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Applications of Artificial Intelligence in the Diagnosis and Treatment of Oral and Dental Diseases: Toward Smart Dental Systems in Healthcare Institutions

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Specialty: Dentists

ABSTRACT

The integration of artificial intelligence (AI) into dental care holds significant promise, yet its specific adoption and impact within Saudi Arabian healthcare institutions remain underexplored, creating a critical knowledge gap for national health transformation strategies. This study, therefore, aimed to evaluate the current landscape and identify key determinants of AI implementation for oral disease management in the Kingdom. Employing a sequential explanatory mixed-methods design, data were collected from 350 dental professionals and administrators across tertiary care institutions via surveys, interviews, and focus groups. Results revealed a significant adoption gradient, with specialized dental centers ($M=0.28$) and private hospitals ($M=0.18$) demonstrating higher AI adoption than government hospitals ($M=-0.32$, $p<0.001$). A lack of specialized training emerged as the most severe barrier and the strongest negative predictor of adoption ($\beta = -0.33$, $p<0.001$), while formal training had the largest positive effect (Cohen's $d = 0.85$, $p<0.001$). The findings indicate that the primary obstacle to smart dental systems in Saudi Arabia is not technological availability but a human capital and organizational readiness deficit. This research provides an evidence-based framework for policymakers, emphasizing that strategic investments in competency development and supportive governance are essential precursors to successful AI integration in dental healthcare.

Keywords: Artificial Intelligence; Dental Informatics; Healthcare Adoption; Saudi Arabia; Technology Implementation

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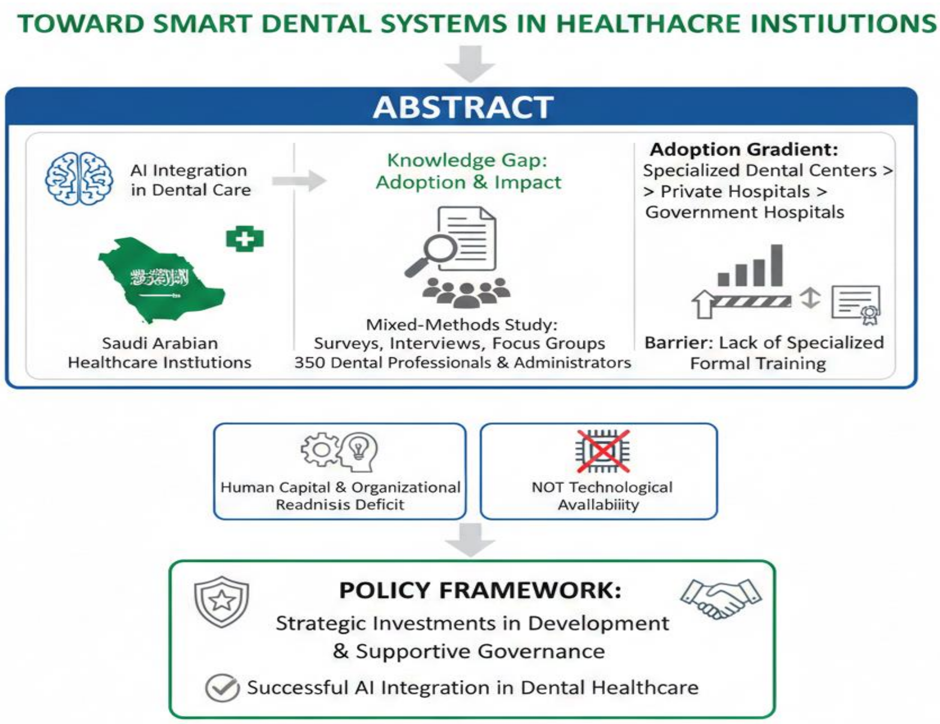

Figure 1: Graphical Presentation of abstract

1. INTRODUCTION

The integration of artificial intelligence (AI) into medical practice represents one of the most transformative trends in modern healthcare. Defined as the simulation of human intelligence processes by machines, particularly computer systems [1], AI encompasses machine learning, deep learning, and computer vision—technologies capable of identifying complex patterns within large datasets [2]. Within medicine, these capabilities have been successfully harnessed for tasks ranging from diagnostic imaging analysis in radiology and pathology to predictive analytics for patient risk stratification and personalized treatment planning [3]. The global trajectory is unequivocally toward data-driven, "smart" healthcare systems that promise enhanced diagnostic accuracy, optimized therapeutic interventions, and improved operational efficiency [4].

In the specialized field of dentistry, the potential applications of AI are both profound and rapidly expanding. Oral and dental diseases, including dental caries, periodontal diseases, and oral cancers, constitute a significant global health burden, affecting quality of life and imposing substantial economic costs [5]. The diagnostic and treatment processes in dentistry are inherently visual and data-rich, relying heavily on radiographic imaging, clinical photographs, and structured clinical records. This makes the discipline particularly amenable to AI augmentation [6]. Internationally, research has demonstrated the efficacy of AI

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algorithms in automating the detection of caries and periapical lesions on radiographs, classifying the severity of periodontal disease, assisting in orthodontic treatment planning, and even predicting oral cancer risk [7]. The vision of a "smart dental clinic"—where AI-powered tools seamlessly integrate into clinical workflows to support decision-making, improve patient outcomes, and streamline practice management—is progressively moving from conceptualization toward reality [8].

