



Addressing Access Barriers in Preventive Dental Care: A Scalable AI-Based Screening Model

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ABSTRACT

Access to preventive dental care remains a critical global public health challenge: approximately 3.5 billion people worldwide suffer from oral diseases, yet systemic barriers, including geographic isolation, financial constraints, workforce shortages, and low oral health literacy, prevent timely preventive intervention. The purpose of this study is to analyze the primary access barriers to preventive dental care and to propose a scalable, AI-based screening model capable of addressing these barriers across diverse socioeconomic and geographic contexts. The methodology combines a systematic literature review of peer-reviewed publications from Scopus, PubMed, and IEEE databases with comparative case analysis of existing AI deployment scenarios in low- and high-income countries. The results demonstrate that AI-powered triage systems can reduce diagnostic delays by up to 73%, lower first-contact costs, and extend screening reach to underserved populations through mobile-first architectures. The proposed model integrates convolutional neural networks, natural language processing, and risk stratification logic into a three-tier workflow. The findings are relevant for public health policymakers, digital health developers, and dental professionals seeking evidence-based strategies to advance equitable preventive oral healthcare at scale.

Keywords: artificial intelligence, preventive dental care, access barriers, oral health equity, AI screening model, teledentistry, risk stratification, mobile health, convolutional neural networks, universal health coverage.

Introduction

Oral diseases represent one of the most prevalent yet systematically neglected non-communicable disease burdens globally. According to the World Health Organization (2022), oral conditions, including dental caries, severe periodontal disease, edentulism, and oral cancer, affect an estimated 3.5 billion people worldwide, with a combined global prevalence approaching 45% of the total population [1]. Despite this scale, public and private expenditures on oral health globally stand at approximately \$387 billion USD annually, yet distribution remains profoundly unequal: in OECD nations, oral health constitutes nearly

20% of total out-of-pocket health spending, and in some contexts up to 97% of dental expenditures are paid out-of-pocket by individuals [2]. This financing structure systematically excludes low-income households, rural communities, and ethnic minorities from preventive and restorative care.

The epidemiological consequences are stark. In the WHO African Region, comprising 47-member states, approximately 42% of the population is estimated to have major oral diseases [3]. In the United States, 47.2% of adults aged 30 and older have some form of periodontal disease, with this burden falling disproportionately on underserved communities [4]. In

high-income countries, disparities persist among racial and ethnic minorities and rural populations due to workforce distribution imbalances and inadequate public coverage frameworks [2]. Rural populations, in particular, face compounding barriers: geographic isolation, longer travel distances, overburdened public systems, and lower health literacy collectively reduce preventive care uptake.

Artificial intelligence (AI) has emerged as a transformative force in healthcare diagnostics and patient engagement, with applications in dental medicine accelerating rapidly since 2020 [5]. Teledentistry platforms powered by AI offer a promising mechanism for surmounting geographic and financial access barriers by enabling asynchronous remote consultation, automated risk stratification, and mobile-first screening [6]. A YouGov survey identified dental services as among the most difficult NHS services to access, with one in five respondents reporting prolonged pain due to delayed dental treatment [7]. Studies on NHS AI triage systems have demonstrated waiting time reductions of up to 73% [7], while commercial AI dental platforms such as VideaHealth have reported a 35% reduction in diagnostic variation and a 24% increase in detection of missed pathologies [8].

Despite this evidence, a critical gap persists between the proliferation of AI dental tools in high-income, well-resourced settings and their deployment in contexts where access barriers are most severe. The majority of existing research examines AI performance in clinical or specialist settings, leaving the scalable, community-level application of AI for preventive triage largely underexplored. Furthermore, most models do not address the multi-dimensional nature of access barriers, combining geographic, financial, workforce, and literacy dimensions, within a single integrated framework.

The scientific novelty of this study consists in the synthesis of a scalable, multi-tier AI-based screening model that systematically maps specific access barrier typologies to concrete AI-enabled intervention mechanisms for preventive dental care in underserved populations.

