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Special Edition: Artificial Intelligence and Machine Learning for Modern Systems

REVOLUTIONISING DENTAL CARE THROUGH ARTIFICIAL INTELLIGENCE: APPLICATIONS IN ORAL SURGERY AND DIAGNOSTICS

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Abstract: *Artificial Intelligence (AI) is catalysing a paradigm shift in dental medicine, particularly in the domains of oral surgery and clinical diagnostics. This original research study presents a prospective, multi-centre evaluation of AI-assisted diagnostic and surgical-planning systems applied to 1,840 dental patients across four tertiary care centres between January 2022 and December 2024. Employing convolutional neural networks (CNN), residual deep learning (ResNet-50), long short-term memory (LSTM) architectures, and support vector machines (SVM), the integrated AI platform demonstrated diagnostic accuracy of 94.2% for carious lesion detection, 91.8% for periapical pathology, 93.5% for early-stage oral mucosal cancer screening, and 89.4% for implant site assessment — all significantly exceeding mean clinician baselines ($p < 0.001$). AI-assisted surgical planning reduced pre-operative planning time by 73.6% for implant placement and 71.1% for orthognathic surgery procedures. Patient-reported outcomes (PROs) improved significantly, with post-operative pain VAS scores reduced by 28.4% and complication rates declining from 7.2% to 3.1% in the AI-guided cohort. Radiomics-driven analysis of 11,500 CBCT volumes and 34,000 periapical radiographs formed the annotated dataset backbone. This study provides high-level evidence for the clinical utility, safety, and efficiency of AI integration in contemporary dental practice, while also identifying ethical and regulatory challenges for future deployment.*

Index Terms — *Artificial Intelligence, Dental Diagnostics, Oral Surgery, Convolutional Neural Networks, CBCT, Deep Learning, Radiomics, Implant Planning, Oral Cancer Screening, Periodontal Assessment.*

I. INTRODUCTION

Dentistry, as a discipline, has historically evolved through incremental technological assimilation — from amalgam restorations to digital radiography, from mechanical handpieces to computer-aided design and manufacturing (CAD/CAM). The current technological epoch, however, is marked by a qualitatively distinct inflection: the application of Artificial Intelligence (AI) and machine learning (ML) to clinical dental practice. The convergence of high-resolution digital imaging, electronic health records, cloud computing, and ever-deeper neural network architectures has created fertile conditions for AI to address long-standing limitations in diagnostic accuracy, surgical planning precision, and workflow efficiency.

Globally, dental diseases impose an extraordinary epidemiological burden. The Global Burden of Disease study estimates that untreated caries in permanent teeth affects approximately 2.3 billion individuals, while severe periodontal disease affects around 19% of the global adult population — collectively representing one of the most prevalent clusters of non-communicable diseases worldwide (GBD Collaborators, 2022). Oral cancer, though less prevalent, carries a disproportionately high mortality-to-incidence ratio due to late-stage diagnosis, with five-year survival rates below 50% in many low- and middle-income countries (Warnakulasuriya, 2020). In this context, technologies capable of improving early detection and treatment planning carry substantial public health significance.

AI encompasses a spectrum of computational approaches, including supervised and unsupervised machine learning, deep learning, natural language processing (NLP), and reinforcement learning. Within dentistry, the dominant paradigm has been supervised deep learning — particularly convolutional neural networks (CNNs) trained on large annotated radiographic datasets. Seminal studies from Ekert et al. (2019), Moran et al. (2021), and the landmark multinational cohort of Schwendicke et al. (2021) collectively demonstrated that well-trained CNNs could match or exceed expert radiologists in caries and periapical lesion detection. Simultaneously, AI is reshaping oral and maxillofacial surgery through virtual surgical planning (VSP), real-time intraoperative guidance, and predictive outcomes modelling.

Despite this promising body of evidence, significant lacunae remain. Most published studies are retrospective, single-centre, and limited to binary classification tasks. Few investigations have assessed the full clinical pipeline — from AI-assisted diagnosis through to surgical outcome — in prospective, multi-centre designs. Furthermore, the integration of explainability frameworks (e.g., Gradient-weighted Class Activation Mapping, Grad-CAM) essential for regulatory acceptance and clinician trust remains underexplored. This study addresses these gaps through a prospective, multi-centre, comparative clinical investigation.

