



Health economic evaluation of artificial intelligence in dentistry

Evaluación económica en salud de la inteligencia artificial en odontología

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ABSTRACT

The health economic evidence on artificial intelligence in dentistry is thin, and this review maps what exists and what is missing. Direct cost-effectiveness evidence is confined to a small number of studies, chiefly a cost-effectiveness model and a randomized trial of artificial intelligence for caries detection, both of which find that the economic value depends on the clinician's baseline accuracy, on the cost of the software, and on how the detection changes treatment, not on the algorithm's accuracy alone. The evidence on workflow and time efficiency is more substantial but is rarely translated into monetary terms, and the evidence on implementation and infrastructure costs, on equity and access, and on reimbursement and adoption is almost entirely absent from the dental literature, so the economic case for dental artificial intelligence currently rests on analogy with medical imaging and on assumptions rather than on demonstrated value. The review organizes the evidence along five thematic axes, cost-effectiveness, efficiency, implementation cost, equity, and adoption, and concludes that the field's next step is not more accuracy studies but economic evaluations that measure what the technology costs and what it changes in the care pathway, reported to the standards that health economics has already established.

Keywords: artificial intelligence; cost-effectiveness; health economics; dentistry; efficiency.

RESUMEN

La evidencia económica en salud sobre la inteligencia artificial en odontología es escasa, y esta revisión traza lo que existe y lo que falta. La evidencia directa de coste-efectividad se limita a un número reducido de estudios, principalmente un modelo de coste-efectividad y un ensayo aleatorizado de inteligencia artificial para la detección de caries, ambos los cuales concluyen que el valor económico depende de la precisión basal del clínico, del coste del programa y de cómo la detección cambia el tratamiento, no solo de la precisión del algoritmo. La evidencia sobre eficiencia de tiempo y de flujo de trabajo es más abundante, pero rara vez se traduce a términos monetarios, y la evidencia sobre costes de implementación e infraestructura, sobre equidad y acceso, y sobre reembolso y adopción está casi ausente de la literatura dental, por lo que el argumento económico de la inteligencia artificial dental descansa hoy en la analogía con la imagen médica y en supuestos más que en valor demostrado. La revisión organiza la evidencia en cinco ejes temáticos, coste-efectividad, eficiencia, coste de implementación, equidad y adopción, y concluye que el siguiente paso del campo no son más estudios de precisión sino evaluaciones económicas que midan lo que la tecnología cuesta y lo que cambia en la vía de atención, comunicadas con los estándares que la economía de la salud ya ha establecido.

Palabras clave: inteligencia artificial; coste-efectividad; economía de la salud; odontología; eficiencia.

INTRODUCTION

Artificial intelligence in dentistry is usually judged by its accuracy, and the literature is correspondingly rich in studies that report a sensitivity, a specificity, or an area under the curve, and correspondingly poor in studies that report what the technology costs and what it changes in the patient's care. The two questions are related but distinct: an algorithm can detect caries more accurately than a clinician and still be a poor investment, if the improvement is small, the software is expensive, or the additional detections do not change treatment in a way that actually improves health.(1)

The dental artificial-intelligence literature is now large and still growing, spanning detection, segmentation, planning, and language models, and its reviews describe a field that is technically ambitious but whose applications are repeatedly framed in terms of accuracy rather than value.(2-4)

The framing matters because it sets the field's own standard of success: a study that reports an improvement in accuracy considers itself complete, and a study that reports what that improvement costs, or whether it changes a treatment decision, is the rare exception rather than the rule, which is why the economic question, though asked in the field's titles and introductions, is so infrequently answered in its results. Health economics exists to answer the second question, the question of value, and its near absence from the dental artificial-intelligence literature is the starting point of this review, a starting point that mirrors the wider history of artificial intelligence in medicine, where the economic evaluation has consistently lagged the technical demonstration, often by years, and where that lag has repeatedly meant that technically sound tools failed to reach practice for want of an economic case.(5,6)

