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AI-Assisted Early Orthodontic Screening and Referral Pathways for Saudi School-Age Children: Impact on Access, Treatment Efficiency, and Malocclusion Outcomes

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Abstract— Background: Malocclusion is common in childhood and adolescence, yet many children reach specialist care only after growth-modification opportunities have narrowed. Saudi Arabia's expanding digital health infrastructure creates a timely opportunity to connect school oral-health checks with AI-assisted orthodontic triage. Aim: This integrative review evaluates how AI-assisted early orthodontic screening and referral pathways could improve access, treatment efficiency and malocclusion-related outcomes among Saudi school-age children. Methods: A structured literature review was designed in line with PRISMA 2020 principles, focusing on English-language evidence from 2020 to 2025. Evidence was synthesised across five domains: population need, AI-enabled diagnosis, remote monitoring, patient-centred outcomes and governance. Findings: Recent orthodontic AI studies report useful performance in cephalometric landmarking, treatment-duration prediction, extraction planning and remote monitoring, but most tools remain adjuncts rather than autonomous clinical systems. School-based deployment is most defensible when AI performs calibrated risk stratification, while orthodontists retain diagnostic responsibility. In Saudi Arabia, potential benefits include earlier identification of severe overjet, crossbite, crowding and psychosocially significant aesthetic concerns; shorter avoidable delays; more consistent referral prioritisation; and better parent-school-clinic communication. The risks are equally material: dataset bias, privacy breaches, algorithmic opacity, over-referral, and inequitable digital access. Conclusion: AI-assisted screening can strengthen Saudi paediatric orthodontic pathways if it is embedded in a human-supervised, consent-based, auditable service model. Priority should be given to multicentre validation, Arabic interface usability, school-nurse training, referral feedback loops and outcome metrics beyond technical accuracy.

Keywords: Artificial Intelligence, Orthodontics, School Health, Saudi Arabia, Malocclusion, Referral Pathway, Teledentistry, Early Screening

I. INTRODUCTION

Orthodontic malocclusion is not a cosmetic inconvenience alone. In school-age children it may influence mastication, speech, oral hygiene, traumatic dental injury risk, self-confidence and participation in classroom or peer activities. The strongest public-health argument for early screening is that some developing problems are time-sensitive. Posterior crossbite with functional shift, severe overjet, ectopic eruption, anterior open bite linked to persistent habits, impacted canine risk and crowding that compromises eruption can be managed more predictably when detected before the late adolescent stage. Recent systematic evidence also indicates that malocclusion has a measurable negative association with adolescent oral-health-related quality of life, even after confounders are considered [26,27].

Saudi Arabia is well placed to reconsider how children move from school screening to orthodontic referral. The national health system has invested in digital infrastructure, unified electronic records and remote consultation capabilities under the e-health transformation agenda [4]. The WHO global oral-health agenda similarly emphasises integration of oral health into universal health coverage, prevention, school health and digital approaches [2,3]. These policy directions matter because conventional orthodontic access pathways often depend on parental awareness, private clinic availability and variable dentist referral practices. In a geographically large country, this can produce late presentation, inconsistent prioritisation and avoidable travel for families.

Artificial intelligence offers a possible coordination layer rather than a replacement for orthodontists. In dentistry, AI refers to computational systems that learn statistical patterns from clinical data and then support classification, prediction or image interpretation [7]. In orthodontics, recent reviews identify applications in cephalometric landmark detection, skeletal classification, treatment planning, extraction decision support, dental monitoring and outcome prediction [8-12]. These applications are relevant to school screening because the task is not to design definitive treatment. The task is to decide which child needs reassurance, preventive advice, routine dental review, early orthodontic assessment, urgent referral or specialist imaging.

AI research becomes clinically meaningful only when model outputs are tied to patient-centred outcomes, workflow decisions and explainable predictors, not accuracy statistics alone. For Saudi school screening, the same principle requires moving beyond a headline sensitivity value. A robust pathway should ask whether AI reduces missed severe cases, improves time to first specialist review, lowers unnecessary referrals, supports equitable access for remote schools and ultimately improves occlusion-related quality of life.