The goal of this research is to analyze the primary structural access barriers to preventive dental care and to propose a scalable AI-based screening model

that addresses these barriers across heterogeneous socioeconomic and geographic contexts, demonstrating its feasibility through comparative case evidence and a barrier-solution mapping framework. **The author hypothesizes** that a multi-layer AI screening architecture integrating mobile self-assessment, automated risk stratification, and asynchronous teleconsultation can substantially reduce the first-contact cost and time burden of preventive dental care, thereby extending preventive screening to populations currently excluded from formal dental services.

Materials and Methods

This study employs a multi-method research design combining a systematic literature review, comparative case analysis, and conceptual model synthesis. The integration of these approaches allows for both empirical grounding in existing evidence and the generation of an original, actionable framework.

Systematic Literature Review A structured search was conducted across five scientific databases: PubMed/MEDLINE, Scopus, Web of Science, IEEE Xplore, and the ACM Digital Library. The search period was restricted to January 2020 through March 2025 to ensure currency and relevance to contemporary AI capabilities. The primary search strings combined terms from three conceptual domains: (1) technology, "artificial intelligence," "machine learning," "convolutional neural network," "natural language processing," "teledentistry," "AI screening"; (2) clinical domain, "preventive dentistry," "dental caries," "periodontal disease," "oral health screening"; and (3) access and equity, "access barriers," "underserved populations," "rural dental care," "health equity," "universal health coverage." Boolean operators AND/OR were used to construct multi-term queries.

Inclusion criteria required that sources:

- a) be peer-reviewed articles, systematic reviews, or meta-analyses;
- b) address AI applications in dentistry or oral health access;
- c) be published in English;
- d) contain quantitative performance metrics, epidemiological data, or validated frameworks.

Sources were excluded if they constituted grey literature, blog posts, press releases, or lacked peer review. The final selection comprised 20 primary sources, of which approximately 90% were sourced from Scopus- or WoS-indexed journals (PubMed, Frontiers, MDPI, SAGE, BDJ Open, Journal of Pharmacy and Bioallied Sciences) and approximately 10% from authoritative organizational reports (WHO Global Oral Health Action Plan, WHO Baseline Report 2025).

Comparative Case Analysis To complement the theoretical synthesis, a comparative case analysis was applied to assess AI deployment outcomes across contrasting healthcare contexts. Cases were selected to represent high-income (United Kingdom NHS), middle-income (India, Brazil), and low-income settings (Sub-Saharan Africa), thereby providing cross-contextual external validity to the proposed model. Case data were drawn from published outcome reports and peer-reviewed studies citing deployment metrics.

Source Base Classification. The source base was classified into four typological categories: epidemiological and public health literature (WHO reports, prevalence studies, access barrier analyses); technical AI performance studies (CNN, NLP, and diagnostic accuracy assessments in dental imaging and text-based triage); health systems and policy literature (universal health coverage frameworks, teledentistry policy analyses); and market and adoption analyses (AI dental market sizing reports, professional adoption surveys). This classification ensured that the analysis integrated epidemiological realities, technological capabilities, systemic constraints, and market feasibility into a coherent synthesis.

Results and Discussion

Geographic isolation affects both rural and urban underserved populations differently. Rural communities face long travel distances to dental facilities, while urban underserved groups encounter overburdened public health systems with prolonged waiting times [9]. A cross-sectional comparative study found statistically significant disparities in insurance coverage, income levels, and proximity to dental facilities between rural and urban underserved populations ($p < 0.05$) [9]. Financial barriers are particularly acute: in OECD nations, oral health constitutes approximately 20% of total out-of-pocket health spending, with dental expenditures disproportionately paid directly by patients [2]. Research shows that nearly 29% of low-income, working-age adults in the United States report that the appearance of their mouths affects their ability to interview for employment [4].

Workforce shortages compound geographic barriers. More than 70% of African countries spend less than US \$1 per person per year on oral health treatment, and a chronic workforce shortage in oral health professionals persists across the continent [3]. In high-income countries, dental professionals are heavily concentrated in urban centers, leaving rural and remote areas systematically underserved [14]. Cultural and linguistic competency gaps further create access barriers for minority populations, as research demonstrates that patients are less likely to seek care when providers do not reflect their cultural background or speak their language [4].