Dentistry is now at the point where that history would predict: the accuracy literature is mature, and the economic literature is not, and the review is an attempt to mark the gap before the field, like its predecessors, discovers it the hard way. The consequence is that a clinician, a payer, or a ministry deciding whether to adopt a dental artificial-intelligence tool currently has very little economic evidence on which to base the decision, and must either extrapolate from medical imaging or proceed on faith, and neither of those is a sound basis for spending.(6)

The economic question is not an afterthought but a precondition, because the adoption of a technology into routine care is, in most health systems, a spending decision, and spending decisions are made, or should be made, on the comparison of cost and consequence. The tools of health economics, the cost-effectiveness analysis, the budget-impact analysis, and the standardized reporting framework that makes them comparable, exist for exactly this purpose, and they are no less applicable to a dental algorithm than to a drug or a device, because an algorithm, like a drug, consumes resources and produces health, and the comparison of the two is the same arithmetic wherever it is applied, in dentistry no less than in oncology.(7)

This review therefore organizes its synthesis around five thematic axes that together constitute the economic case: cost-effectiveness, the comparison of the additional cost of artificial intelligence against the additional health it produces; efficiency, the time and workflow savings that are the technology's most commonly claimed benefit; implementation and infrastructure cost, the fixed and recurring expense of running the technology in a real practice; equity and access, whether the technology narrows or widens the gap between those who receive care and those who do not; and adoption and reimbursement, the regulatory and payment context that determines whether an economically sound tool is actually taken up. Each axis has a different maturity of evidence in dentistry, and the contrast between them is itself a finding, because a field that has invested in one axis and neglected the others has, in effect, answered only part of the question a payer would ask.

The five axes are not a checklist imposed from outside but a decomposition of the single question that a payer asks of any technology, whether the health it buys is worth what it costs, and each axis is one of the terms that the answer requires, a term without which the answer is incomplete and, therefore, unusable.

The objective of this review was to map the health economic evidence on artificial intelligence in dentistry and to identify what a credible economic case would require. The review anticipates those five axes and, in doing so, states its central claim: the economic evidence on dental artificial intelligence is concentrated on efficiency and almost empty on cost-effectiveness, implementation, and equity, and the consequence is that the field's economic case is, at present, more an analogy than an argument.

The analogy is to medical imaging, where cost-effectiveness and budget-impact studies of artificial intelligence are more numerous and more mature, and where the same lesson recurs, that value depends on the baseline, the cost, and the pathway, not on the algorithm alone.(8,9) What dentistry needs to borrow from that literature is not its conclusions but its method, and the review

closes by spelling out the evaluations that would turn the analogy into evidence, evaluations that are, as the review shows, within the reach of the studies the field already conducts, were they to measure and report the economic parameters they currently omit.

DEVELOPMENT

Cost-effectiveness: the core evidence is two studies

The direct cost-effectiveness evidence in dental artificial intelligence is, to the best of this review's retrieval, confined to two studies, both concerned with caries detection and both from the same research group, and their near-solitude is the most important fact about this axis. The solitude is not for want of a suitable target: caries detection is the oldest and best-studied application of dental artificial intelligence, the disease is common enough that small per-patient changes aggregate into large system effects, and the decision-support framing, an algorithm that augments a clinician's reading rather than replacing it, is exactly the framing that cost-effectiveness analysis is designed to evaluate, so the fact that only one group has done the evaluation speaks to the field's priorities rather than to any inherent difficulty.⁽¹⁾

The first is a cost-effectiveness model that assessed artificial intelligence as a decision-support system for the detection and grading of melanoma, dental caries, and diabetic retinopathy, and it found that the value of the system depends critically on the clinician's baseline accuracy, because an artificial-intelligence tool adds most where the human reader is weakest, and adds little where the human is already accurate.⁽¹⁰⁾

The second is a randomized controlled clustered trial of artificial-intelligence-supported proximal caries detection, which measured cost-effectiveness directly and reached the same qualitative conclusion, that the tool's value is conditional on the baseline, the software cost, and the change in treatment decisions, rather than on the detection accuracy alone.⁽¹¹⁾

The two studies also share a methodological property that the rest of the field lacks: they model or measure the treatment consequence of the additional detections, not just the detections themselves, and it is this step, from detection to consequence, that turns an accuracy result into an economic one, and that the field's accuracy studies, however careful, do not take.

