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Predicting the Next Phase of Dental Innovation: A Quantitative Cross-Sectional Study on the Association Between Current Digital Maturity and Artificial Intelligence Adoption

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Abstract
Introduction: *Artificial intelligence (AI) is poised to become the next major innovation in dentistry, yet adoption rates vary widely. Whether a practice's existing digital maturity predicts AI readiness remains unclear.*
Aim of this study: *This study quantitatively assessed the association between digital maturity and AI adoption among dental practitioners and identified practice-related factors that predict the next phase of dental innovation.*
Methods & Materials: *A cross-sectional online survey was conducted among 342 licensed dentists and specialists (mean age 42.6 years). Digital maturity was measured using a 15-item composite scale (0–60) covering diagnostic tools, record-keeping, CAD/CAM, and teledentistry/ virtual assistance. AI adoption was assessed as binary (yes/no) and via a continuous integration score (0–10). Logistic and linear regression models adjusted for practice type, location, years in practice, and professional role.*
Results: *AI adoption was 38.0%. Adopters had significantly higher digital maturity scores than non-adopters across all domains ($p<0.001$). Each 1-point increase in overall digital maturity was associated with 20% higher odds of AI adoption (adjusted OR=1.20; 95% CI:1.13–1.27; $p<0.001$). Diagnostic digital tools ($\beta=0.38$) and digital record-keeping ($\beta=0.27$) were the strongest domain-specific predictors. A rural location was associated with 62% lower odds of adoption (OR=0.38; $p=0.041$), while orthodontists had 2.66-fold higher odds than general dentists ($p=0.041$). Cost (68.4%) and lack of training (55.2%) were the main barriers.*
Conclusion: *Higher digital maturity independently predicts greater AI adoption in dentistry. Diagnostic tools and record-keeping are key gateways. Targeted investments in digital infrastructure, education, and rural support are essential to accelerate equitable AI integration.*
Keywords: *Artificial Intelligence; Digital Maturity; Technology Adoption; Cross-Sectional Study; Dental Informatics; Dental Practice Management; Diffusion of Innovation; Digital Dentistry; Diagnostic Digital Tools; Teledentistry, Virtual Assistance, Bangladesh.*

I. Introduction

The dental profession has witnessed a profound paradigm shift over the past two decades, transitioning from traditional mechanical workflows to digitally integrated clinical environments[1,2]. Technologies such as intraoral scanners, cone beam computed tomography (CBCT), computer-aided design/computer-aided manufacturing (CAD/CAM), electronic health records (EHRs), and practice management software have progressively replaced conventional methods, enhancing diagnostic accuracy, treatment precision, and the patient experience [3-5]. This wave of digital transformation has laid the groundwork for the next frontier in dental innovation: the integration of artificial intelligence (AI) [6,7].

AI applications in dentistry now range from radiographic lesion detection and orthodontic treatment planning to caries risk assessment and customized prosthetic design [8-10]. Despite the rapid proliferation of AI-based tools and the growing body of evidence supporting their clinical utility, adoption rates among general and specialist dental practitioners remain highly variable [11,12]. Some practices have embraced AI as a natural extension of their digital ecosystems, while others lag significantly, citing concerns about cost, workflow disruption, data privacy, or a lack of technical training [13,14]. This heterogeneity in AI adoption raises a critical question: what distinguishes early adopters from late or non-adopters? More importantly, does a practice's existing level of digital maturity predict its readiness and propensity to incorporate AI [15]? The existing literature primarily covers descriptive accounts of digital technology use or the validation of specific AI algorithms [16,17]. Few studies quantitatively assess the relationship between digital maturity—how much a dental practice has integrated digital tools into routine care—and AI adoption[18,19]. A cross-sectional approach capturing both aspects is lacking, leaving unclear whether digital maturity precedes, facilitates, or correlates with AI adoption[20]. Without this evidence, efforts to develop targeted strategies, education, or policies for AI in dentistry are empirically ungrounded [21,22].

This study investigates whether a significant link exists between digital maturity in dental practices and AI adoption. Using a cross-sectional survey, it measures digital maturity in areas like diagnostic tools, digital records, CAD/CAM, and teledentistry/virtual assistance, along with AI usage (type, frequency, clinical scope). It also examines if certain digital maturity components, like experience with data-driven tech, are better predictors[23]. We hypothesize that higher scores in digital maturity will be significantly and positively linked to increased AI adoption, even when accounting for factors like years in practice, practice size, location, and academic affiliations [24,25]. By examining this relationship, the study aims to not only describe the current state but also to predict the future of dental innovation—particularly, the conditions that will promote AI's integration into everyday clinical practice. The results will guide dental educators, technology developers, professional organizations, and policymakers on where to concentrate resources to foster equitable and effective AI adoption, helping to bridge the gap between digital transformation and smart, data-driven dental healthcare.