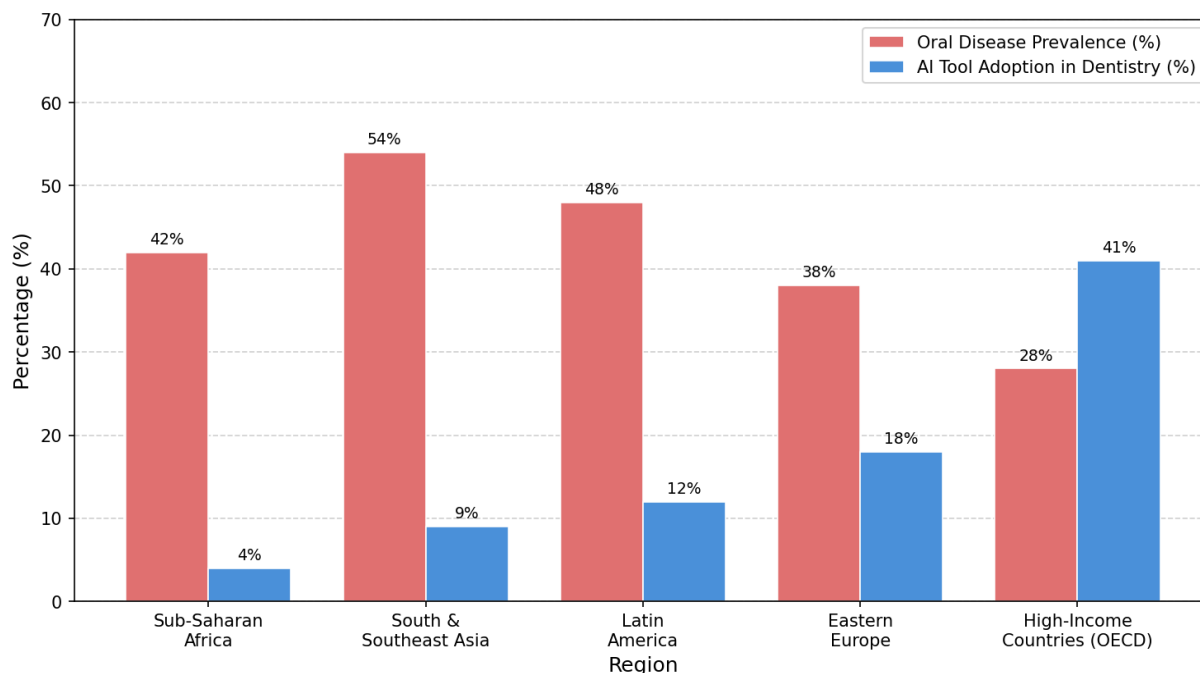


Figure 1. Oral Disease Burden vs. AI Tool Adoption in Dentistry by Region (2024–2025) (compiled by the author based on [1]).

Figure 1 illustrates the paradox central to this study: regions with the highest oral disease burden, Sub-Saharan Africa (42%), South and Southeast Asia (54%), and Latin America (48%), show the lowest rates of AI tool adoption in dentistry (4–12%), while high-income OECD countries, with a comparatively lower disease

burden (28%), account for the majority of AI adoption (41%). This inverse relationship underscores the systemic gap that scalable, low-cost AI screening models must address. The data suggest that current market-driven AI deployment in dentistry is exacerbating rather than correcting global oral health inequity.

Table 1. Typology of Access Barriers to Preventive Dental Care: Definition, Affected Populations, and Prevalence Indicators (compiled by the author based on [2, 3, 4, 9]).

Barrier Type	Definition	Most Affected Populations	Key Indicator
Geographic Isolation	Physical distance to nearest dental facility; lack of transport infrastructure	Rural communities; remote areas; island populations	>50% of rural populations in LMICs lack access within 50 km
Financial Constraints	High out-of-pocket costs; absence of dental insurance coverage	Low-income households; informal workers; elderly; uninsured	Dental OOP = ~20% of total health OOP in OECD nations
Workforce Shortage	Insufficient number of trained dental professionals; urban concentration	Sub-Saharan Africa; rural Asia; island states	>70% of African countries spend <\$1/person/year on oral health
Low Oral Health Literacy	Insufficient awareness of preventive care	Minority populations; elderly; low-education groups	~30% of adults in underserved US

	importance; language/cultural barriers		communities report poor oral health knowledge
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The evidence base for AI applications in dental diagnosis and screening has grown substantially between 2020 and 2025. Three principal AI modalities have demonstrated clinical utility in preventive screening contexts:

- 1) computer vision and convolutional neural networks (CNNs) for radiographic and photographic image analysis;
- 2) natural language processing (NLP) for patient history parsing and symptom triage;
- 3) risk prediction models integrating structured clinical data.