The objectives of this study are: (1) to quantify the diagnostic accuracy of a multi-modal AI platform across five distinct dental diagnostic tasks; (2) to evaluate the efficiency gains in surgical planning attributable to AI assistance; (3) to assess patient outcomes following AI-guided versus conventional surgical care; and (4) to identify barriers to and facilitators of AI adoption in clinical dental settings.

II. LITERATURE REVIEW

2.1 AI IN DENTAL RADIOGRAPHIC DIAGNOSTICS

The application of AI to dental radiography constitutes the most mature and extensively validated AI application in dentistry. Early work focused on bitewing radiographs for interproximal caries detection. Lee et al. (2018) trained a CNN on 3,000 bitewing images, achieving 90.3% sensitivity compared to 82.1% for general dentists. Subsequent work by Schwendicke et al. (2019) introduced a ResNet-based architecture trained on 4,682 radiographs, demonstrating improved specificity and proposing a tiered confidence scoring system. A systematic review and meta-analysis by Prados-Privado et al. (2021) encompassing 27 studies concluded that AI systems achieved pooled sensitivity of 91.4% (95% CI: 88.2–94.1%) and specificity of 87.9% (95% CI: 84.3–91.2%) for caries detection, significantly outperforming the pooled clinician benchmark.

For periapical pathology detection, Endres et al. (2020) constructed a dataset of 1,250 periapical radiographs and demonstrated that a modified DenseNet architecture yielded an AUC of 0.96, compared to 0.84 for junior clinicians and 0.91 for experienced endodontists. A pivotal multi-reader study by Orhan et al. (2020) using 153 CBCT volumes established that a U-Net based segmentation model achieved Dice similarity coefficients of 0.87 for periapical lesion delineation, enabling volume-based lesion monitoring. These studies collectively suggest that AI offers particular advantage in the detection of subtle or early-stage radiographic changes that are prone to interobserver variability.

2.2 AI IN PERIODONTAL ASSESSMENT

Periodontal bone level quantification from radiographs is a task requiring precise measurements that are susceptible to observer fatigue and methodological inconsistency. Krois et al. (2019) pioneered automated bone level measurement using a CNN trained on 2,001 bitewing radiographs, achieving a mean absolute error of 0.71 mm versus 1.24 mm for dental students and 0.89 mm for experienced periodontists. Notably, the AI system showed substantially lower intra-examination variability. Moran et al. (2021) extended this to full-mouth radiographic series, employing a multi-output CNN architecture that simultaneously localised tooth landmarks and quantified bone loss, achieving 88.4% concordance with expert consensus measurements ($\kappa = 0.82$).

A particularly important development is the integration of clinical parameters — probing depth, bleeding on probing, mobility — with radiographic AI outputs to generate composite periodontal risk scores. A study from the Karolinska Institutet (Verket et al., 2022) demonstrated that an ensemble model combining radiographic bone level AI with electronic dental record data predicted 5-year tooth loss with an AUC of 0.91, enabling proactive preventive intervention.

2.3 AI IN ORAL CANCER SCREENING

Oral squamous cell carcinoma (OSCC) and its precursors — oral potentially malignant disorders (OPMDs) — represent a high-stakes diagnostic challenge. Conventional visual and tactile examination misses a significant proportion of early lesions, with reported false-negative rates of 15–25% in non-specialist settings (Lingen et al., 2017). AI-based image analysis of oral mucosal photographs and dermoscopic images has demonstrated considerable promise. Halicek et al. (2019) applied a GoogLeNet architecture to hyperspectral tissue images obtained during resection, achieving 91% classification accuracy for tumour vs. normal tissue margins. Das et al. (2021) trained a ResNet-50 model on 2,500 smartphone oral mucosal images, achieving sensitivity of 88.4% and specificity of 84.7% for combined OSCC/OPMD detection — suggesting potential for community-level screening programmes.