However, the evidence base remains uneven. AI landmarking can be promising, but an umbrella review concluded that expert supervision remains necessary because landmark accuracy is not uniform and 3D CBCT landmarking may be less reliable than 2D radiographs [11]. Treatment-planning AI may perform well in retrospective datasets, yet external validation and prospective utility are still limited [15-18]. Remote orthodontic monitoring and mobile interventions may improve hygiene, compliance and visit efficiency, although implementation depends on patient engagement and clinician response protocols [19-22,28]. These limitations are not reasons to abandon AI; they are reasons to design the pathway as a safety-conscious public-health intervention.

This review therefore examines AI-assisted early orthodontic screening as a Saudi access pathway problem. It synthesises evidence from orthodontic AI, teledentistry, digital aligner research, quality-of-life studies and clinical AI reporting guidance. The focus is not on selling a software platform. It is on defining what a publishable, ethically defensible, school-to-specialist model should include if Saudi policymakers, universities or health clusters pilot AI-supported orthodontic screening.

II. AIM AND OBJECTIVES OF THE STUDY

The overarching aim of this review is to evaluate the potential impact of AI-assisted early orthodontic screening and structured referral pathways on access, treatment efficiency and malocclusion-related outcomes among Saudi school-age children.

The first objective is to map the clinical rationale for early orthodontic screening in mixed and early permanent dentition, with attention to malocclusion features that merit timely referral. The second objective is to appraise recent evidence on AI applications that could support screening, triage, remote monitoring and referral prioritisation. The third objective is to assess how digital pathways may influence treatment efficiency, including reduced delays, fewer unnecessary appointments, improved monitoring and better matching between treatment need and specialist capacity. The fourth objective is to identify patient-centred outcomes relevant to Saudi children, including oral-health-related quality of life, family burden, school attendance and satisfaction with communication. The fifth objective is to propose a Saudi implementation model that aligns with data protection, AI ethics, human oversight and high-quality journal standards.

III. REVIEW METHODOLOGY

This paper is an integrative review with systematic search logic, rather than a full meta-analysis. The method was chosen because the topic joins several evidence streams: orthodontic epidemiology, AI diagnostic performance, teledentistry, clear aligner monitoring, school health and regulatory governance. The search framework followed PRISMA 2020 principles for transparent identification, eligibility and synthesis, while recognising that heterogeneity in designs and outcomes made pooled quantitative estimation inappropriate [1].

The conceptual population was Saudi school-age children, broadly defined as children in mixed dentition and early permanent dentition, usually 6-15 years. The intervention of interest was AI-assisted screening, triage, monitoring or referral decision support. Comparators included conventional visual school screening, dentist-led referral without AI, orthodontist-only assessment and remote monitoring without algorithmic support. Outcomes of interest were access, referral appropriateness, time to

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assessment, treatment efficiency, malocclusion detection, oral-health-related quality of life, safety, equity, privacy and acceptability.

Search terms were structured around three clusters: artificial intelligence and orthodontics; school dental screening and teledentistry; and malocclusion outcomes in children and adolescents. Eligible sources were peer-reviewed articles, systematic reviews, clinical AI reporting guidelines and official policy documents published between 2020 and 2025. Priority was given to PubMed-indexed articles, major dental journals, WHO documents and Saudi health or data-governance sources. Older studies were not used for citation because the user requirement specified 2020-2025 evidence.

Inclusion criteria were: English language; relevance to orthodontic diagnosis, treatment planning, remote monitoring, oral-health-related quality of life, teledentistry or AI governance; human clinical, review or policy focus; and publication between 2020 and 2025. Exclusion criteria were: unrelated dental specialties without transferable screening relevance; purely technical AI papers without clinical interpretation; opinion-only material without methodological value; and studies in syndromic populations unless the finding informed access or triage design.

Evidence was synthesised narratively in five stages. First, studies were grouped by function: image interpretation, decision support, monitoring, patient outcome, or governance. Second, each evidence stream was interpreted for school screening, where the required output is triage, not definitive diagnosis. Third, likely Saudi implementation barriers were identified, including regional access variation, consent, Arabic communication, data hosting and referral capacity. Fourth, the pathway was evaluated against clinical AI reporting expectations, particularly CONSORT-AI and DECIDE-AI, which emphasise intervention context, human factors, failure modes and clinical utility [29,30]. Fifth, an impact logic model was produced to connect screening inputs with access, efficiency and outcome metrics.

No original patient data, school records or radiographs were analysed for this review. Accordingly, no institutional ethics approval was required for the manuscript itself. Any future Saudi pilot should obtain ethics approval, parental consent, child assent when age-appropriate, data-processing agreements and predefined escalation rules for urgent findings. The recommended minimum dataset would include age, sex, region, school type, screening images, occlusal indicators, AI confidence score, clinician triage decision, referral outcome, time interval to appointment and patient-reported impact.