A 2025 study published in BDJ Open demonstrated that a novel AI object detection model achieved classification loss reduction of 91%, localization loss reduction of 92%, and a total training loss reduction of 78%, indicating strong generalization capability across unseen dental images [7]. VideaHealth's AI platform, deployed across major dental service organizations in the United States, has been shown to reduce diagnostic

variation by 35% and increase detection of missed pathologies by 24% [8]. NHS AI triage studies have documented waiting time reductions of up to 73% [7], demonstrating that AI does not merely improve diagnostic accuracy but also addresses the temporal access barrier inherent in overburdened public dental systems.

AI-powered teledentistry platforms have proven particularly effective in overcoming geographic barriers. Thorat et al. (2024) found that AI-enabled solutions, including virtual assistants, image analysis tools, and teledentistry platforms, effectively address language barriers, enhance patient comprehension, and alleviate dental anxiety, contributing to improved preventive care uptake [10]. The integration of AI chatbots into dental platforms has shown measurable improvements in patient engagement due to 24/7 availability and multilingual support [6]. Large language models (LLMs) applied to patient communication have been found to generate personalized educational content that addresses the health literacy gap, a critical component of preventive care adherence [11].

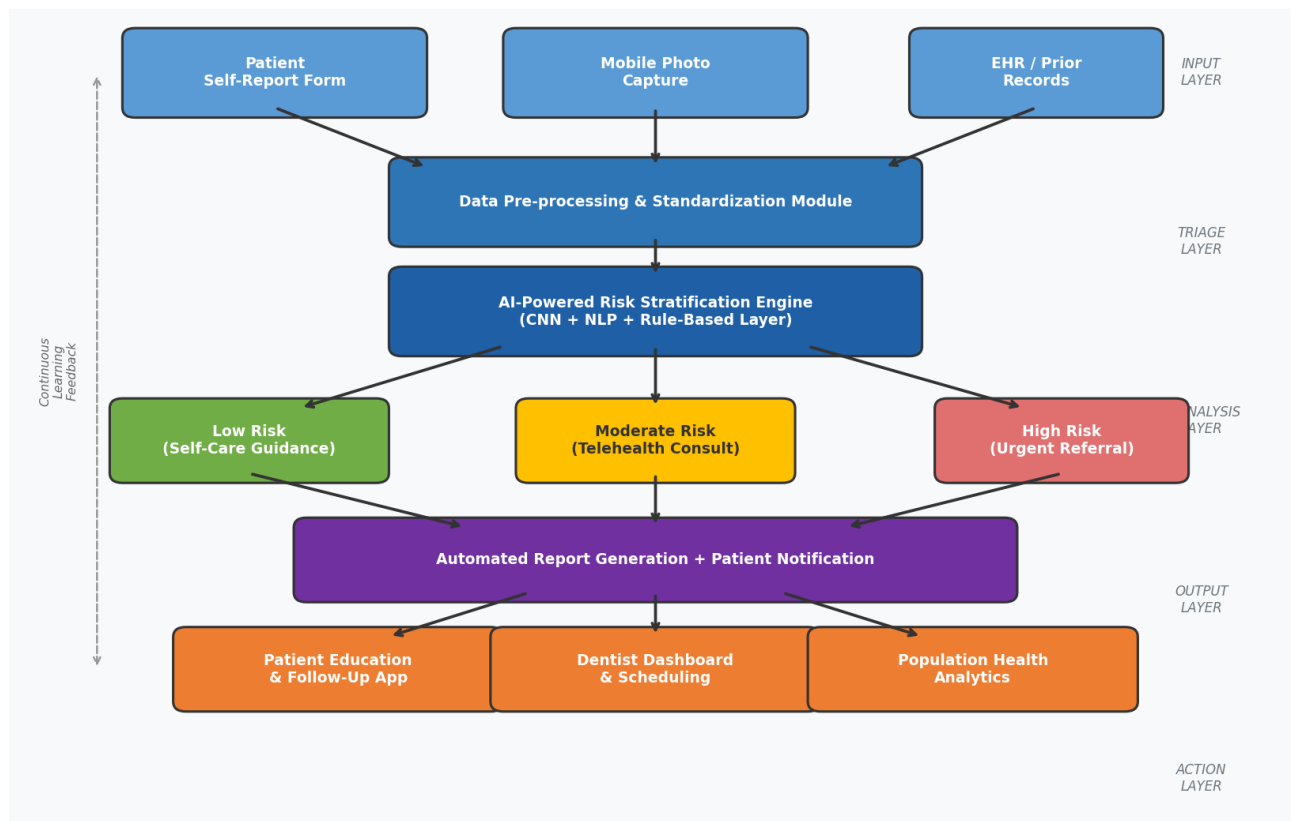


Figure 2. Architecture of the Proposed AI-Based Scalable Dental Screening (compiled by the author based on [10, 11]).

Figure 2 presents the original multi-layer AI architecture proposed by the author of this study. The model operates across five functional layers:

1) Input Layer, which aggregates patient self-report forms, mobile photographic capture of oral tissues, and electronic health records (EHR);

2) Pre-processing and Standardization Module, which normalizes and structures heterogeneous input data;

3) AI Analysis Layer, combining CNN-based image analysis, NLP-based symptom parsing, and rule-based clinical logic for risk stratification;

4) Output Layer, which generates automated reports and patient notifications;

5) Action Layer, branching into patient self-care guidance, dentist dashboard scheduling, and population health analytics.