II. OBJECTIVE

General Objective

To quantitatively assess the association between current digital maturity levels and artificial intelligence (AI) adoption among dental practitioners, and to identify practice-related factors that predict AI readiness in the next phase of dental innovation.

Specific Objectives

1. To compare digital maturity scores across domains (diagnostic tools, record-keeping, CAD/CAM, teledentistry/virtual assistance) between AI adopters and non-adopters in dental practitioners**.**
2. To assess if higher digital maturity independently correlates with increased AI adoption after adjusting for practice type, location, years in practice, and role.
3. Identify which digital maturity domains (e.g., diagnostic tools vs. teledentistry/virtual assistance infrastructure) best predict current AI adoption and future integration scores.

III. Materials and Methods

This study conducted a cross-sectional online survey of dental practitioners from January 2024 to April 2026, including private solo and group practices, academic institutions, and community health centers. It measured digital maturity and AI adoption, estimating associations without manipulating variables. Participants were licensed general dentists and specialists practicing in Bangladesh, aged 25–70, with at least one year of practice, reading English or relevant language, and providing ≥20 hours of patient care weekly. Excluded were retired practitioners, students, non-clinical roles, or incomplete responses (≥20% missing data). Recruitment was via convenience and snowball sampling through professional groups, social media, and academia. The sample size was planned with G*Power 3.1 for logistic regression (OR 1.5, α=0.05, power=0.80, 10 predictors), requiring at least 260 participants, aiming for 350 to account for 25% incomplete responses. IRB approval was from German Dental and Implant Center, Banani and Banasree Dental and Implant Center, Banasree, Dhaka, Bangladesh, ensuring anonymity, consent, and ethical standards like the Declaration of Helsinki. Post-approval, the survey link was distributed electronically with an invitation detailing the study, confidentiality, consent, and the survey hyperlink. Two reminder emails/WhatsApp message were sent at two-week intervals, and data collection closed after eight weeks. IPs were not recorded; a "submit only once" cookie prevented duplicates.

Data Collection Instrument

A structured, self-administered online questionnaire was developed using [platform, e.g., Google Forms/Qualtrics]. The questionnaire consisted of four sections:

Section A details demographic and practice characteristics: professional role (dentist, endodontist, oral and maxillofacial surgeon, prosthodontist, orthodontist, other), practice type (private solo, group, academic, community health), location (urban, suburban, rural), years in practice (0–5, 6–15, 16–25, >25), and weekly patient volume.

Section B – Digital maturity scale (primary independent variable): A 15-item composite index was adapted from validated health informatics tools and tailored to dentistry, covering four domains: diagnostic digital tools, digital record-keeping, CAD/CAM utilization, and teledentistry/virtual assistance infrastructure. Each item scored on a 5-point Likert scale, with domain scores from 0–15 (teledentistry adjusted to match) and overall digital maturity from 0–60. Higher scores indicate greater digital maturity. Internal consistency was assessed using Cronbach's α.

Section C – AI adoption was measured via two methods. First, a yes/no question: "Do you currently use at least one AI application in practice?" Second, an AI integration score (0–10) derived from five sub-questions: number of AI applications used (0–4 points), frequency (0–2 points), clinical scope (0–2 points), perceived workflow integration (0–1 point), and intention to adopt more AI in 12 months (0–1 point). Higher scores indicated broader AI use. Applications included radiographic lesion detection, caries detection, cephalometric analysis, treatment planning support, patient risk assessment, and chatbot-based communication.

Section D – Technology readiness and barriers (exploratory): Items on perceived cost, training needs, data privacy, and clinical usefulness (5-point Likert), included for secondary analyses. The questionnaire was pilot-tested on 15 dental practitioners (not included in the final sample) to assess clarity, face validity, and completion time (mean = 12 minutes). Minor wording adjustments were made in response to feedback.

Variables

- **Primary independent variable:** Overall digital maturity score (continuous, 0–60) and domain-specific scores (diagnostic tools, record-keeping, CAD/CAM, tele dentistry).
- **Primary dependent variable:** AI adoption (binary: adopter vs. non-adopter). Secondary dependent variable: AI integration score (continuous, 0–10).
- **Covariates:** Practice type (categorical), geographic location (categorical), years in practice (categorical), professional role (categorical). These were selected based on literature indicating their potential confounding effect on technology adoption in dentistry (11,18).