Table 1. Methodological framework for the integrative review

Domain	Review decision	Rationale for this topic
Population	Saudi school-age children in mixed and early permanent dentition	Captures ages when interceptive assessment can alter timing and referral priority.
Intervention	AI-assisted image review, risk scoring, triage and referral support	Reflects realistic use of AI as decision support rather than autonomous diagnosis.
Outcomes	Access, referral appropriateness, treatment efficiency, OHRQoL, safety and equity	Moves evaluation beyond accuracy toward patient-centred and health-system value.
Evidence window	2020-2025 peer-reviewed studies and official policy documents	Matches the required contemporary citation period and current governance context.
Synthesis approach	Narrative integration with systematic search logic	Appropriate for heterogeneous evidence across AI, teledentistry, orthodontics and policy.

Abbreviations: AI, artificial intelligence; OHRQoL, oral-health-related quality of life.

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IV. EVIDENCE SYNTHESIS

4.1 The need for earlier and fairer orthodontic access

The WHO estimates that oral diseases affect a very large global population and argues that oral health should be integrated into prevention, primary care and universal health coverage [2,3]. Orthodontic problems are not listed in the same way as caries or periodontal disease, yet malocclusion becomes a service-planning issue when it produces functional risk, psychosocial impact or complex late treatment. School-age screening is attractive because schools provide near-universal reach, including children whose parents may not seek orthodontic advice until aesthetics become socially distressing.

For Saudi Arabia, a school-based model could reduce dependence on opportunistic referral. Children in metropolitan areas may have easier access to private orthodontists, whereas families in peripheral regions may face travel, appointment scarcity and cost barriers. AI-assisted triage could create a standardised first layer: not a final diagnosis, but a reproducible method for identifying children who should be prioritised. The greatest public value would come from detecting high-impact cases earlier, not from labelling every mild irregularity as treatment need.

Quality-of-life evidence supports this targeted approach. Reviews show that adolescent malocclusion can negatively affect oral-health-related quality of life, especially when aesthetic, functional and psychosocial concerns overlap [26,27]. Clear aligner and orthodontic treatment literature also shows that patient experience matters during therapy, not only at the final occlusal endpoint [23,24]. Therefore, a Saudi pathway should record child-centred outcomes such as embarrassment when smiling, bullying, difficulty biting, oral hygiene problems and parent concern. Such outcomes can help clinicians distinguish mild crowding from malocclusion that materially affects wellbeing.

4.2 AI-supported screening functions

AI in orthodontics has matured from experimental landmark detection toward broader decision support. Systematic reviews report applications in cephalometric analysis, diagnosis, treatment planning and monitoring [8,10,12]. Automated cephalometric systems can reduce repetitive measurement work, but accuracy varies by landmark and imaging type, making orthodontist review essential [11-14]. For school screening, this implies that AI should not demand routine radiographs. Most school cases can begin with extraoral and intraoral photographs, brief occlusal examination and dental-history questions; radiographs should be reserved for clinically justified referrals.

A practical school-screening algorithm would classify visible features: anterior crossbite, posterior crossbite, increased overjet, reverse overjet, severe crowding, open bite, deep bite trauma, eruption asymmetry, missing permanent teeth by age expectation, and facial asymmetry requiring specialist review. Computer vision could also support image quality checks, ensuring that poor photographs are retaken rather than misclassified. The output should be a risk category with explanation, for example: high-priority orthodontic referral because of suspected anterior crossbite and mandibular shift; routine referral because of moderate crowding; or dental review because caries or oral hygiene, not orthodontics, is the main issue.

Machine-learning studies in orthodontics show that predictive models can estimate treatment duration and treatment changes using pre-treatment variables [16,17]. Extraction-planning reviews suggest high specificity but more variable sensitivity, highlighting the danger of treating AI recommendations as definitive [18]. These findings are relevant because a school pathway should not promise treatment plans. It should use AI to identify probable need and then direct the child to the correct level of human assessment.

4.3 Referral pathway design

A safe AI-assisted pathway needs a defined sequence. The first layer is school registration, consent and basic oral-health education. The second layer is image capture by trained dental hygienists, school nurses or mobile dental teams using standardised views. The third layer is AI pre-screening, generating risk categories and highlighting visible reasons. The fourth layer is asynchronous review by a dentist or orthodontist, who can accept, modify or reject the AI label. The fifth layer is referral navigation, with parent notification, appointment options and feedback to the school health team.