The step is where the value is actually created or lost, because a detection that changes no treatment produces no health however accurate it is, and a detection that changes a treatment from invasive to preventive, or from late to early, produces the health that the accuracy alone cannot capture, which is why the two studies, by taking the step, are the field's only economic evidence rather than merely its best. The two studies are methodologically serious and are the field's best evidence, but two studies, both in caries, both by one group, do not constitute a generalizable economic case, and the rest of dental artificial intelligence, segmentation, orthodontics, implants, oral cancer, has no cost-effectiveness evidence at all.

The contrast with medical imaging is stark and instructive: cost-effectiveness studies of artificial intelligence in lung-cancer screening and in colorectal-cancer risk stratification exist and report their incremental cost-effectiveness ratios explicitly, and they show, as the dental studies do, that the conclusion is sensitive to the baseline, the cost, and the pathway, but they also show that the evaluation can be done and reported to a standard that dentistry has not yet approached.^(12,13)

The absence of such studies in dentistry is not a gap that a single paper can close, but it is a gap that a single well-conducted economic evaluation in each major application would begin to close, and none yet exists.

Efficiency: the most reported, least monetized benefit

The efficiency axis is where the dental literature is richest, and also where it is least economic, because the studies measure time and workload but in most cases do not attach a monetary value to the savings. The efficiency claim is plausible on its face, because much of dental work is repetitive and image-based, and an algorithm that performs a routine analysis in seconds where a clinician takes minutes is, in principle, a direct saving of the most expensive input in the practice, the clinician's time, but a saving of time is only an economic benefit if the freed time is used for something of value, and no dental study measures what happens to the saved time, which is the step that separates a workflow observation from an economic result.

The most direct evidence is the cephalometric-analysis work, which found that a web-based artificial-intelligence platform performs the analysis faster and more cheaply than manual tracing,

and the artificial-intelligence-assisted diagnostics work that used eye-tracking to show how the tool changes the clinician's reading behavior, both of which point to the same benefit, that artificial intelligence compresses the time of a routine task.(14,15)

The eye-tracking study is worth singling out, because it measures the efficiency benefit not as a claim but as a change in where the clinician looks and how long they take, and it is precisely this kind of behavioral measurement, rather than a self-reported time saving, that an economic analysis would need as its input, so the study is, in effect, half of an economic evaluation that has not yet been completed.

The cone-beam-generated cephalogram work adds the same point in a different way, by showing that artificial-intelligence cephalometric analysis can substitute for a step that would otherwise require additional imaging or manual labor, a substitution that is itself an economic decision, because the avoided step has a cost and the substituted step has a price, and the study measures the substitution without pricing either side of it.(16)

The implant-planning and digital-smile-design literature reports the efficiency of automated planning in similar terms, as a saving of clinical time whose economic value is asserted rather than calculated, and the broader reviews of the future of dental implants and of risk assessment in caries management frame the same benefit as a matter of personalization and precision, without translating it into a price, which is the same pattern at a higher level of generality.(17-20)

The virtual-reality training literature adds an adjacent efficiency, the time and cost of education, and the data-augmentation work adds the efficiency of using scarce data more completely, both of which are economic in nature but reported without an economic frame.(21,22)

The recurring pattern is that efficiency is demonstrated and monetization is left to the reader, and the consequence is that the field's most common claim, that artificial intelligence saves time, is its least quantified in the terms that a payer would recognize.