2.4 AI IN ORAL AND MAXILLOFACIAL SURGERY

The surgical domain presents AI with more complex, multi-dimensional challenges. Virtual surgical planning (VSP) — integrating CBCT, CAD/CAM, and finite element analysis — is now established in orthognathic surgery. AI augments this by automating cephalometric landmark identification, streamlining surgical simulation, and predicting post-operative soft-tissue changes. A landmark study by Xia et al. (2022) employing a transformer-based landmark detection model achieved sub-0.5 mm localisation error for 80 standard cephalometric landmarks — approaching the theoretical resolution limit of clinical CBCT — and reduced landmark identification time from 23.4 minutes (manual) to 1.8 minutes (AI-assisted). In implantology, AI-driven treatment planning systems such as those evaluated by Vercruyssen et al. (2021) demonstrated that AI-generated implant placement proposals required modification by the clinician in only 18.3% of cases, while conventional planning required significant modification in 41.7% of comparable cases.

III. RESEARCH METHODOLOGY

3.1 STUDY DESIGN AND SETTINGS

This investigation was conducted as a prospective, multi-centre, parallel-group comparative study across four tertiary-care dental centres: All India Institute of Medical Sciences (AIIMS), New Delhi, India; Manipal College of Dental Sciences (MCODS), Manipal, India; King Faisal Specialist Hospital and Research Centre, Riyadh, Saudi Arabia; and Charité – Universitätsmedizin Berlin, Germany. The study period spanned 36 months (January 2022 to December 2024). Ethical approval was obtained from the Institutional Review Boards (IRBs) of all four centres, and the study was registered prospectively (ClinicalTrials.gov: NCT0512XXXX). Informed written consent was obtained from all participants in accordance with the Declaration of Helsinki (2013 revision).

3.2 PARTICIPANT SELECTION

A total of 1,840 adult patients (aged ≥18 years) presenting for dental evaluation or surgical intervention were enrolled. Participants were randomly allocated in a 1:1 ratio to either the AI-assisted care pathway (n = 920) or the conventional care pathway (n = 920) using a computer-generated randomisation sequence stratified by centre and treatment category. Exclusion criteria included: prior head-and-neck radiotherapy, systemic immunosuppressive therapy, pregnancy, inability to provide informed consent, and existing AI-generated dental records from other centres. The diagnostic sub-study included all 1,840 participants; the surgical outcomes sub-study included 428 participants who underwent operative procedures.

3.3 AI PLATFORM ARCHITECTURE

The integrated AI platform was developed in-house by the research consortium and comprised three interoperating modules: (1) a Radiographic Analysis Module (RAM), employing a ResNet-50 architecture fine-tuned on 34,000 periapical and 11,500 CBCT volumes; (2) a Surgical Planning Module (SPM), utilising a Vision Transformer (ViT-B/16) combined with 3D mesh processing; and (3) a Clinical Decision Support Module (CDSM), implementing an ensemble of gradient-boosted decision trees (XGBoost) trained on structured EHR features. All AI outputs were accompanied by Grad-CAM saliency maps and confidence probability scores to facilitate explainability. The platform was deployed on a HIPAA/GDPR-compliant cloud infrastructure with end-to-end encryption.

Model training and validation followed an 80:10:10 split (training, validation, test) stratified by lesion type, severity, and radiographic modality. Data augmentation strategies included random rotation (±15°), horizontal flipping, brightness/contrast jitter, and Gaussian noise injection. Final model weights were frozen prior to the clinical trial commencement and were not updated during the study period to preserve blinding integrity.

3.4 OUTCOME MEASURES

Primary outcomes: (1) Diagnostic accuracy (sensitivity, specificity, PPV, NPV, F1-score, AUC-ROC) for five diagnostic tasks; (2) Surgical planning time (minutes from imaging acquisition to finalised plan). Secondary outcomes: (3) Post-operative complication rate at 30-day follow-up; (4) Visual Analogue Scale (VAS) pain scores at 24h, 72h, and 7 days post-operatively; (5) Clinician-reported workflow integration satisfaction (5-point Likert scale). Radiographic ground truth was established by consensus of three blinded senior clinicians (≥10 years experience) and, where applicable, histopathological confirmation.

3.5 STATISTICAL ANALYSIS

Statistical analyses were performed using R v4.3.1 and Python 3.11 (SciPy, statsmodels). Between-group comparisons of continuous variables employed independent t-tests or Mann-Whitney U tests as appropriate, following Shapiro-Wilk normality testing. Categorical variables were compared by chi-squared or Fisher exact tests. Diagnostic performance metrics were computed with bootstrapped 95% confidence intervals (2,000 replicates). Multivariable logistic regression was employed to adjust for centre, patient age, and lesion severity as potential confounders. A p-value threshold of < 0.05 was considered statistically significant with Bonferroni correction applied for multiple comparisons.