Such a pathway is stronger than a standalone app because it connects screening to action. Teledentistry

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reviews indicate that virtual screening and monitoring can be useful, particularly when combined with clear communication and clinician oversight [21,22]. Orthodontic dental monitoring reviews similarly suggest potential reductions in in-office visits and earlier detection of problems, although certainty depends on study quality and workflow adherence [19,20]. In Saudi school screening, this means that digital triage should be linked to referral capacity before launch. A pilot that screens thousands of children but cannot provide appointments may increase frustration rather than access.

The pathway should include three referral streams. High-priority referrals include suspected skeletal discrepancy affecting growth, crossbite with displacement, severe overjet with trauma risk, impacted tooth risk, facial asymmetry and functional impairment. Routine referrals include moderate crowding, spacing, deep bite without trauma, aesthetic concern with psychosocial effect and malocclusion needing monitoring. Advice-only outcomes include mild irregularity, normal variation, eruption stage that warrants observation, or cases where dental disease should be treated before orthodontic assessment.

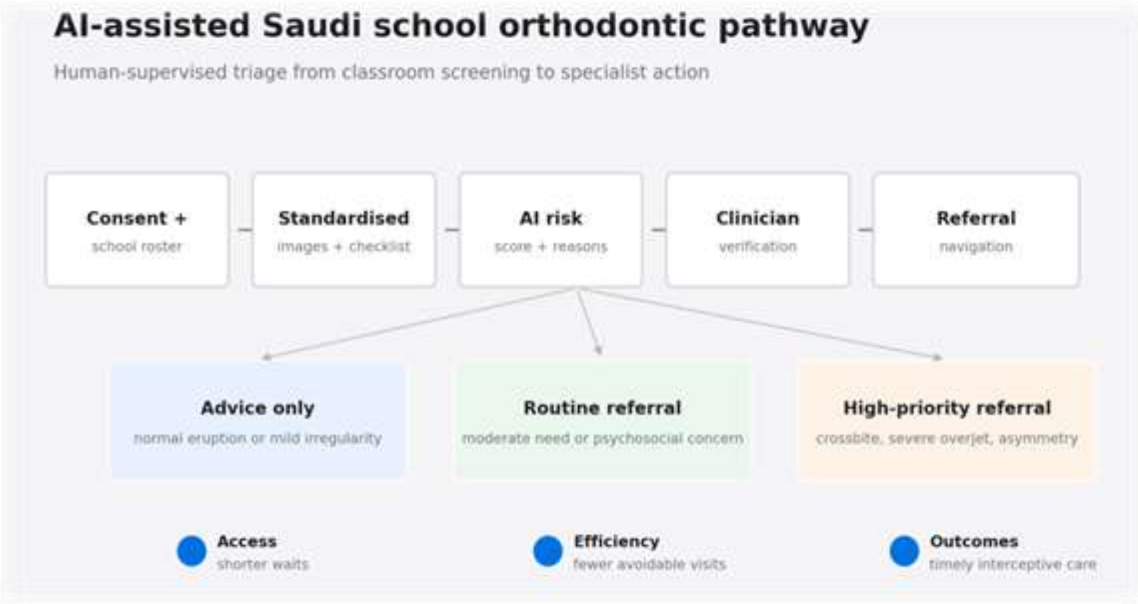

Figure 1.conceptual pathway for AI-assisted school orthodontic screening, clinician verification and referral routing.

4.4 Treatment efficiency and malocclusion outcomes

Treatment efficiency is often misunderstood as faster tooth movement. In a public-health pathway it should mean better timing, better matching of cases to provider skill and less wasted travel. Early triage may reduce avoidable delays for interceptive appliances, habit management, space supervision or growth-modification assessment. It may also reduce unnecessary specialist appointments for children who require reassurance or primary dental care instead.

Evidence from clear aligner research shows that digital planning can be helpful but movement predictability differs by movement type [23-25]. This matters for school pathways because early referral should not be framed as a promise of simple treatment. A severe malocclusion may still require complex fixed appliances, functional appliances, extractions, surgery in adulthood or long-term retention. AI should improve the start of the journey, not oversimplify the biological limits of orthodontics.