The monetization step is not a technical nicety but the difference between an observation and an argument: a payer cannot reimburse a saving of minutes, but it can reimburse a procedure or a consultation, and until the saved time is expressed as a redeployed activity with a price, the efficiency literature, however careful, remains upstream of the decision it is meant to inform.

Implementation and infrastructure cost: a mostly blank axis

The cost of running artificial intelligence in a real dental practice, the hardware, the software subscription, the integration with existing imaging systems, the training, and the maintenance, is almost entirely absent from the dental literature, and what exists is indirect. The omission is consequential because these costs are not trivial and are not optional: a practice that adopts a detection or segmentation tool commits to a recurring software fee, a workflow that depends on the tool's availability, and a training burden for its staff, and these costs, not the one-time purchase, are what determine whether the adoption pays for itself, yet the dental literature reports none of them.

The medical-imaging literature provides the nearest evidence, with protocols and evaluations of artificial intelligence in chest diagnostics that measure implementation cost and experience explicitly, mixed-methods studies of lung-cancer detection software that assess clinical effectiveness and acceptability alongside the workflow change, and economic evaluations of digital technologies in vision care that attach costs to the deployment, and these are the templates that dentistry has not yet applied to itself.(23-25)

The cost-effectiveness model of Gomez Rossi and colleagues incorporates a software-cost assumption and shows, in sensitivity analysis, that the conclusion flips with the price, which is a warning that the economic case for dental artificial intelligence is fragile to a parameter that the dental literature in most cases does not even state.(10)

The absence of implementation-cost data means that a dental practice cannot currently budget for adoption, and a payer cannot estimate the budget impact, and this axis is therefore not so much weakly evidenced as unmeasured. The gap is all the more striking because implementation cost is where the economic case is most likely to be decided in practice: a tool whose software fee is low relative to the time it saves will be adopted even without a formal study, and a tool whose fee is high will be rejected however accurate it is, so the parameter that the literature omits is precisely the parameter that the market will set in its absence.

The omission also matters for the field's own credibility, because a technology whose proponents cannot state what it costs to run is a technology whose economic claims, however enthusiastic, rest on an unexamined term, and the absence of the number invites the suspicion that the number, were it stated, would not support the enthusiasm, a suspicion that only the field itself can dispel by stating it.

Equity and access: promise without demonstration

The equity axis is where the promise of dental artificial intelligence is strongest and its evidence is weakest. The argument is that artificial intelligence, particularly in the form of teledentistry and smartphone-based tools, could extend care to populations that currently receive none, and the teledentistry evidence-gap map and the portable-dentistry and access studies document that the reach problem is real and that digital tools are being proposed to address it.(26-28)

The argument has a clear economic form, because the populations that receive no care are also the populations whose disease burden is highest and whose treatment, once reached, is least expensive, so the economic case for extending reach is, in principle, strong, and the absence of the demonstration is a gap of evidence rather than a failure of the logic.

The intraoral-photograph screening work and the mobile-health acceptability studies show the mechanism, that a low-cost capture device and an automated analysis can bring screening to a setting that has no specialist, and the tele-ophthalmology referral trial in the medical literature demonstrates that the same logic, a connected pathway with artificial-intelligence support, can be evaluated for its effect on referral and outcome, which is the economic demonstration that the dental literature lacks, and which, once conducted for dentistry, would be the equity axis's first piece of evidence.(29-31)

The national oral-health strategy documents that equity is now an explicit policy goal in some systems, and a policy that names equity as a goal has, by naming it, committed itself to asking whether a given technology serves it, which is another way of saying that the economic evaluation, with its explicit accounting of who benefits and who pays, is the instrument that such a policy needs.(32)

What is missing is the economic demonstration, the evidence that an artificial-intelligence tool, deployed in an underserved setting, actually improves access or outcomes at a cost that the system can bear, and the analogue studies in low- and middle-income settings, of artificial-intelligence-assisted screening in cervical cancer and other conditions, show both that the demonstration is possible and that it is not automatic, because the cost of the tool can consume the benefit if it is not deliberately controlled.(33)

The equity question is also the place where the economic case for dental artificial intelligence is, in principle, strongest, because the baseline accuracy of the clinicians who serve underserved populations is, on average, lower, and the cost-effectiveness studies show that the tool's value is highest where the baseline is lowest, which means the very settings that the economic literature has neglected are the settings where the value is likely to be largest, an inversion that the field has not yet exploited.(10)

The dental literature, so far, stops at the promise, and the promise, without the demonstration, is not yet an argument a ministry can act on.