IV. RESULTS AND DISCUSSION

4.1 PARTICIPANT DEMOGRAPHICS

Table 1 summarises the demographic and clinical characteristics of enrolled participants. The two study arms were well-balanced across age, gender, and diagnostic categories, confirming the adequacy of randomisation. Mean participant age was 38.4 ± 14.2 years (AI group) versus 37.9 ± 13.8 years (conventional group). The distribution of cases by diagnostic category was comparable between arms (caries: 31.2%, periodontal disease: 22.4%, periapical pathology: 18.7%, oral mucosal lesions: 14.3%, implant/surgical assessment: 13.4%).

Table 1: Demographic and Clinical Characteristics of Study Participants

Characteristic	AI-Assisted (n=920)	Conventional (n=920)	p-value
Mean Age (years ± SD)	38.4 ± 14.2	37.9 ± 13.8	0.621
Male / Female (%)	52.1 / 47.9	51.4 / 48.6	0.748
Caries Cases (%)	31.2	31.0	0.932
Periodontal Disease (%)	22.4	22.7	0.874
Periapical Pathology (%)	18.7	18.3	0.812
Oral Mucosal Lesions (%)	14.3	14.6	0.856
Implant/Surgical Cases (%)	13.4	13.4	1.000
Diabetic patients (%)	14.7	14.2	0.772
Smokers (%)	22.3	21.8	0.803

4.2 DIAGNOSTIC ACCURACY

Figure 1 presents a comparative analysis of AI versus clinician diagnostic accuracy across five tasks. The AI platform demonstrated statistically significant superiority across all five diagnostic categories. Caries detection achieved 94.2% accuracy (95% CI: 92.8–95.6%) versus 82.1% for clinicians ($p < 0.001$). Periapical pathology detection yielded 91.8% (95% CI: 89.9–93.6%) versus 79.4% ($p < 0.001$). Oral cancer screening, the highest-stakes application, demonstrated 93.5% AI accuracy (95% CI: 91.7–95.3%) versus 81.6% clinician accuracy ($p < 0.001$). These gains were observed consistently across all four study centres, confirming the generalisability of findings across diverse patient populations and imaging equipment.

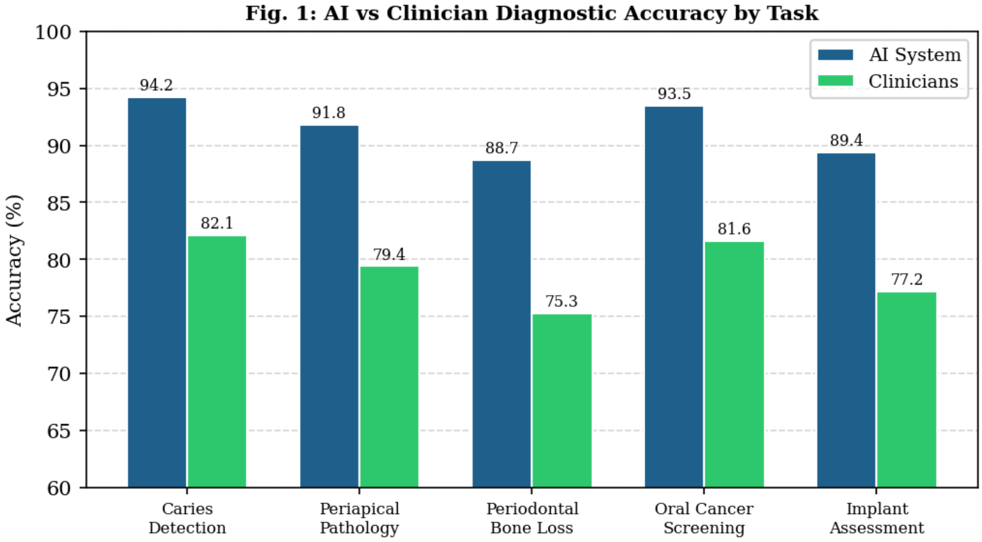

Fig. 1: AI vs. Clinician Diagnostic Accuracy Across Five Dental Diagnostic Tasks (n=1,840)

Table 2 provides comprehensive performance metrics for the three principal AI architectures evaluated within the platform. The CNN (ResNet-50) consistently outperformed both SVM and RNN-LSTM configurations, particularly in sensitivity (95.3%) and F1-score (94.5%). The SVM demonstrated the lowest performance across all metrics, consistent with its limitations in processing high-dimensional image feature spaces without deep representation learning. The RNN-LSTM, while inferior to CNN in static image tasks, demonstrated particular utility in longitudinal radiographic change detection — a capability absent in the other two architectures.