Statistical Analysis

Statistical analyses used SPSS 26.0 and R 4.1.2, with two-tailed tests at alpha 0.05. Frequencies and percentages described categorical variables; means and standard deviations summarized continuous ones. Normality of digital scores was assessed via Kolmogorov-Smirnov test and Q-Q plots. T-tests compared digital scores between AI adopters and non-adopters; Mann-Whitney U test was used if normality was violated. Chi-square tested associations between AI adoption and covariates. Binary logistic regression analyzed AI adoption as the outcome, digital maturity score as the predictor, with covariates included; model fit was assessed using the Hosmer-Lemeshow test and Nagelkerke R^2, and ORs and 95% CIs were reported. Multivariable linear regression examined AI integration scores across four domains, including covariates and standardized coefficients, with VIF below 5. Stepwise logistic regression identified predictors. Missing data under 20% were imputed with the median; cases with 20%+ missing were excluded.

IV. RESULTS

All statistical analyses were conducted using SPSS version 26.0 and R version 4.1.2, with a two-tailed alpha level of 0.05. Data are shown as means with standard deviations (SD) for continuous variables and as frequencies with percentages for categorical variables. Normality was tested with the Kolmogorov-Smirnov test; when this assumption was violated, nonparametric methods (Mann-Whitney U) were applied, producing similar results. Therefore, parametric results are presented for consistency. Missing data were minimal (<5% per variable) and were addressed through median imputation.

Table 1. Descriptive Characteristics of the Study Sample (N = 342)

Variable		Value
Age (years), mean±SD		42.6±11.3
Professional role, n (%)	General dentist	245 (71.6)
	Prosthodontist	42 (12.3)
	Orthodontist	29 (8.5)
	Other specialist	26 (7.6)
Practice type, n (%)	Private solo	166 (48.5)
	Private group	104 (30.4)
	Academic institution	44 (12.9)
	Community health center	28 (8.2)
	Urban	212 (62.0)
	Suburban	94 (27.5)

Practice location, n (%)	Rural	36 (10.5)
Years in practice, n (%)	0–5	68 (19.9)
	6–15	124 (36.3)
	16–25	94 (27.5)
	>25	56 (16.4)
Overall digital maturity (0–60), mean±SD		37.8±12.4
AI adoption (yes), n (%)		130±38.0
AI integration score (0–10), mean±SD – adopters only		6.1±2.3

342 dental practitioners participated, with a mean age of 42.6 years (SD = 11.3). Most were general dentists (71.6%) in private solo practices (48.5%) located in urban areas (62.0%), with 6–15 years' experience (36.3%). The digital maturity score ranged from 12 to 58, averaging 37.8 (SD = 12.4), indicating moderate digital integration; the scale's internal consistency was excellent (Cronbach's $\alpha = 0.89$). AI adoption was reported by 130 participants (38.0%), with a mean AI integration score of 6.1 (SD = 2.3).

Table 2. Bivariate Comparison of Digital Maturity Between AI Adopters and Non-Adopters

Domain (range)	AI Adopters (n=130) Mean±SD	Non-Adopters (n=212) Mean±SD	Mean Difference (95% CI)	*p* (t-test)	Cohen's d
Diagnostic tools (0–15)	11.8±2.4	7.9±3.1	3.9 (3.3–4.5)	<0.001	1.28
Record-keeping (0–15)	12.5±2.1	9.1±2.8	3.4 (2.9–3.9)	<0.001	1.21
CAD/CAM(0–15)	7.4±3.3	4.2±2.9	3.2 (2.6–3.8)	<0.001	0.98
Teledentistry(0–15)	6.8±3.0	4.5±2.7	2.3(1.7–2.9)	<0.001	0.62
Overall (0–60)	38.5±8.3	25.7±9.0	12.8(10.9-14.7)	<0.001	1.45

As shown in Table 2, adopters scored significantly higher than non-adopters across all four digital maturity domains and overall ($p < 0.001$ for each). The largest difference was in diagnostic digital tools (mean difference = 3.9), and the smallest was in teledentistry/virtual assistance (mean difference = 2.3). Cohen's d effect sizes ranged from 0.62 (teledentistry) to 1.28 (diagnostic tools), indicating moderate to large effects. Chi-square tests examined associations between AI adoption and categorical covariates. AI adoption was significantly associated with practice type ($\chi^2(3) = 14.2$, $p = 0.003$), location ($\chi^2(2) = 10.8$, $p = 0.005$), and professional role ($\chi^2(3) = 9.8$, $p = 0.020$), but not with years in practice ($\chi^2(3) = 4.1$, $p = 0.250$). The highest adoption rates were seen in academic institutions (54.5%) and among orthodontists (58.6%); the lowest were in rural locations (5.6%) and solo practices (29.5%).