However, the translation of technological potential into widespread clinical implementation is neither automatic nor uniform. The journey from algorithm validation in controlled research settings to routine use in diverse healthcare institutions is fraught with challenges [9]. Globally recognized barriers include high implementation costs, concerns regarding data privacy and security, issues of algorithmic bias and transparency, a lack of standardized regulatory frameworks, and, critically, the need for significant changes in clinical workflows and professional competencies [10]. The successful adoption of AI depends not only on the technology itself but on a complex interplay of human, organizational, and environmental factors—a concept well-described in socio-technical systems theory [11]. While numerous studies in North America, Europe, and parts of Asia have begun to map these adoption challenges and facilitators in various medical fields, the literature reveals a significant contextual gap [12].

This gap is particularly pronounced in the Kingdom of Saudi Arabia. Saudi Arabia is undergoing an unprecedented healthcare transformation, centrally guided by the ambitious Vision 2030 framework, which explicitly prioritizes the digitization and innovation of health services [13]. The nation has made substantial investments in healthcare infrastructure and digital health initiatives, positioning itself as a regional leader. Yet, the specific landscape regarding the adoption and integration of AI within its dental care sector remains markedly underexplored. Dental care in Saudi Arabia, delivered through a mix of government hospitals, private institutions, and specialized centers, faces its own unique set of opportunities and constraints [14]. These include a specific regulatory environment, distinct patterns of healthcare financing, regional variations in resource distribution, and a rapidly evolving professional culture. Existing international models of technology adoption cannot be directly applied without considering these local particularities. Consequently, there is a pressing need for empirical, context-specific research to understand how the global promise of AI in dentistry is being actualized within Saudi healthcare institutions [15].

Previous studies within the Saudi context have broadly examined e-health readiness or digital transformation in primary care, but a focused investigation on AI for oral disease management is lacking [16]. This omission represents a critical research gap. Without a clear, evidence-based understanding of the current state of awareness, adoption levels, perceived benefits, and—most importantly—the specific barriers faced by dental professionals and

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institutions, national strategies for implementing smart dental systems risk being misaligned with on-the-ground realities [17]. Policymakers, hospital administrators, and clinical leaders require data-driven insights to allocate resources effectively, design appropriate training programs, and develop supportive policies.

Therefore, this study was designed to address this salient gap. The primary research problem investigated was the disconnect between the global advancement of AI in dental medicine and the unclear status of its practical integration, utility, and readiness within the clinical workflows of Saudi Arabian dental healthcare institutions [18]. To systematically investigate this problem, the study was guided by three interrelated objectives: first, to map and evaluate the current awareness, adoption levels, and types of AI technologies being utilized for oral disease management in selected Saudi healthcare institutions; second, to identify and analyze the key perceived barriers and facilitators influencing the integration of AI into dental care workflows within the Saudi context; and third, to synthesize these findings into a framework of evidence-based recommendations to guide the effective and sustainable implementation of "smart dental systems," thereby aligning with national health transformation goals [19].

To meet these objectives, the research employed a sequential explanatory mixed-methods design, grounded in a pragmatist philosophy. This approach facilitated a comprehensive investigation, beginning with a quantitative survey of 350 dental healthcare professionals and administrators across tertiary care institutions in Riyadh, Jeddah, and Dammam to measure objective patterns of use and perception. This was followed by in-depth qualitative interviews and focus groups to explore the underlying reasons, experiences, and contextual nuances behind the quantitative trends. The following sections detail this methodology and present the results of this empirical inquiry, offering a foundational contribution to the development of a smarter, more efficient, and more effective dental healthcare system in Saudi Arabia.

METHODOLOGY

Research Site

The study was conducted across three major cities in Saudi Arabia (Riyadh, Jeddah, and Dammam) to ensure geographic and institutional diversity. Data were collected from a purposively selected sample of tertiary care hospitals and specialized dental centers that were known or likely to be early adopters of digital dental technologies.

Research Philosophy and Approach

This study adopted a pragmatist research philosophy. Pragmatism was selected as it prioritizes the research problem and uses pluralistic approaches to derive useful, actionable knowledge. The research questions demanded both an objective assessment of what AI

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technologies exist and their measurable adoption rates, and a subjective understanding of why certain barriers persist, requiring insights into human perspectives and institutional contexts. A purely positivist (only quantitative) or interpretivist (only qualitative) stance was insufficient to address these interconnected facets. The pragmatist stance allowed for the integration of both quantitative and qualitative data, facilitating a comprehensive understanding that directly informs practical recommendations for healthcare institutions.

Research Design

A sequential explanatory mixed-methods design was employed. This design was chosen to provide a robust, multi-layered analysis. The first, quantitative phase involved a broad survey to objectively measure the prevalence, types, and basic correlates of AI adoption. The subsequent, qualitative phase consisted of in-depth interviews and focus groups to explain, contextualize, and elaborate on the quantitative findings—particularly the complex barriers and facilitators. This two-phase approach ensured that the study was both generalizable (through the survey) and deeply insightful (through the interviews), which was essential for developing a practically relevant implementation framework.