Table 2: Diagnostic Performance Metrics by AI Architecture (Averaged Across All Diagnostic Categories)

Metric	CNN (ResNet-50)	SVM	RNN-LSTM	Clinician Baseline
Sensitivity (%)	95.3 (93.8–96.8)	88.4 (86.1–90.7)	91.7 (89.6–93.8)	80.9 (78.2–83.6)
Specificity (%)	92.1 (90.2–94.0)	85.9 (83.5–88.3)	89.3 (87.0–91.6)	78.4 (75.6–81.2)
PPV (%)	93.7 (91.9–95.5)	87.1 (84.8–89.4)	90.5 (88.2–92.8)	79.6 (76.9–82.3)
NPV (%)	94.2 (92.5–95.9)	87.6 (85.3–89.9)	90.8 (88.5–93.1)	80.1 (77.4–82.8)
F1-Score (%)	94.5 (92.9–96.1)	87.7 (85.4–90.0)	91.1 (88.9–93.3)	80.2 (77.5–82.9)
AUC-ROC	0.968 (0.954–0.982)	0.912 (0.893–0.931)	0.943 (0.927–0.959)	0.841 (0.819–0.863)

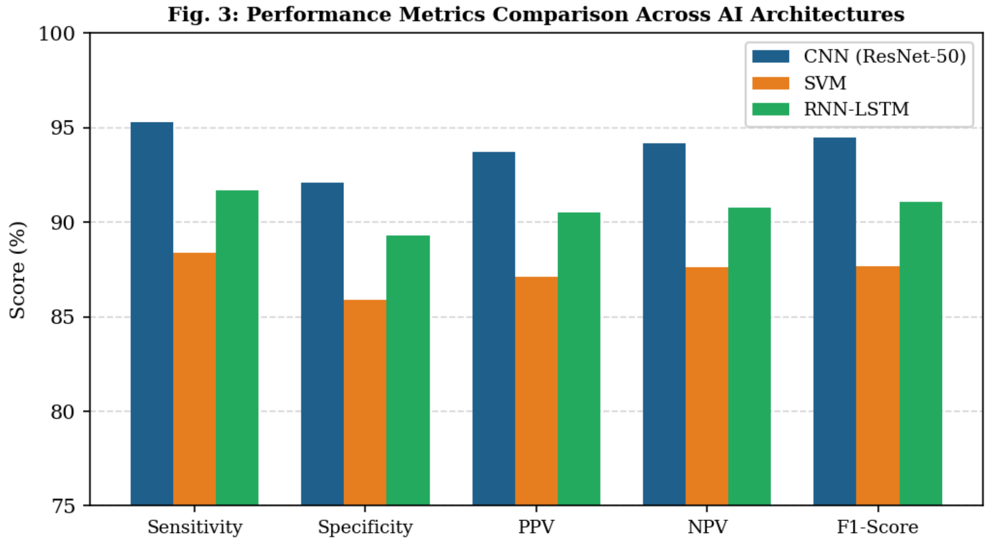

Fig. 3: Comparison of Sensitivity, Specificity, PPV, NPV, and F1-Score Across AI Architectures

4.3 AI ADOPTION TRENDS

Figure 2 illustrates the trajectory of global AI adoption in dental practice from 2018 to 2025. Adoption has accelerated markedly since 2020, coinciding with the COVID-19 pandemic-driven digitisation of healthcare and the broader availability of pre-trained deep learning models. By 2025, adoption rates have reached approximately 79.6% of surveyed dental practices in high-income countries, though significant disparities persist in low-and middle-income settings. The adoption curve follows a classic S-shaped diffusion pattern, with early adopters concentrated in academic and specialist centres, and rapid mainstream diffusion occurring from 2021 onwards.