Remote monitoring can contribute after referral. AI-driven systems have been studied for oral hygiene improvement and real-time tracking during orthodontic treatment [19,20]. Mobile and social-media interventions can influence behaviour when reminders are clear and clinically integrated [28]. For Saudi adolescents, this could support compliance with oral hygiene, appliance wear, appointment attendance and retention instructions. The efficiency gain would come from reducing preventable breakages, missed appointments and late recognition of poor tracking.

Malocclusion outcomes should be measured on several levels. Technical outcomes include change in overjet, crossbite correction, crowding resolution and reduction in Index of Orthodontic Treatment Need category. Service outcomes include referral conversion, waiting time, appointment attendance and proportion of referrals judged appropriate by orthodontists. Patient outcomes include OHRQoL, parent satisfaction, anxiety reduction and perceived clarity of information. Equity outcomes include rural coverage, public-private referral balance, language accessibility and inclusion of children with disabilities.

Stakeholder roles should be assigned before implementation. The Ministry or regional health cluster would define eligibility, procurement, data hosting and referral targets. Education authorities would coordinate school access, parent communication and safeguarding. Dental colleges and public dental centres would provide calibration, specialist review and outcome evaluation. School nurses or dental hygienists would capture images, deliver age-appropriate education and identify children who need immediate dental attention. Parents would receive understandable reports and retain the right to decline referral or request human explanation. Children would be treated as participants in care, not passive data sources, through respectful language and privacy during image capture.

Training should therefore cover more than software use. Screeners need basic occlusal terminology, infection control, photography angles, child communication, consent procedures and escalation rules. Clinicians need orientation on dashboard interpretation, uncertainty thresholds, override documentation and parent-facing explanations. Administrators need training on appointment routing and data-retention duties. A short competency assessment before launch would reduce variation and provide evidence that workflow quality was managed, which is a frequent weakness in digital-health implementation studies.

Acceptability should be tested before any large trial. A formative phase could use parent interviews, child-friendly explanation cards and clinician usability testing to refine the pathway. The aim would be to discover whether families understand that AI is only a screening aid, whether reports create anxiety, and whether parents prefer school-based or clinic-based confirmation. Feedback should be analysed quickly and used to simplify language, adjust urgency labels and remove any visual material that may embarrass children. This participatory step would make the pathway more culturally responsive and more likely to sustain consent rates.

A second formative task is threshold setting. Orthodontists, paediatric dentists and public-health leaders should agree which findings require urgent, routine or advice-only categories before the model is evaluated. This prevents post-hoc adjustment that inflates apparent performance. Thresholds should reflect Saudi service capacity as well as clinical risk. In a resource-constrained region, the same AI probability may justify tele-review first, whereas in a dense urban cluster it may justify direct appointment booking. This preserves equity, protects specialist clinics from overload, and spares families unnecessary journeys during pilot-cycle implementation locally.

4.5 Saudi implementation, ethics and governance

Saudi implementation must be designed around trust. Screening children creates sensitive data: facial photographs, intraoral images, school identity, location and health status. The Saudi Personal Data Protection Law, enforced through SDAIA, emphasises protection of personal data, privacy and controls over processing [5]. SDAIA's AI ethics principles also foreground fairness, privacy, security, transparency, reliability and accountability [6]. These principles should be operational, not decorative. Parents should know what data are collected, who reviews them, where they are stored, how long they are kept and how to request deletion when legally permissible.

Bias is a central risk. An AI model trained mainly on non-Saudi images may perform differently in Saudi children because of variation in dentition, imaging conditions, skin tone, mixed-dentition presentation, camera devices and clinical thresholds. Therefore, validation should include Saudi regions, boys and girls, public and private schools, different age groups and Arabic documentation. Model performance should be reported by subgroup, with calibration plots and false-negative review. For screening, false negatives are particularly important because a missed severe case undermines the purpose of early detection.

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Human oversight must be explicit. Clinical AI reporting guidance stresses that AI interventions should describe the user, setting, input data, output, human interaction and failure management [29,30]. In this pathway, the responsible clinician remains the dentist or orthodontist. AI can flag, prioritise and summarise; it should not independently diagnose a child, prescribe appliances or deny referral. Each high-risk AI-negative sample should be audited during pilot phases to estimate safety. Each AI-positive but clinician-negative case should be logged to monitor over-referral.