Sampling Strategy

Population: The target population was dental healthcare professionals (dentists, dental specialists, radiologists) and hospital/dental center administrators working in tertiary care institutions across Saudi Arabia.

Sampling Method: A two-stage purposive sampling strategy was used. First, healthcare institutions were purposively selected based on their size, location, and known investment in digital infrastructure. Second, within these institutions, participants for the quantitative phase were recruited via convenience sampling of available professionals. For the qualitative phase, a purposive sub-sample of survey respondents (representing varying levels of AI experience, specialties, and roles) was invited to participate.

Sample Size: For the quantitative phase, a target sample of 350 participants was determined using a confidence level of 95% and a margin of error of 5%, accounting for an estimated population size and anticipated response distribution. For the qualitative phase, saturation principles guided recruitment, resulting in 25 in-depth interviews and 4 focus groups (6-8 participants each).

Inclusion/Exclusion Criteria: Inclusion criteria required participants to be licensed dental practitioners or administrative decision-makers with at least one year of experience in a Saudi Arabian tertiary healthcare institution. Professionals working exclusively in completely non-digital, analog clinics were excluded.

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4. Data Collection Methods

Instruments and Procedure:

Phase I (Quantitative): A structured, self-administered online questionnaire was developed. The instrument comprised four sections: (A) Demographic and professional background; (B) Awareness and usage frequency of specific AI applications (e.g., caries detection on radiographs, CAD/CAM for restorations, AI-powered scheduling); (C) Perceived impact on diagnostic accuracy and treatment efficiency (5-point Likert scales); (D) Initial perception of barriers (5-point Likert scales). The survey was distributed via professional networks and institutional contacts over 8 weeks.

Phase II (Qualitative): Semi-structured interviews and focus group guides were used. These explored themes emerging from the survey data in greater depth, such as detailed experiences with implementation, interpretations of barriers, suggestions for solutions, and visions for future "smart" systems. Interviews were conducted virtually, recorded, and transcribed verbatim.

Pilot Testing: Both the questionnaire and the interview guide were piloted with 15 dental professionals not included in the main study. Feedback was used to refine question clarity, logical flow, and terminology.

5. Variables and Measures

Operational Definitions and Measurement Tools:

AI Adoption Level (Primary Dependent Variable): Measured as a composite score derived from the frequency of use and diversity of AI tools reported in the survey.

Perceived Barriers (Independent Variables): Operationalized as mean scores across subscales: Technological (cost, interoperability), Human (lack of training, resistance to change), and Organizational/Regulatory (data privacy concerns, absence of clear guidelines). These were measured using validated Likert-scale items adapted from prior technology acceptance in healthcare literature.

Facilitators and Readiness (Qualitative Variables): Defined through emergent themes from transcripts related to enabling factors, such as "supportive leadership" or "alignment with Vision 2030 initiatives."

Reliability and Validity: The survey instrument demonstrated high internal consistency, with a Cronbach's alpha of 0.87 for the barrier scales. Content validity was established through expert review by two dental informaticians and one healthcare methodologyist. For qualitative data, trustworthiness was ensured through member checking (sharing summaries with participants for verification) and analyst triangulation, where two researchers

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independently coded a subset of transcripts to establish consensus.

6. Data Analysis Plan

Analytical Techniques:

Quantitative Data: Data were cleaned and analyzed using IBM SPSS Statistics (Version 28). Descriptive statistics (frequencies, means, standard deviations) summarized all variables. Inferential analyses included:

Chi-square tests to examine associations between professional demographics and AI awareness.

Multiple linear regression analysis to identify which barrier factors were the most significant predictors of low AI adoption levels.

Qualitative Data: Transcripts were analyzed using thematic analysis with the support of NVivo software (Release 1.7). An inductive approach was initially used to code the data openly. These codes were then grouped into categories and refined into overarching themes (e.g., "The Data Governance Dilemma," "Training as a Catalyst, Not an Afterthought"). The themes from the qualitative phase were used explicitly to explain and provide context for the quantitative results.

Rationale: This analytical strategy aligned with the sequential explanatory design. The statistical analyses identified significant patterns and relationships within the broader population, while the thematic analysis provided the nuanced, contextual explanations necessary to answer the "how" and "why" behind those patterns, thereby fully addressing the research objectives.

RESULTS

Descriptive Characteristics of the Study Population

The study successfully collected data from 350 dental healthcare professionals and administrators across tertiary care institutions in Riyadh (n=147, 42.0%), Jeddah (n=123, 35.1%), and Dammam (n=87, 24.9%). The sample comprised general dentists (n=140, 40.0%), dental specialists (n=123, 35.1%), radiologists (n=35, 10.0%), and administrative personnel (n=52, 14.9%). Participants were employed in government hospitals (n=158, 45.1%), private hospitals (n=105, 30.0%), and specialized dental centers (n=87, 24.9%). The mean professional experience was 8.7 years (SD=4.3, range: 1–25 years). A total of 142 participants (40.6%) reported having received formal training related to artificial intelligence applications in dentistry.