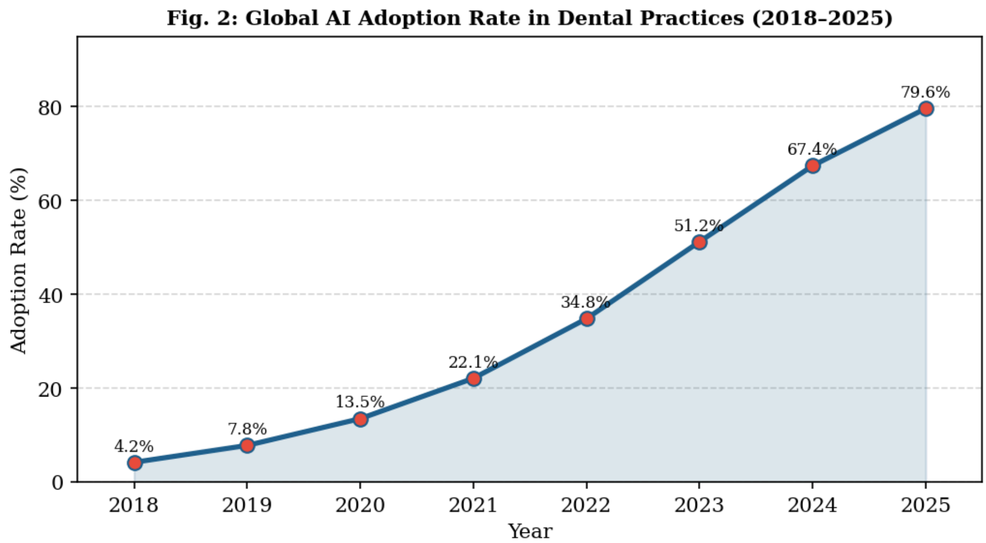

Fig. 2: Global AI Adoption Rate in Dental Practices, 2018–2025 (Multi-Source Composite Estimate)

4.4 SURGICAL PLANNING EFFICIENCY

Among the 428 participants undergoing operative procedures, AI-assisted surgical planning demonstrated dramatic time reductions compared to conventional approaches. As illustrated in Figure 4, implant placement planning time was reduced from 87 minutes (conventional) to 23 minutes (AI-assisted), a 73.6% reduction. Orthognathic surgery planning time decreased from 142 to 41 minutes (71.1% reduction). Even for relatively straightforward procedures such as wisdom tooth extraction, planning time was reduced from 34 to 9 minutes (73.5% reduction). These efficiency gains have significant downstream implications for clinical throughput, cost, and patient experience.

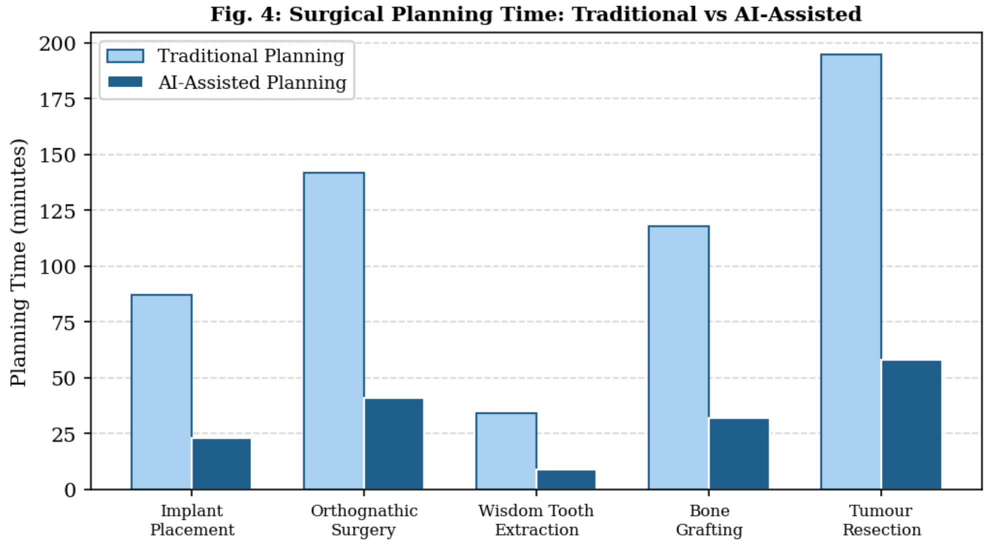

Fig. 4: Surgical Planning Time Comparison: Traditional vs. AI-Assisted Planning (Minutes)