Cultural and communication design are also important. Parents may accept screening more readily when reports are short, bilingual and reassuring. Children should not receive stigmatising labels at school. Reports should avoid language such as deformity and instead state observations, recommended next step and urgency. Schools should be partners in scheduling and education, but clinical confidentiality must remain protected. For families in remote regions, the pathway should provide options for teleconsultation, mobile specialist days or coordinated referral to the nearest dental centre.

V. PROPOSED SAUDI MODEL

The proposed model is a stepped, human-in-the-loop service. Step one is annual screening for selected school years, for example ages 7-8 and 11-12, because these stages capture mixed-dentition and early permanent-dentition decisions. Step two is standardised image capture and a short symptom questionnaire. Step three is AI-assisted risk scoring with explainable visual prompts. Step four is clinician verification within a secure dashboard. Step five is referral routing, parent communication and follow-up. Step six is outcome monitoring at six and twelve months.

The model should begin as a multicentre pilot rather than national deployment. A suitable pilot would include urban, semi-urban and rural schools in at least three regions. The primary feasibility outcomes would be consent rate, successful image capture rate, clinician review time, referral appropriateness and time to orthodontic appointment. The primary safety outcome would be the rate of missed high-priority cases after clinician audit. Secondary outcomes would include parent understanding, child-reported impact, reduced unnecessary referrals and cost per appropriate referral.

VI. OUTCOME MEASUREMENT AND ANALYTICAL FRAMEWORK

A publishable Saudi pilot should define its outcome hierarchy before recruitment. Diagnostic accuracy is necessary, but it is not sufficient. The first outcome tier should be screening validity: sensitivity for high-priority malocclusion, specificity for non-referral, image rejection rate, calibration across schools and agreement between AI, dentist and orthodontist. The second tier should be service performance: days from screening to parent notification, days from notification to appointment, proportion of children attending, proportion receiving interceptive advice, and proportion discharged without specialist treatment. The third tier should be family-centred benefit: parent understanding, child anxiety, perceived fairness and reduction of unnecessary travel. The fourth tier should be clinical outcome: correction or improvement of the index problem, prevention of traumatic risk, improved oral hygiene access, or timely transition to comprehensive treatment.

Data analysis should mirror this hierarchy. Accuracy should be reported with confidence intervals and subgroup analyses by age, sex, region and school type. Referral efficiency should be analysed as time-to-event data because waiting time is a core access outcome. Appropriateness should be assessed by blinded orthodontist review using predefined criteria. Patient-centred outcomes should use short validated scales where possible, supplemented by brief Arabic parent-reported questions. Cost analysis should distinguish fixed implementation costs from marginal costs per screened child and per appropriate referral. These choices would make the work meaningful to clinicians, health economists and policy readers, not only computer scientists.

The pathway should also include a learning-health-system feedback loop. Each clinician decision should return to the audit database with a reason code: agree with AI, upgrade urgency, downgrade urgency, request new images, dental treatment first, or no orthodontic action. When treatment begins, the initial screening category should be linked to later diagnostic findings. This creates a dataset for monitoring drift, identifying under-performing schools or cameras, and improving referral thresholds. Importantly, model retraining should not happen silently. Version changes should be approved, documented and evaluated on a locked validation set before deployment.

A journal-quality manuscript would report implementation context in detail: who captured images, what training they received, how consent was obtained, what device was used, how missing data were handled, who reviewed AI outputs, and what happened when AI and clinician disagreed. Such information is essential because AI performance depends on the service environment. A model that performs well with orthodontist-quality photographs may fail when images are taken in a busy school room. Conversely, a modest model may be useful if image capture, clinician review and referral support are excellent.

Equity should be treated as an outcome, not an afterthought. The pilot should compare consent, image success, referral completion and treatment uptake across regions, school sectors and socioeconomic proxies. If rural children are screened but cannot attend appointments, the pathway has improved detection without improving access. Possible remedies include mobile orthodontic assessment days, teleconsultation before travel, referral to regional dental centres and transport-sensitive appointment scheduling. Equity reporting would align the project with global oral-health policy and Saudi digital-health priorities.

Finally, the proposed pathway should include a minimum safety dashboard. The dashboard should display false-negative audits, urgent referrals not yet booked, data breaches, parent complaints, image failures, model downtime and cases where a child was distressed by screening. These indicators may appear operational, but they are central to paediatric AI governance. For a child-health system, safety includes technical accuracy, emotional acceptability, confidentiality and timely human response. Framing safety broadly would strengthen the manuscript for high-impact peer review and make the pathway more credible for national adoption.