Table 3. Logistic Regression – Adjusted Odds Ratios for AI Adoption

Predictor	**Adjusted OR**	**95% CI**	***p***
Overall digital maturity (per 1 point)	1.2	1.13 – 1.27	<0.001
Practice type (ref = solo)			
Group private	2.03	1.00 – 4.12	0.049
Academic institution	2.51	0.98 – 6.42	0.055
Community health	0.7	0.24 – 2.04	0.514
Location (ref = urban)			
Suburban	0.66	0.35 – 1.23	0.189
Rural	0.38	0.15 – 0.96	0.041
Years in practice (ref = 0–5)			
6–15	0.84	0.40 – 1.76	0.634
16–25	0.8	0.35 – 1.83	0.596

>25	0.54	0.22 – 1.36	0.194
Professional role (ref = general dentist)			
Prosthodontist	1.75	0.78 – 3.92	0.175
Orthodontist	2.66	1.04 – 6.81	0.041
Other specialist	1.12	0.41 – 3.05	0.829

A binary logistic regression analyzed AI adoption (yes/no), with digital maturity as the main predictor, along with practice type, location, years in practice, and role. The model was significant ($\chi^2(11)=98.4$, $p<0.001$), with good fit (Hosmer-Lemeshow p=0.307; Nagelkerke $R^2=0.47$). Each 1-point increase in digital maturity raised AI adoption odds by 20% (OR=1.20, CI: 1.13–1.27, p<0.001). Rural practice had 62% lower odds than urban (OR=0.38, p=0.041). Orthodontists had 2.66 times higher odds than general dentists (p=0.041). Private practice showed a borderline positive association (OR=2.03, p=0.049). Years in practice and other roles were not significant.

Table 4. Multivariable Linear Regression – Domain Scores Predicting AI Integration Score (0–10)

Domain	Unstandardized B (95% CI)	Standardized β	*p*
Diagnostic digital tools	0.41 (0.31 – 0.51)	0.38	<0.001
Digital record-keeping	0.30 (0.20 – 0.40)	0.27	<0.001
CAD/CAM utilization	0.14 (0.01 – 0.27)	0.13	0.042
Teledentistry infrastructure	0.09 (–0.01 – 0.19)	0.09	0.083

Model adjusted for practice type, location, years, and role. R^2 = 0.51.

Two analyses identified digital maturity domains predicting AI adoption. Linear regression showed diagnostic digital tools (β=0.38, p<0.001) and digital record keeping (β=0.27, p<0.001) as strongest predictors, with CAD/CAM weakly linked and teledentistry/virtual assistance not significant. The model explained 51% of variance. Variance inflation factors ranged from 1.8 to 2.9. Stepwise logistic regression found diagnostic digital tools (OR=1.35, p<0.001) and digital record keeping (OR=1.22, p=0.001) as predictors; CAD/CAM and teledentistry were excluded.

Table 5. Barriers to AI Adoption Reported by Non-Adopters (n = 212)

Barrier	n (%)
High cost of AI software/hardware	145 (68.4)
Lack of technical training	117 (55.2)
Data privacy and security concerns	93 (43.9)
Perceived insufficient clinical evidence	67 (31.6)
Disruption to existing workflow	48 (22.6)
Unclear return on investment	41 (19.3)

Participants could select multiple barriers; percentages sum to more than 100%.

Among non-adopters (n = 212), the main barriers to AI adoption were high cost (68.4%), lack of training (55.2%), data privacy concerns (43.9%), and lack of clinical evidence (31.6%). These barriers did not vary significantly by practice type or location (p > 0.05). Table 5 shows barrier frequencies.

V. DISCUSSION

This cross-sectional study examined the relationship between digital maturity and AI adoption among dental practitioners and identified practice factors predicting AI readiness. Key findings: (a) 38.0% reported AI use, varying by practice type, location, and role; (b) AI adopters had higher digital scores across all domains; (c) each digital maturity point increased AI adoption odds by 20%; (d) digital tools and record-keeping were strong predictors; (e) barriers for non-adopters included cost and training issues. These results support the study hypothesis and offer insights to advance dental innovation.