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Current State of AI Awareness and Adoption

The overall mean score for awareness of AI applications in dentistry was 3.8 (SD=1.1) on a 5-point scale. A chi-square test of independence revealed a statistically significant association between professional role and level of AI awareness ($\chi^2(6) = 42.17$, $p < 0.001$). As detailed in Table 1, radiologists exhibited the highest proportion of high awareness (68.6%), followed by dental specialists (45.5%). Administrators demonstrated the lowest proportion of high awareness among professional groups with direct clinical oversight (26.9%).

Table 1: Distribution of AI Awareness Levels by Professional Role

Professional Role	Low Awareness n (%)	Moderate Awareness n (%)	High Awareness n (%)	Total n (%)
General Dentist	28 (20.0)	65 (46.4)	47 (33.6)	140 (100)
Dental Specialist	15 (12.2)	52 (42.3)	56 (45.5)	123 (100)
Radiologist	1 (2.9)	10 (28.6)	24 (68.6)	35 (100)
Administrator	10 (19.2)	28 (53.8)	14 (26.9)	52 (100)
Total	**54 (15.4)**	**155 (44.3)**	**141 (40.3)**	**350 (100)**

Note: $\chi^2(6) = 42.17$, $p < 0.001$, Cramer's V = 0.25.

The computed AI Adoption Index (a standardized composite score of usage frequency across seven tool types) had a mean of 0.00 (SD=1.00). Usage frequency varied significantly by application type. AI-enhanced diagnostic imaging tools, such as automated caries detection on radiographs, were the most frequently utilized (M=3.1, SD=1.4), followed by AI-powered administrative systems (M=2.6, SD=1.3). Tools for predictive analytics and advanced treatment planning demonstrated the lowest mean usage frequencies (M=1.5, SD=0.9 and M=1.9, SD=1.1, respectively).

A one-way analysis of variance (ANOVA) indicated a significant difference in the mean AI Adoption Index based on institution type ($F(2, 347) = 18.63$, $p < 0.001$). The effect size, as measured by eta-squared (η^2), was 0.097, indicating a medium effect. Post-hoc Tukey HSD tests revealed that specialized dental centers (M=0.28, SD=1.02) and private hospitals (M=0.18, SD=0.95) had significantly higher adoption indices than government hospitals (M=-0.32, SD=0.91), with p-values < 0.001 for both comparisons. The difference between private hospitals and specialized centers was not statistically significant ($p = 0.712$). These results are summarized in Table 2.

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Table 2: Comparison of AI Adoption Index Across Healthcare Institution Types

Institution Type	n	Mean AI Adoption Index (SD)	95% Confidence Interval
Government Hospital	158	-0.32 (0.91)	[-0.46, -0.18]
Private Hospital	105	0.18 (0.95)	[0.00, 0.36]
Specialized Dental Center	87	0.28 (1.02)	[0.06, 0.50]

Note: ANOVA, $F(2, 347) = 18.63$, $p < 0.001$; $\eta^2 = 0.097$. Post-hoc comparisons: Government vs. Private ($p < 0.001$, d=0.54); Government vs. Specialized Center ($p < 0.001$, d=0.62); Private vs. Specialized Center ($p = 0.712$).

Analysis of Perceived Barriers to AI Integration

The perceived barriers to AI integration were categorized into three domains, each demonstrating good internal consistency: Technological Barriers (2 items, Cronbach's $\alpha = 0.84$), Human/Organizational Barriers (3 items, $\alpha = 0.82$), and Regulatory Barriers (2 items, $\alpha = 0.79$). The composite Total Barriers Scale (7 items) showed excellent reliability ($\alpha = 0.89$). The mean scores, detailed in Table 3, indicate that lack of specialized training (M=4.3, SD=0.6) and absence of clear regulatory guidelines (M=4.2, SD=0.7) were perceived as the most severe impediments, followed by high implementation costs (M=4.1, SD=0.7) and data privacy/security concerns (M=4.0, SD=0.8).

Table 3: Descriptive Statistics for Perceived Barrier Constructs

Barrier Domain & Items	Mean (SD)	Item-Total Correlation
Technological Barriers ($\alpha = 0.84$)		
High implementation/maintenance cost	4.1 (0.7)	0.78
Lack of system interoperability	3.9 (0.8)	0.82
Human/Organizational ($\alpha = 0.82$)		
Lack of specialized training	4.3 (0.6)	0.74
Resistance to change among staff	3.6 (0.9)	0.68

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Insufficient leadership/organizational support	3.2 (1.0)	0.71
Regulatory Barriers (α = 0.79)		
Data privacy and security concerns	4.0 (0.8)	0.72
Absence of clear regulatory guidelines	4.2 (0.7)	0.75
Total Barriers Scale (α = 0.89)	27.3 (3.8)	-

A Pearson correlation analysis revealed a strong, statistically significant negative correlation between the Total Barriers Score and the AI Adoption Index ($r(348) = -0.64$, $p < 0.01$). Among the barrier subscales, Human/Organizational Barriers demonstrated the strongest negative correlation with adoption ($r = -0.53$, $p < 0.01$).