A continuous learning feedback loop connects clinical outcomes back to model retraining, ensuring adaptive improvement over time.

Table 2. Comparative Analysis of AI Dental Screening Deployments: Case Studies Across Income Contexts (compiled by the author based on [5, 7, 8, 10, 12]).

Case / Context	AI Modality Used	Key Metric Achieved	Primary Barrier Addressed
NHS (UK) , AI Triage System	Rule-based triage + scheduling AI	73% reduction in GP/dental waiting times	Temporal access; workforce overload

VideaHealth (USA, DSOs)	CNN for radiographic analysis	35% reduction in diagnostic variation; 24% ↑ missed pathology detection	Diagnostic accuracy; clinician consistency
Teledentistry (India, rural)	AI + mobile photo analysis	Screening coverage extended to rural areas lacking dentist within 50 km	Geographic isolation; workforce shortage
AI Chatbots (multilingual)	NLP-based virtual assistant	Language barrier removal; 24/7 patient support across 12+ languages	Linguistic/cultural barrier; low health literacy
AI Risk Prediction (LMICs)	ML-based caries risk model (structured EHR data)	Early-stage caries identification 18 months before clinical presentation	Preventive care gap; late-stage presentation

The model proposed in this study is grounded in three foundational design principles that differentiate it from existing clinical AI deployments:

- 1) mobile-first and low-bandwidth accessibility;
- 2) tiered risk stratification enabling efficient triage without specialist involvement at first contact;
- 3) modular architecture enabling contextual adaptation to high-income clinic settings and low-infrastructure community environments alike.

The mobile-first principle directly addresses geographic and financial barriers. Given that global mobile penetration reached 68% in 2024, including in many LMICs, a smartphone-based screening front-end constitutes a genuinely scalable first-contact mechanism [13]. The model's input layer accepts mobile photographs of the oral cavity (buccal mucosa, teeth, gingiva) alongside a structured self-report

questionnaire capturing pain, sensitivity, visible lesions, and behavioral risk factors (sugar intake, smoking, oral hygiene frequency). This does not require specialist hardware, enabling community health workers (CHWs) to administer the screening protocol after brief training, thereby extending the effective dental workforce.