Adoption, reimbursement, and regulation: the gate that is not yet open

The adoption axis concerns the regulatory and payment context, and here the dental literature is informative but thin. The Food and Drug Administration's clearance of a periodontal-diagnosis artificial-intelligence model was a milestone, and the reviews of cleared dental devices document that the number of regulated dental artificial-intelligence products is growing, but clearance is not reimbursement, and the gap between a cleared device and a paid-for service is where many medical artificial-intelligence tools have stalled.(34,35)

Clearance establishes that a device is safe and does what it claims; it says nothing about whether a payer will reimburse its use, and in the absence of a reimbursement code or a payment pathway, a cleared device can remain unused however accurate it is, which is why the adoption axis, more than any other, determines whether the economic case, once made, is ever realized.

The general literature on the challenges of delivering clinical impact with artificial intelligence is explicit that adoption fails at the workflow, the trust, and the payment, more than at the accuracy, and the dental reviews of how to evaluate artificial-intelligence papers, and of the peer-review and governance questions it raises, point to the same gap in the dental context.(6,36,37)

The governance point is itself economic, because a tool whose evidence is not evaluable is a tool whose value cannot be priced, and the reviews of how to evaluate dental artificial-intelligence papers are therefore, in effect, laying the evidentiary groundwork that the economic evaluation requires, a groundwork that is only now being laid. The patient-trust and public-attitude studies add the demand side, showing that acceptance of artificial-intelligence advice is real but conditional, and that acceptance, like accuracy, is a parameter the economic model must include, because a tool that patients decline is a tool that produces no health however accurate it is.(38,39)

The large-language-model studies, which test whether models can answer crown-restoration inquiries, detect supernumerary teeth from radiographs, predict treatment-autonomy preferences, or pass licensing examinations, belong to this axis in a different way, because they raise the question of what a general-purpose model adds over a purpose-built tool, and whether that addition is worth its cost, a question that no study yet prices.(40-43)

The general-purpose model is, in economic terms, a different proposition from the purpose-built one: it is already paid for by its developer, it is accessible through an interface the clinician already knows, and it can be repurposed across tasks, which may make its marginal cost near zero even as its marginal value is uncertain, and this difference, between a model whose cost is sunk and a device whose cost must be recovered, is one the reimbursement discussion has not yet absorbed, and one that may, in time, rewrite the economic case for dental artificial intelligence entirely.

The axis, in short, is where the technology meets the system, and the meeting has not yet produced, in dentistry, a clear pathway from accuracy to payment. The five axes and their evidence are summarized in (Table 1).

Table 1. Synthesis of the economic evidence by thematic axis.

Axis	Representative evidence	Maturity	Main gap
Cost-effectiveness	Caries detection model and RCT	Low	No evidence beyond caries
Efficiency	Cephalometric and workflow studies	Moderate	Time savings not monetized
Implementation cost	Indirect, via medical imaging	Very low	No dental cost data
Equity and access	Teledentistry and access studies	Low	Promise without demonstration
Adoption and reimbursement	FDA clearances, trust studies	Low	Clearance without payment

Note: Maturity reflects the strength and directness of the dental-specific evidence for each axis. Source: Summary of the reviewed literature.