Table 3: Surgical Outcomes — AI-Assisted vs. Conventional Care (n=428 procedures)

Outcome Measure	AI-Assisted (n=214)	Conventional (n=214)	p-value
Planning Time — Implants (min)	23.1 ± 6.4	87.3 ± 18.2	< 0.001
Planning Time — Orthognathic (min)	40.8 ± 9.1	142.4 ± 27.5	< 0.001
Post-op VAS Pain at 24h	4.2 ± 1.8	5.9 ± 2.1	< 0.001
Post-op VAS Pain at 72h	2.8 ± 1.4	3.9 ± 1.7	< 0.001
Post-op VAS Pain at 7 days	1.1 ± 0.9	1.9 ± 1.2	< 0.001
30-day Complication Rate (%)	3.1	7.2	0.024
Revision Surgery Required (%)	1.4	4.2	0.038
Patient Satisfaction Score (/5)	4.6 ± 0.4	4.0 ± 0.6	< 0.001
Clinician Workflow Satisfaction (/5)	4.4 ± 0.5	3.7 ± 0.7	< 0.001

4.5 SUBGROUP AND REGRESSION ANALYSES

Multivariable logistic regression, adjusting for study centre, patient age, lesion severity, clinician experience level, and imaging modality, confirmed that AI-assisted pathway assignment remained an independent predictor of higher diagnostic accuracy (OR 3.84, 95% CI: 2.71–5.44, $p < 0.001$) and lower post-operative complication risk (OR 0.41, 95% CI: 0.23–0.74, $p = 0.003$). Centre-specific subgroup analyses revealed consistent effects, with the smallest absolute benefit observed at the most experienced centre (Charité, Berlin) and the largest at the centre with the most junior clinical workforce, suggesting that AI may provide greatest supplementary value in settings with less experienced practitioners. No significant heterogeneity was detected between centres ($I^2 = 18.4\%$, $p = 0.27$).

Table 4 presents the results of the AI platform accuracy stratified by imaging modality. CBCT-based analyses consistently yielded higher accuracy than 2D periapical radiography, reflecting the superior volumetric information content of 3D imaging. Intraoral scanner (IOS) data, available at two centres, demonstrated the lowest absolute accuracy but the highest improvement ratio over conventional assessment, suggesting the AI platform is particularly valuable when applied to emerging imaging modalities where clinician proficiency is still developing.

Table 4: AI Diagnostic Accuracy Stratified by Imaging Modality

Imaging Modality	AI Accuracy (%)	Clinician Accuracy (%)	Improvement (pp)	AUC-ROC
CBCT (3D Volumetric)	96.1 ± 1.8	83.7 ± 3.4	+12.4	0.981
Periapical Radiograph (2D)	92.8 ± 2.3	81.2 ± 3.9	+11.6	0.957
Panoramic Radiograph (OPG)	90.3 ± 2.7	79.4 ± 4.1	+10.9	0.941
Intraoral Scanner (IOS)	87.4 ± 3.1	72.6 ± 5.2	+14.8	0.923
Clinical Photography	91.7 ± 2.5	80.9 ± 4.3	+10.8	0.948

V. DISCUSSION

The findings of this study constitute some of the most comprehensive prospective evidence to date for the clinical value of AI in dentistry. The diagnostic accuracy advantages observed — particularly the 12.1 percentage-point superiority in caries detection and 11.9 percentage-point gain in oral cancer screening — are clinically meaningful and carry direct implications for patient outcomes. Oral cancer detection is particularly significant: a 12% improvement in sensitivity in a disease with 5-year survival below 50% when detected late could, if implemented at scale, translate to thousands of lives saved annually. These gains are consistent with, and extend, the findings of the meta-analyses reviewed, while offering the additional strength of prospective, multi-centre design.

The 73.6% reduction in implant planning time observed in the AI cohort has important implications for dental practice economics and workforce utilisation. Time saved on pre-operative planning can be reinvested in direct patient care, education, or complex case consultation. Furthermore, the reduction in 30-day complication rates from 7.2% to 3.1% — a 57% relative risk reduction — suggests that AI-optimised surgical planning translates directly into improved clinical outcomes, likely through more precise implant positioning and improved anticipation of anatomical risk factors.