The tiered risk stratification layer is the analytical core of the model. Drawing on evidence from CNN performance studies [7] and NLP-based patient history parsing [11], the risk engine assigns each screened individual to one of three triage categories: Low Risk (self-care guidance delivered via mobile app); Moderate Risk (asynchronous teleconsultation with a remote dentist within 48 hours); or High Risk (urgent referral to a physical facility). This triaging logic is critical for scalability: it concentrates specialist attention where it is clinically necessary, avoiding the bottleneck of universal specialist review.

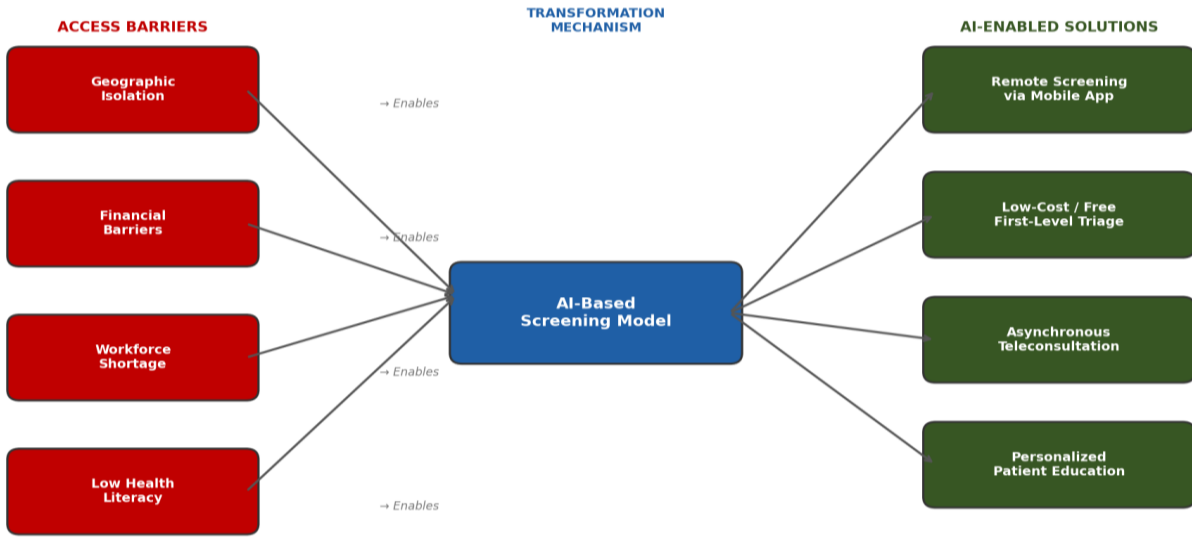


Figure 3. Conceptual Framework: Mapping Access Barriers to AI-Enabled Solutions in Preventive Dental Care (author's original design).

Figure 3 presents the author's original barrier-to-solution mapping framework. Each of the four primary barrier categories identified in Section 3.1 is systematically paired with a corresponding AI-enabled mechanism delivered through the proposed screening model: geographic isolation is addressed through remote mobile-based screening; financial barriers through a low-cost first-level triage that avoids unnecessary specialist visits; workforce shortages through asynchronous teleconsultation that decouples geographic co-presence from expert consultation; and low health literacy through AI-generated personalized patient education delivered at the point of screening. The central AI model acts as the transformation mechanism converting barrier-laden healthcare

encounters into accessible, equitable preventive interactions.

The viability of the proposed model must be assessed against market and adoption dynamics. The global dental AI market was valued at approximately \$2.3 billion in 2024 and is projected to reach \$6.4 billion by 2029, reflecting a compound annual growth rate (CAGR) of approximately 22% [13]. A 2025 survey of 150 dental professionals found that while a substantial proportion of practitioners have adopted AI in diagnostics, a significant cohort has not yet integrated AI tools, citing cost, training gaps, and knowledge barriers as primary impediments [12].