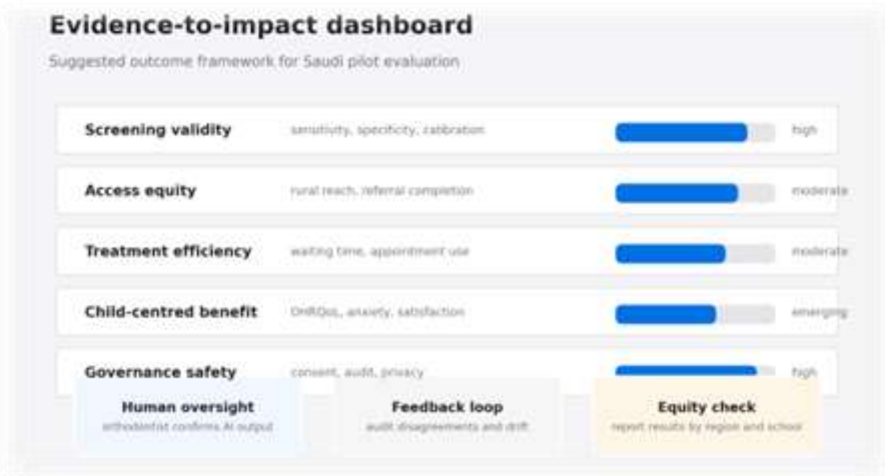

Figure 2. evaluation dashboard linking screening validity, access equity, efficiency, child-centred benefit and governance safety.

Table 2. Proposed AI-assisted Saudi school screening pathway and evaluation metrics

Step	Core action	AI function	Human responsibility	Key metric
1	Consent and registration	Eligibility flagging and record linkage	School and health team explain purpose and obtain consent	Consent rate; withdrawal rate
2	Image and checklist capture	Image-quality prompts and missing-view alerts	Trained screener retakes poor images and records symptoms	Usable image rate
3	Risk stratification	Visible malocclusion detection and confidence scoring	Clinician reviews AI reasons and overrides when needed	Sensitivity for high-priority cases

4	Referral routing	Urgency label and appointment suggestions	Dental team contacts parents and books suitable care level	Median days to appointment
5	Follow-up audit	Dashboard tracks outcomes and disagreement	Orthodontist confirms diagnosis and closes feedback loop	Referral appropriateness; false-negative rate

VII. RESEARCH GAPS AND FUTURE DIRECTIONS

The first gap is Saudi-specific validation. International orthodontic AI tools cannot be assumed to generalise to Saudi schoolchildren. The second gap is outcome selection. Many studies emphasise accuracy, sensitivity or AUC, but decision-makers need evidence on waiting time, referral quality, parent satisfaction and occlusal improvement. The third gap is economic evaluation. A digital pathway may save specialist time, but it also requires software, training, cybersecurity, storage, audit and referral coordination.

The fourth gap is explainability. Clinicians and parents should see why a case was flagged. A black-box score without visible features is unsuitable for child screening. The fifth gap is longitudinal follow-up. Early screening is justified only if it changes the course of care. Therefore, pilots should track whether children actually attend appointments, receive appropriate intervention and show improved outcomes. The sixth gap is equity. A pathway that works only in well-equipped urban schools may widen disparities. Future work should test low-cost cameras, offline capture, mobile dental units and accessible Arabic interfaces.

VIII. CONCLUSION

AI-assisted early orthodontic screening can be a valuable addition to Saudi school oral-health services if implemented as a supervised pathway rather than a standalone algorithm. The strongest expected benefits are earlier detection of high-priority malocclusion, more consistent referral triage, reduced avoidable delays, better use of orthodontic capacity and clearer communication with parents. Evidence from orthodontic AI, teledentistry, remote monitoring and quality-of-life research supports cautious implementation, but it also warns against overclaiming. Current tools require clinical supervision, local validation and transparent governance.

For Saudi Arabia, the opportunity is strategic. Digital health infrastructure, school reach and national AI governance can be combined to create an equitable screening model. The recommended pathway should use AI for risk stratification, image quality control and referral support; dentists and orthodontists should retain diagnosis and treatment responsibility. Future research should prioritise multicentre Saudi validation, child-centred outcomes, audit of false negatives, economic evaluation and long-term malocclusion follow-up. If these conditions are met, AI may improve not only the speed of referral but also the fairness, safety and efficiency of early orthodontic care.

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