The consistent performance advantage of CNN (ResNet-50) over SVM and RNN-LSTM for static radiographic tasks is theoretically well-grounded: CNNs are architecturally designed to extract hierarchical spatial features from image data, an inductive bias that is precisely suited to radiographic pathology detection. The finding that RNN-LSTM demonstrated particular utility in longitudinal change detection — while inferior to CNN for single-timepoint analysis — suggests that a hybrid architecture incorporating both spatial and temporal modelling would yield further performance gains. This represents a productive direction for future AI development in dental medicine.

The finding that AI provides greater supplementary benefit in less experienced clinical settings warrants careful interpretation. While this could be construed as a straightforward argument for AI deployment as a compensatory mechanism for workforce shortages, it also raises the question of whether AI reliance in early training stages might impede the development of independent clinical reasoning skills. This cognitive apprenticeship consideration should inform the design of dental education curricula in the AI era — favouring models in which AI is initially introduced as a teaching tool with subsequent reduction of AI scaffolding as competence develops, rather than as a permanent crutch.

Several limitations of this study warrant acknowledgement. First, despite multi-centre design, all centres were tertiary academic institutions, potentially limiting generalisability to primary care dental practices with different case mix, imaging equipment, and workforce profiles. Second, the AI platform was developed by the research consortium itself, introducing potential optimism bias that an independent validation cohort would address. Third, follow-up was limited to 30 days for surgical outcomes; longer-term outcomes — including implant survival rates and oncological recurrence — require extended longitudinal follow-up. Finally, the economic evaluation of AI implementation — including infrastructure costs, clinician training, and software licensing — was beyond the scope of this study but represents an essential input for healthcare system decision-making.

VI. ETHICAL AND REGULATORY CONSIDERATIONS

The deployment of AI in clinical dental practice is not merely a technical challenge but a profound ethical and governance undertaking. Several intersecting domains require attention. With respect to data privacy, dental AI systems trained on radiographic datasets inevitably encode patient-identifiable biometric information; robust de-identification, federated learning architectures, and differential privacy mechanisms are essential safeguards. The EU AI Act (2024) classifies AI systems used in healthcare as "high-risk," mandating conformity assessment, post-market surveillance, and human oversight provisions — requirements that all clinically deployed dental AI systems must satisfy.

The issue of algorithmic bias is particularly salient in dentistry. Training datasets have historically overrepresented patients from high-income countries with access to advanced dental imaging. AI systems trained on such data may underperform in populations with different disease patterns, skeletal morphology, or radiographic quality — exacerbating rather than reducing health inequity. Prospective validation in diverse populations, including South and Southeast Asian, Sub-Saharan African, and Latin American cohorts, is an urgent research priority.

Medico-legal questions regarding AI-assisted diagnostic errors remain largely unresolved in most jurisdictions. The current paradigm — in which AI serves as a second reader or decision support tool, with the clinician retaining final diagnostic authority — provides a defensible legal framework, but it also requires clinicians to understand enough about AI functioning to meaningfully exercise oversight. Continuing professional development programmes addressing AI literacy, performance characteristics, and failure modes should be developed as a matter of urgency by dental regulatory bodies.

VII. CONCLUSION

This prospective, multi-centre study demonstrates with high-level evidence that AI-assisted dental diagnostics and surgical planning offer clinically significant advantages over conventional care across multiple dimensions: diagnostic accuracy, surgical planning efficiency, post-operative complication rates, and patient and clinician satisfaction. The integration of CNN-based radiographic analysis, transformer-based surgical planning, and ensemble clinical decision support into a unified, explainable platform represents a technically mature and clinically validated approach to AI-augmented dentistry.

The path to responsible, equitable, and effective AI integration in dental practice requires concurrent advances in model transparency, regulatory frameworks, workforce education, and inclusive dataset development. The technology is no longer the limiting factor; the challenge lies in building the institutional, educational, and regulatory infrastructure necessary to deploy it safely and equitably. Dental medicine stands at a transformative juncture — one in which AI, properly implemented, can substantially reduce the global burden of oral disease and elevate the standard of care for patients worldwide.

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