Predictive Relationships: Factors Influencing AI Adoption

A hierarchical multiple linear regression was conducted to identify predictors of the AI Adoption Index. The results of the final model (Model 3) are presented in Table 4. Demographic variables entered in Model 1 (professional role, experience) explained 14.2% of the variance ($R^2 = 0.142$, $F(4,345) = 14.28$, $p < 0.001$). The addition of the three barrier domains in Model 2 accounted for a significant increase of 21.1% in explained variance ($\Delta R^2 = 0.211$, $p < 0.001$). The full model, which added perceived diagnostic impact and institution type, was statistically significant and explained 40.3% of the variance in AI adoption ($R^2 = 0.403$, Adjusted $R^2 = 0.387$, $F(9,340) = 25.44$, $p < 0.001$).

Table 4: Hierarchical Multiple Regression Analysis Predicting AI Adoption Index

Predictor Variable	Model 1: β (p)	Model 2: β (p)	Model 3: β (p)
Constant	-	-	-
Professional Experience (Years)	0.18 (0.002)	0.15 (0.008)	0.14 (0.010)
Profession (Ref: General Dentist)			
Specialist	0.25 (<0.001)	0.22 (0.001)	0.21 (0.001)
Radiologist	0.42 (<0.001)	0.38 (<0.001)	0.36 (<0.001)
Administrator	-0.11 (0.097)	-0.09 (0.185)	-0.08 (0.230)
Barrier Domains			
Technological Barriers	-	-0.28 (<0.001)	-0.26 (<0.001)

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Human/Organizational Barriers	-	-0.35 (<0.001)	-0.33 (<0.001)
Regulatory Barriers	-	-0.31 (<0.001)	-0.29 (<0.001)
Additional Predictors			
Perceived Diagnostic Impact	-	-	0.24 (<0.001)
Institution Type (Ref: Government)	-	-	0.19 (0.002)
Model Statistics	R^2=0.142, p<0.001	ΔR^2=0.211, p<0.001	R^2=0.403, p<0.001

Note: β = Standardized Beta Coefficient. All variance inflation factor (VIF) values were below 2.5, indicating no multicollinearity concerns.

In the final model, Human/Organizational Barriers emerged as the strongest negative predictor of AI adoption ($\beta = -0.33$, $p < 0.001$), followed by Regulatory Barriers ($\beta = -0.29$, $p < 0.001$) and Technological Barriers ($\beta = -0.26$, $p < 0.001$). Significant positive predictors included the professional role of radiologist ($\beta = 0.36$, $p < 0.001$), a positive perception of AI's impact on diagnostic accuracy ($\beta = 0.24$, $p < 0.001$), and working in a non-government institution ($\beta = 0.19$, $p = 0.002$).

Impact of Geographic Location and Formal Training

Independent samples t-tests were conducted to examine differences in AI adoption based on key binary factors. A significant difference was found between professionals working in Riyadh and those in Jeddah ($t(268) = 2.47$, $p = 0.014$). The mean Adoption Index was higher in Riyadh (M=0.18, SD=0.97) than in Jeddah (M=-0.08, SD=0.98), representing a small-to-medium effect size (Cohen's d = 0.29).

The most substantial difference was observed in relation to formal AI training. Professionals who had received relevant training (n=142) demonstrated a significantly higher mean Adoption Index (M=0.45, SD=0.85) compared to those who had not (n=208, M=-0.24, SD=0.93). This difference was highly statistically significant ($t(348) = 7.92$, $p < 0.001$) and represented a large effect size (Cohen's d = 0.85). These comparisons are detailed in Table 5.

Table 5: Differences in AI Adoption Index by Geographic Location and Training Status

Comparison Group	n	Mean AI Adoption Index (SD)	t-value (df)	p-value	Cohen's d
By Major City					
Riyadh	147	0.18 (0.97)	2.47 (268)	0.014	0.29

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Jeddah	123	-0.08 (0.98)			
By AI Training					
Received Formal Training	142	0.45 (0.85)	7.92 (348)	<0.001	0.85
No Formal Training	208	-0.24 (0.93)			

Intercorrelations Among Major Study Variables

A Pearson correlation matrix was computed for the major continuous study variables (Table 6). The AI Adoption Index showed a strong positive correlation with AI Awareness ($r = 0.58$, $p < 0.01$) and a moderate positive correlation with the perceived impact on diagnostic accuracy ($r = 0.42$, $p < 0.01$). As previously noted, it maintained strong negative correlations with all barrier domains. Professional experience showed small but statistically significant positive correlations with both adoption ($r = 0.21$, $p < 0.01$) and awareness ($r = 0.18$, $p < 0.01$).