DISCUSSION

The five axes, read together, reveal a field whose economic evidence is not so much weak as lopsided. The axis where the field has done the most work, efficiency, is the one that is least economic in form, because time savings are reported without being priced, while the axis that would be most decision-relevant, cost-effectiveness, is represented by two studies in a single clinical domain, and the axis that determines whether any of it matters, adoption, is represented by anecdotes of clearance rather than by evidence of payment.(6,11)

This lopsidedness is not accidental but follows from the incentives of a research field that rewards the demonstration of accuracy and leaves the economics to someone else, and the consequence is that the dental artificial-intelligence literature can claim technical maturity and economic immaturity at the same time, which is exactly where it now stands.

The lopsidedness is also a form of information asymmetry: the parties who could use economic evidence, the payers and the ministries, are not the parties who produce the accuracy studies, and the parties who produce the accuracy studies have no incentive to answer the economic question, so the question falls into the gap between them and remains unanswered.

The result is a market in which the technology is sold on a promise that the buyer cannot verify, and the buyer, in the absence of evidence, either refuses to buy, which is the safe choice, or buys on faith, which is the risky one, and neither outcome serves the field's stated goal of improving oral health, which is the ultimate purpose that the economic evaluation, whatever its axis, is ultimately meant to serve.

The two caries cost-effectiveness studies deserve to be read closely, because they are the field's best evidence and they are also the field's clearest warning. Both find that the value of artificial intelligence depends on the clinician's baseline accuracy, which is the single most transferable lesson of the axis: an algorithm that outperforms a specialist adds less than one that outperforms a novice, and the populations and settings where the tool would add most value, the underserved, the low-resource, the minimally trained, are exactly the settings where the economic evidence is thinnest.(10,11)

The same dependence on baseline recurs in the medical-imaging cost-effectiveness studies, in lung-cancer screening and colorectal-cancer risk stratification, where the incremental value of the algorithm is conditional on the same parameters, and this recurrence suggests the lesson is a

property of decision-support artificial intelligence generally rather than of dentistry specifically.(12,13)

The lesson has a direct implication for study design: an economic evaluation that is conducted in a specialist setting, where the baseline is high, will systematically underestimate the value that the same tool would deliver in a generalist or low-resource setting, and the field's habit of validating its tools in specialist settings therefore biases its economic evidence toward the settings where the value is least, a bias that compounds the neglect of the equity axis and that only a deliberate choice of study setting can correct.

This inversion, that the evidence is best where the value is least and worst where the value is greatest, is the review's most consequential finding, and it connects the cost-effectiveness axis directly to the equity axis, which the literature has kept separate but which an economic analysis cannot.

The relationship between the axes is the substance of the economic case, and the review's third point is that the axes must be analyzed together, not in isolation. A cost-effectiveness estimate that ignores implementation cost will overstate value, a workflow-efficiency study that ignores whether the saved time is redeployed will understate or overstate it, and an equity claim that ignores the cost of the tool will not survive contact with a budget.(10,23)

The five axes are in fact one system: efficiency determines the time a clinician can redeploy, implementation determines the fixed cost against which that redeployment is weighed, equity determines who receives the benefit, adoption determines whether the system is ever paid for, and cost-effectiveness is the summary statistic of the whole, which is why a literature that reports them separately, or reports one and omits the rest, cannot produce a coherent economic case however accurate its individual findings.

The medical-imaging literature reached this integration the hard way, through a series of studies that each initially reported one axis and were then assembled into the fuller picture, and dentistry can skip that intermediate step by adopting the integrated frame from the outset, a shortcut that the field's current position, with its accuracy literature already mature, makes available to it, and one that its late start on the economic question paradoxically permits.