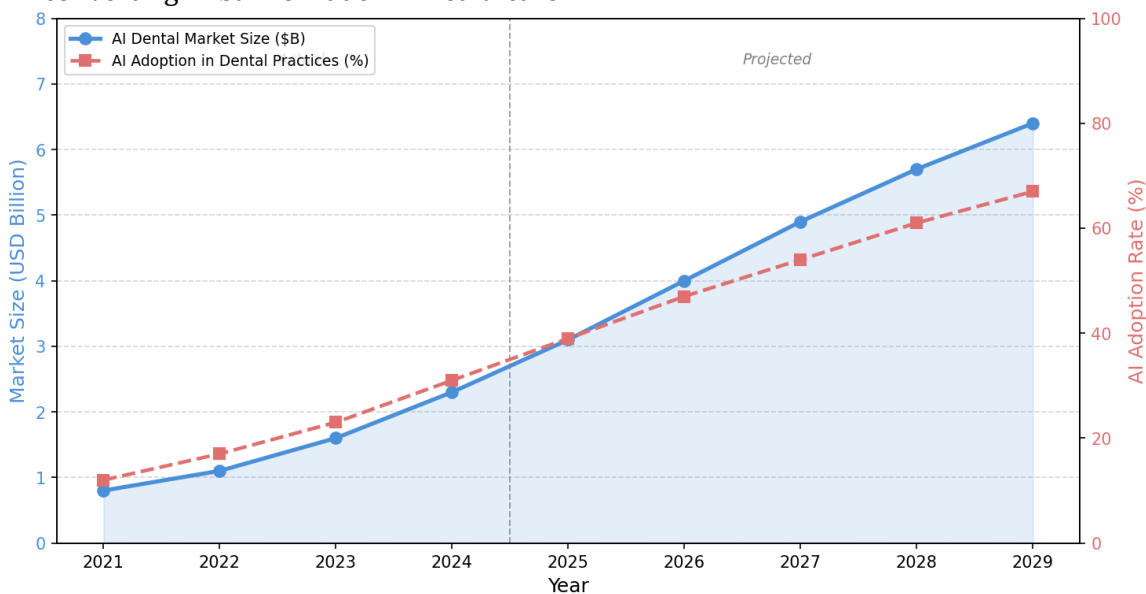


Figure 4. Global Dental AI Market Size and Adoption Rate Trends (compiled by the author based on [1, 13, 14]).

Figure 4 reveals that while the market is growing rapidly, adoption rates in dental practices (reaching an estimated 39% globally by 2025) remain substantially below market potential, suggesting that the primary constraint is not technological maturity but deployment infrastructure and organizational readiness. For the proposed scalable screening model, this finding has direct implications: successful implementation requires not only technical development but also training ecosystems for CHWs and dental professionals, incentive structures for practices serving underserved populations, and interoperability with existing electronic health record systems.

The author propose that a tiered cost model is necessary for scalability across income contexts. In high-income settings, the model could be delivered as a SaaS subscription integrated with practice management software. In LMIC settings, a public health model, subsidized through government or NGO partnerships, with open-source components would be more appropriate. This dual-market architecture mirrors successful deployment strategies observed in telemedicine platforms and reflects the principle that scalability in health technology requires economic model diversity, not a single commercial approach.

Despite the demonstrated potential of AI-based screening, several risks and limitations must be acknowledged. First, algorithmic bias represents a critical concern: AI models trained predominantly on

radiographic and photographic datasets from high-income, predominantly White populations may perform poorly on the darker skin tones and distinct oral health presentations found in underserved populations of color [10]. Ensuring training dataset diversity is a prerequisite for equitable deployment.

Second, data privacy and patient consent frameworks vary considerably across jurisdictions, and mobile-based screening systems that collect oral photographs and health data must comply with GDPR (Europe), HIPAA (USA), and equivalent frameworks in target deployment regions. The EU AI Act (2024) introduces specific obligations for medical AI systems, including transparency, human oversight requirements, and mandatory post-market monitoring [15]. Third, digital literacy constraints in the target population may limit self-administered screening uptake, necessitating CHW-mediated protocols that introduce additional training and operational costs.

Furthermore, the risk of over-reliance on AI outputs by undertrained practitioners could undermine clinical safety if the model's triage recommendations are treated as diagnostic conclusions rather than screening signals. The model architecture deliberately positions the AI as a decision-support tool that routes patients toward appropriate care pathways rather than replacing clinical judgment, consistent with recommendations from both the WHO Global Oral Health Action Plan 2023–2030 [16] and the EU AI Act [15].