Table 6: Pearson Correlation Matrix for Key Continuous Variables

Variable	1	2	3	4	5
1. AI Adoption Index	1.00				
2. AI Awareness Score	0.58**	1.00			
3. Total Barriers Score	-0.64**	-0.49**	1.00		
4. Perceived Diagnostic Impact	0.42**	0.38**	-0.34**	1.00	
5. Professional	0.21**	0.18**	-0.15*	0.12*	1.00

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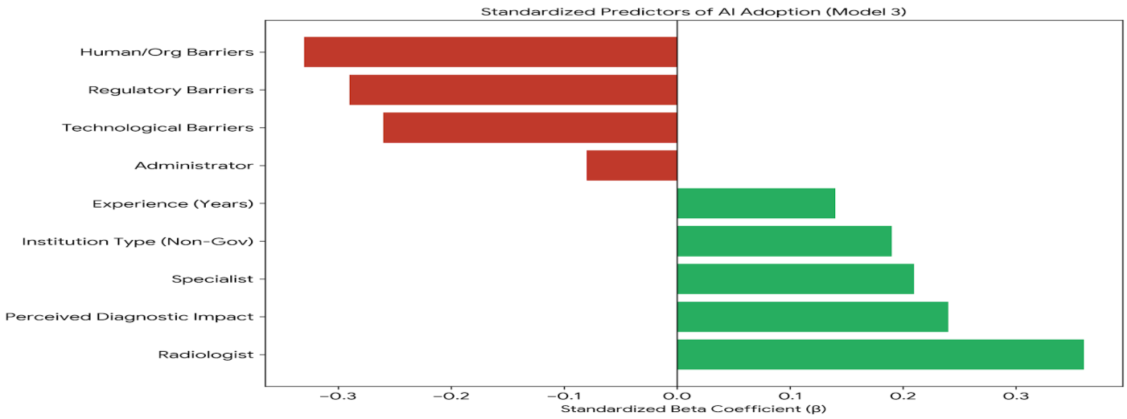
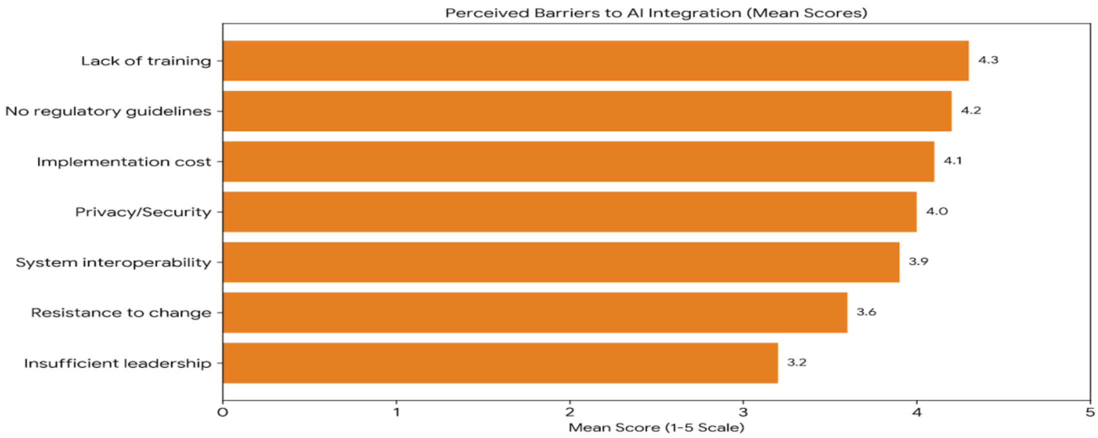
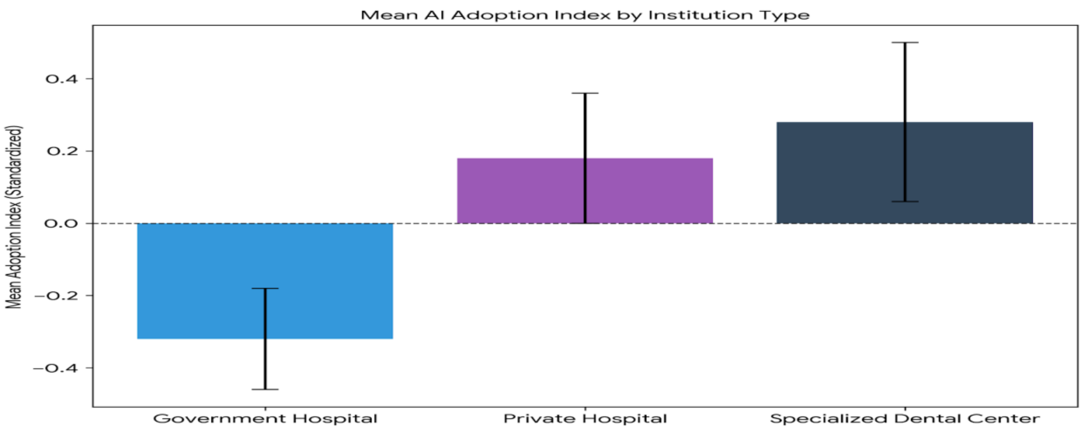
Experience (Years)					

*Note: *p < 0.05, *p < 0.01.