The medical-imaging literature has learned to integrate these, with economic evaluations that carry the cost of deployment and the pathway change through to the incremental cost-effectiveness ratio, and the dental literature has not, which is why the dental economic case currently reads as a set of separate and incompatible claims rather than as a single, coherent argument.(8,9)

The cost-benefit study of artificial-intelligence-based triage in Parkinson's disease, and the systematic reviews of artificial intelligence for skin-cancer detection in primary care, are further examples from adjacent fields of the integrated evaluation that dentistry lacks, and they share with the dental studies the same dependence on baseline and setting that an economic analysis must make explicit.(44,45)

The transversal gaps follow directly. The field lacks, first, cost-effectiveness studies beyond caries; second, the monetization of the efficiency gains it already demonstrates; third, any measurement of implementation and infrastructure cost in dental practice; fourth, an economic demonstration of the equity benefit it claims; and fifth, a study of the reimbursement and payment pathway that would convert a cleared device into an adopted one.

These are not five separate gaps but one gap expressed five ways, the absence of the economic evaluation that would join the technology's demonstrated accuracy to its claimed value, and the review's agenda is therefore singular: conduct the evaluations that measure cost and consequence together, and report them to the standards that health economics has already established for every other technology.(7)

The standards are not optional decoration but the condition of comparability, because an economic result that cannot be compared to another is a result that cannot inform a choice, and a payer choosing between two dental artificial-intelligence tools, or between a tool and no tool, needs the comparison that only a standardized evaluation can provide. The agenda is realistic, because the inputs it requires, the baseline accuracy, the software cost, the time saved, and the treatment change, are all quantities that the existing accuracy studies already contain or could report with modest additional effort, and the obstacle is not feasibility but convention, the field's habit of stopping at the accuracy and calling the work done.

The agenda is also urgent, because the window in which a technology's economic case is made and its adoption decided does not stay open indefinitely, and a field that postpones its economic evaluation risks having the decision made for it, by default and without evidence, in the form of non-adoption that no subsequent accuracy study will reverse.

The review has limitations that follow from its method. It is narrative rather than systematic, its selection of sources is guided by relevance, and a systematic search of the economic literature

specifically might retrieve studies that this review's broader search did not surface, though the sparsity of the axis is unlikely to be an artifact of the search alone, because the same sparsity is reported by the reviews that have looked. It does not appraise the risk of bias of the individual studies with a formal tool, and its synthesis is qualitative, so the statements about value should be read as indicative rather than as quantitative findings.

The reliance on analogy with medical imaging, though justified by the thinness of the dental literature, is itself a limitation, because the economic parameters of dentistry, the lower unit costs, the different payment structures, and the different workforce, may not transfer cleanly, and the review's conclusions inherit that uncertainty.

The review also does not attempt its own economic modeling, and its statements about value are therefore a synthesis of the evidence rather than an independent estimate, and a reader who needs a specific incremental cost-effectiveness ratio for a specific tool in a specific setting will not find it here, because the field has not produced it.

These limitations bound the precision of the conclusions without changing their direction, which is that the economic evidence is thin and the economic question is open, and the openness is the point: the question is answerable, and the field has simply not answered it.

CONCLUSIONS

The health economic evidence on artificial intelligence in dentistry is thin, lopsided, and, at its best, concentrated in two cost-effectiveness studies of caries detection whose lesson is that value depends on the clinician's baseline, the cost of the software, and the change in treatment, not on the algorithm alone.

The efficiency benefit is demonstrated but not monetized, the implementation and infrastructure cost is unmeasured, the equity benefit is promised but not shown, and the reimbursement pathway is clear neither in evidence nor in practice.

The economic case for dental artificial intelligence therefore currently rests on analogy with medical imaging rather than on demonstration, and the field's next step is not more accuracy studies but economic evaluations that measure what the technology costs and what it changes in the care pathway, reported to the standards that health economics has already established.

Until those evaluations exist, the honest summary is that the technology has shown it can detect, and has not yet shown that it is worth paying for, and the two claims are different in kind, the first a technical achievement, the second an economic one, and the field has, so far, earned only the first.

The distinction is not a dismissal but a description of where the work stands, and it is offered in the expectation that the field, having mastered the technical question, will turn its attention, and its methods, to the economic one that is now the binding constraint on its usefulness.

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