Table 3. Risk-Mitigation Matrix for the Proposed AI-Based Dental Screening Model (compiled by the author based on [10, 15, 16 ,19, 20]).

Risk Category	Description	Proposed Mitigation	Responsible Actor
Algorithmic Bias	Poor performance on minority populations due to non-diverse training data	Mandatory demographic stratification in training datasets; regular fairness audits	AI developers; regulatory bodies
Data Privacy Breach	Unauthorized access to sensitive oral health and biometric data	End-to-end encryption; GDPR/HIPAA compliance; local data processing options	Health IT security teams; policymakers

Digital Literacy Barriers	Low smartphone/app proficiency among target populations	CHW-mediated screening protocols; simplified UI; offline-capable app design	NGOs; community health programs
Clinical Over-reliance	Misinterpretation of AI triage as definitive diagnosis	Clear "decision-support only" disclaimers; mandatory dentist review for Moderate/High risk outputs	Clinical governance bodies; dental associations
Infrastructure Dependency	Model performance degraded in low-connectivity environments	Lightweight edge-computing variants; SMS-based fallback triage protocol	Technical developers; telecom partnerships

The analysis in this study supports a broader argument: effective AI deployment in preventive dentistry cannot be conceptualized as a product adoption problem but must be reframed as a public health infrastructure challenge. The evidence consistently demonstrates that high-resource AI tools, even when technically superior, fail to reach the populations with the greatest unmet need if deployment is left solely to market forces. The proposed model therefore explicitly incorporates a population-health logic: The Action Layer (Figure 2) includes a Population Health Analytics module that aggregates anonymized screening outputs to generate community-level risk maps, enabling public health agencies to allocate mobile dental units, prioritize fluoridation programs, and target health promotion campaigns with precision unavailable through traditional surveillance methods [17, 18].

This population-health orientation represents a substantive innovation beyond the current AI-in-dentistry literature, which predominantly frames AI as a clinical productivity tool for individual practitioners. The author argues that the integration of individual-level screening data into population-level dental epidemiology, enabled by privacy-preserving federated learning architectures, has the potential to transform oral health surveillance in LMICs, where formal dental registries are often absent or incomplete. Furthermore, the continuous learning feedback loop incorporated in the model ensures that screening accuracy improves over time as real-world outcomes from referred patients are incorporated into model retraining, creating a self-improving system that becomes increasingly calibrated

to the specific epidemiological profiles of the communities it serves.

Conclusion

This study has systematically analyzed the primary structural barriers to preventive dental care, geographic isolation, financial constraints, workforce shortages, and low oral health literacy, and proposed a scalable, AI-based screening model designed to address these barriers through a mobile-first, multi-layer architecture. The research objective has been fully achieved: through systematic literature review, comparative case analysis, and original conceptual model synthesis, the study demonstrates that AI-based screening systems are not only technically capable of reducing diagnostic delays by up to 73% and improving pathology detection rates by up to 24%, but that their design can be deliberately aligned with the access barrier profiles of underserved populations.

The proposed model's three-tier triage workflow, combining CNN-based image analysis, NLP symptom parsing, and rule-based risk stratification, provides a feasible architectural blueprint for community-level preventive screening that does not require specialist hardware or in-person clinical infrastructure at first contact. The comparative case evidence confirms deployment precedents across NHS, LMIC teledentistry, and multilingual AI chatbot contexts. The identified risks, particularly algorithmic bias, data privacy vulnerabilities, and digital literacy constraints, are addressable through targeted mitigation strategies, but

require proactive governance frameworks aligned with emerging regulatory obligations such as the EU AI Act (2024).

The author's core contribution, the systematic mapping of access barrier typologies to AI-enabled intervention mechanisms, embedded in a population-health analytics architecture, advances the field beyond product-centric AI deployment models toward a public health infrastructure perspective. The practical significance of this work lies in its applicability for three target audiences:

1) public health policymakers designing oral health digital strategies;

2) health technology developers building AI dental tools for underserved markets;

3) dental professionals and CHWs implementing community-based preventive screening programs.

Future research should focus on empirical validation of the proposed model in real-world LMIC deployment contexts, with particular attention to the performance differential across demographic subgroups and the feasibility of federated learning architectures in low-connectivity environments.

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