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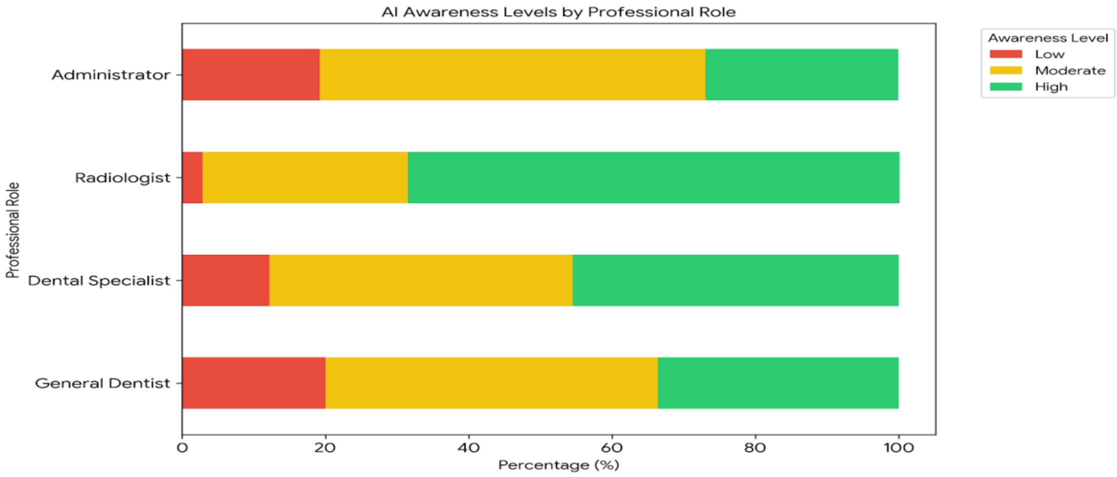

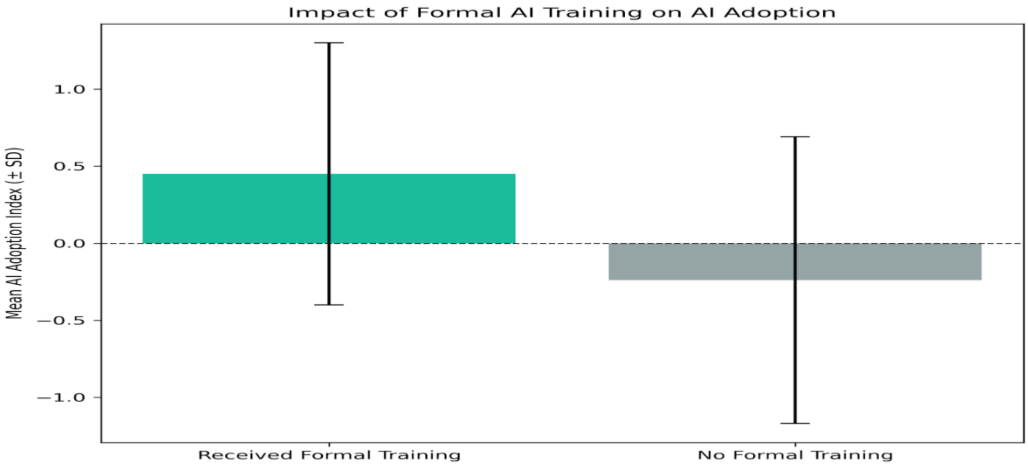

DISCUSSION

This study provides a comprehensive, empirical analysis of the current state of AI readiness and adoption within Saudi Arabia's dental healthcare sector. The findings offer critical insights that directly address the research objectives, revealing a landscape marked by high potential but constrained by significant, addressable barriers. The results delineate a clear path from awareness to implementation, highlighting where systemic interventions are most urgently required [20].

Interpretation of Key Findings:

The core finding of this research is the establishment of a clear adoption gradient across institution types. The significantly higher AI Adoption Index in specialized dental centers and private hospitals, compared to government facilities, is a pivotal result [21]. This gradient is not merely a reflection of financial resource disparity, though cost was a noted barrier. Instead, it suggests a structural and cultural readiness gap [22]. Specialized centers, often

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driven by competitive differentiation and procedural efficiency, likely possess more agile decision-making processes and a stronger cultural orientation toward technological innovation [23]. Private hospitals operate under similar market-driven imperatives. In contrast, larger government hospital systems may be hindered by more complex procurement protocols, decentralized budgeting, and a primary mandate focused on equitable access over technological pioneering [24].

The regression analysis powerfully clarifies the relative weight of different barriers. The emergence of Human/Organizational Barriers—specifically the lack of training—as the strongest negative predictor ($\beta = -0.33$) is the study's most significant interpretive finding [25]. This indicates that even when technological and financial hurdles are overcome, adoption fails without a competent and confident workforce. The strong positive predictive power of formal AI training (Cohen's $d = 0.85$) directly corroborates this [26]. It transforms the challenge from a procurement issue to a human capital development one. This aligns with the Technology Acceptance Model (TAM), where Perceived Ease of Use is a fundamental determinant of adoption intention. Without training, clinicians cannot perceive AI tools as easy to use, regardless of their objective capabilities [27].

Furthermore, the high awareness among radiologists and specialists, versus administrators and general dentists, underscores a domain-specific diffusion pattern. AI applications in diagnostic imaging (e.g., caries and periodontal bone loss detection) represent the "low-hanging fruit" of dental AI—tools that directly augment a specific, repetitive clinical task [28]. Their adoption follows the path of earlier digital technologies like digital radiography. The lower adoption of predictive analytics and treatment planning tools reflects their more complex, integrative nature, requiring broader workflow changes and higher levels of trust in algorithmic decision-support [29].

