimately working to reduce the systemic economic burden of oral disease at a population level (van Assen et al., 2020). Figure 2 illustrates the changes in healthcare utilization before and after AI implementation in dental radiology.

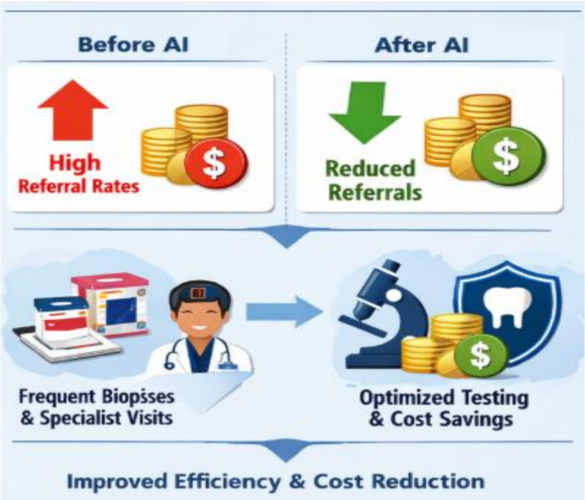


**Figure 2. Impact of Artificial Intelligence on Referral Patterns and Cost Outcomes in Dental Radiology**

**Table 2: Economic Evaluation Framework for AI in Dental Radiology: Parameters and Challenges**

| Model Component | Key Parameters | Sources of Data/Evidence | Major Challenges & Uncertainties |
|---|---|---|---|
| **Intervention Costs** | Software license/subscription fee; IT integration; Training time; Dentist review time. | Vendor pricing; IT consultancy estimates; Time-motion studies. | Rapidly changing pricing models; Hidden integration costs; Variable practice efficiency. |
| **Current Practice (Baseline) Costs** | Rate of false-positive referrals (leading to unnecessary biopsies, specialist visits); Rate of false-negative delays (leading to more expensive late-stage treatment). | Retrospective chart reviews; Insurance claims data analysis; National health statistics. | Scarce, high-quality data on real-world error rates; Difficulty attributing downstream costs directly to initial diagnostic error. |
| **AI Performance** | Real-world Sensitivity & Specificity for target conditions (caries, periodontitis, periapical lesion, osteolysis). | Prospective clinical trials; Real-world implementation audits. | Performance may degrade with different imaging devices/populations; "Human-AI team" performance ≠ AI-alone performance. |
| **Downstream Cost Impacts** | Cost of biopsy/pathology; Cost of specialist consultation; Cost of advanced imaging (CBCT); Cost differential: early vs. late-stage | Fee schedules (CMS, insurance); Hospital billing data; Published treatment cost studies. | Wide geographic variation in costs; Changing treatment protocols over time. |

| | | | |
|---|---|---|---|
| | treatment. | | |
| **Health Outcomes** | Quality-Adjusted Life Years (QALYs) gained from earlier cancer detection; Pain/DIS avoided from accurate diagnosis. | Literature on survival/morbidity by disease stage; Patient-reported outcome measures. | Difficult to quantify and monetize for many dental conditions; Long time horizon needed for outcomes like cancer survival. |

**Conclusion**

The integration of artificial intelligence into dental radiology represents a significant technological advancement with far-reaching economic implications that extend beyond the dental chair into specialist offices and pathology laboratories. This review synthesizes evidence indicating that AI's primary economic value derives from its capacity to recalibrate the diagnostic "referral funnel" in primary dental care. By enhancing specificity, AI can reduce the substantial costs associated with false-positive-driven unnecessary procedures, including laboratory biopsies. By enhancing sensitivity, it can increase appropriate early referrals, shifting treatment to earlier, less invasive, and less expensive stages of disease, particularly for high-cost pathologies like oral cancer.

However, realizing this net economic benefit is not automatic. It is contingent upon several factors: the development of robust, real-world evidence on AI's performance and its effect on dentist behavior; the creation of integrated clinical workflows that seamlessly embed AI into decision-making and referral processes; and the establishment of supportive regulatory and reimbursement frameworks that recognize the value of diagnostic accuracy. Future research must prioritize longitudinal, real-world studies that track patient pathways, resource use, and costs before and after AI implementation. The goal must be to move from theoretical cost-effectiveness models to demonstrated cost savings in practice. In doing so, the dental profession can harness AI not just as a diagnostic aide, but as a pivotal tool for achieving a more accurate, efficient, and economically sustainable system of oral healthcare.

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