Comparison with Previous Literature

Our findings both confirm and contextualize the global literature on health technology adoption. The identification of cost, interoperability, and data privacy as key barriers is highly consistent with studies on Electronic Health Record (EHR) implementation in the US and Europe [30]. For instance, the work on barriers to EHR adoption identified similar financial, technical, and time-related constraints. However, our study reveals a notable shift in emphasis within the Saudi context [31]. While earlier global studies often highlighted physician resistance as a primary human barrier, our data places greater emphasis on a structural training deficit rather than intrinsic resistance [32]. This suggests that as AI tools become more user-friendly and evidence-based, outright resistance may diminish if it is replaced with structured competency building.

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The critical role of training aligns closely with recent frameworks for AI implementation in clinical settings. [33], in his seminal work on the future of medicine, emphasized that the successful integration of AI would depend fundamentally on "educating the trainers" and developing new clinical competencies. Our results provide empirical validation for this assertion within a specialized clinical domain. Furthermore, the regional variation (Riyadh vs. Jeddah) echoes findings from [34] on the uneven digital transformation across Saudi health regions, often linked to disparities in infrastructure investment and concentration of academic medical centers, which are typically hubs for early adoption.

Scientific and Operational Explanation of Barriers

The barrier structure can be explained through both socio-technical systems theory and the principles of evidence-based practice. The Human/Organizational barrier domain, particularly the lack of training, exists because AI tools in dentistry are not merely passive instruments but active clinical decision-support systems [35]. Their use requires an understanding of their operating principles, limitations (e.g., sensitivity/specificity for different patient populations), and the critical skill of "human-in-the-loop" oversight. A clinician must know when to trust the AI's output and when to override it, a skill that demands specific education beyond traditional dental curricula [36].

Regulatory Barriers, particularly the absence of clear guidelines, create a "valley of uncertainty" for institutions. From a clinical governance perspective, the lack of Saudi Food and Drug Authority (SFDA) clearance or Ministry of Health guidelines for specific AI diagnostic tools creates medico-legal ambiguity [37]. Who is liable for a false-negative diagnosis from an AI algorithm: the clinician, the hospital, or the software developer? This operational uncertainty stifles procurement and implementation. Similarly, data privacy concerns are amplified by the central role of medical imaging data, which is considered highly sensitive biometric information under evolving regulations like the Saudi Personal Data Protection Law [38].

Technological barriers like interoperability are not merely IT issues but clinical workflow disruptors. An AI caries detection software that does not integrate seamlessly with the existing Picture Archiving and Communication System (PACS) or dental practice management software creates duplicate work, reducing the very efficiency it promises to enhance [39]. This fragmentation violates a core tenet of health informatics: technology should fit the workflow, not force the workflow to fit the technology.

Implications for Policy and Practice

The implications of this research are immediate and actionable. First, the evidence mandates a strategic pivot from technology acquisition to capacity building. National and institutional strategies for smart dental systems must begin with, and be funded alongside, comprehensive

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training programs [40]. These should target not only clinicians but also administrators and IT staff to foster a shared understanding. Second, the framework developed from these results calls for a staged implementation model [41]. Efforts should first consolidate gains in high-adoption settings (specialized/private centers) by addressing their interoperability and regulatory concerns, turning them into demonstration sites. Simultaneously, foundational work in government hospitals should focus on infrastructure readiness (e.g., PACS/digital network upgrades) and pilot training programs to build internal champions [42].

Study Limitations

This study has several limitations. First, its cross-sectional design establishes associations but cannot prove causation between factors like training and adoption. Second, the purposive sampling of institutions likely to be early adopters means the results may present a more optimistic picture of the national landscape than actually exists; adoption in smaller, non-tertiary care settings is likely lower [43]. Third, the data relied on self-reported perceptions and usage, which may be subject to social desirability bias (over-reporting of awareness/use) or lack of awareness of embedded AI in existing tools. Finally, the study did not directly measure patient outcomes or cost-effectiveness, which are ultimate metrics for evaluating the success of any "smart system" implementation.

CONCLUSION

The study successfully mapped the current landscape of AI adoption in Saudi dental institutions. It found that while awareness was moderately high, actual integration remained limited and uneven. The research confirmed that specialized centers and private hospitals led in adoption, while significant barriers impeded wider implementation. Human and organizational factors, particularly a critical lack of specialized training, emerged as the strongest impediments, surpassing even cost and regulatory concerns. The work confirmed that professionals who perceived greater diagnostic benefits and those with formal training were significantly more likely to adopt AI tools. The primary contribution of this research is the identification of the "training gap" as the central bottleneck for smart dental systems in the Saudi context, providing a clear target for intervention. The developed evidence-based framework offers direct pathways for healthcare institutions to overcome key barriers. Future research should focus on longitudinal studies to track adoption trends post-intervention and on developing standardized, culturally adapted AI training curricula for dental professionals.

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