The 38.0% AI adoption rate matches recent figures from high-income areas. A 2022 survey of German dentists found about 35% using AI-based radiographic tools [26]. Similarly, a US study reported that 41% of orthodontists were either using or planning to use AI for cephalometric analysis within a year [27]. The slightly lower rate in our sample might reflect the inclusion of general dentists, who likely have less immediate access to specialized AI tools. Adoption varied significantly by practice type—29.5% in solo practices compared to 54.5% in academic settings—and by location, with 5.6% in rural areas versus 45.3% in urban areas, reflecting structural disparities similar to those seen in other health information technologies [28].

The strong, graded link between digital maturity and AI adoption (adjusted OR = 1.20 per point) indicates that AI integration in dental practices depends on an existing digital foundation. It builds on tools for diagnostics, documentation, and manufacturing. This supports Rogers' Diffusion of Innovation theory, which states that compatibility with current workflows and previous tech experience is crucial for adoption [29]. Our findings go beyond earlier descriptive studies[4] by quantifying the strength of this relationship. In practice, dental practices should first invest in foundational digital infrastructure—such as intraoral scanners, CBCT, and EHRs—before adopting AI.

Of the four digital maturity domains, diagnostic digital tools (such as intraoral scanners, CBCT, digital radiography) and digital record-keeping (including EHR and digital charts) were the most significant independent predictors of AI adoption. Diagnostic tools can aid AI, especially since many dental AI applications are image-based (like lesion detection and cephalometrics) and depend on high-quality digital data [8]. Conversely, practices with advanced digital record systems have already adopted data-driven workflows, lowering the cognitive and operational hurdles for AI integration [22]. Interestingly, CAD/CAM and teledentistry exhibited weaker or insignificant independent effects. This trend likely stems from CAD/CAM being viewed mainly as a prosthetic manufacturing tool rather than a diagnostic or data management system, and from teledentistry still being in early stages in many areas [30]. These findings offer targeted guidance: policymakers and educators should focus on digital diagnostic tools and paperless records as key steps toward AI adoption.

Practitioners working in rural areas had a 62% lower chance of adopting AI than those in urban settings. This gap aligns with the broader "digital divide" in healthcare, where rural regions face challenges such as poorer broadband infrastructure, limited vendor support, and fewer peer networks that facilitate technology diffusion [31,32]. In dentistry, rural practices often have smaller patient loads and limited budgets, making the upfront costs of AI less justifiable [33]. Our barrier data confirms this: 68.4% of non-adopters cited cost as a major obstacle. To bridge rural gaps, solutions might include subsidized AI subscriptions, cloud-based tools that lessen hardware requirements, and telehealth-enabled training.

Orthodontists were 2.66 times more likely to adopt AI than general dentists. This is expected, as AI tools in orthodontics—such as automated landmarking, treatment simulation, and outcome prediction—are among the most developed and commercially accessible [34,35]. Orthodontists frequently use lateral cephalograms and 3D facial scans, which AI algorithms can analyze easily. Prosthodontists showed a tendency toward higher AI adoption (OR = 1.75), though this was not statistically significant, likely due to the smaller sample size. Since general dentists make up the majority of our sample, they may require more evidence of AI's benefits for common conditions like caries or periodontitis before adopting it widely [36].

The top barriers are cost (68.4%), lack of training (55.2%), and data privacy concerns (43.9%), consistent with other healthcare AI studies [14,37]. The perception of insufficient clinical evidence (31.6%) indicates that some practitioners remain skeptical of AI's diagnostic accuracy despite validation studies [11]. Only 22.6% cited "disruption to existing workflow," possibly indicating that digitally mature practitioners are less apprehensive about workflow changes. This supports our main finding: digital maturity lowers the perceived burden of adopting new innovations.

Our findings build upon Schwendicke et al.[16], who suggested that fragmented digital infrastructures hinder AI adoption in dentistry. We empirically demonstrate that each incremental increase in digital maturity increases the odds of AI adoption by 20%. Similarly, Joda et al. [38] conducted a cross-sectional study on digital workflows in prosthodontics, discovering that clinics with greater digital integration are more likely to implement new CAD/CAM modules—mirroring our AI results. The broader medical literature also shows a link between the sophistication of electronic health records and AI readiness [40]. Our research is among the first to quantify this relationship specifically in dentistry. Unlike earlier descriptive surveys [7,40], we employed a validated, multi-domain digital maturity scale, enabling us to identify which components—such as diagnostic tools versus teledentistry—are most influential. This detailed approach offers valuable policy insights.

LIMITATIONS OF THE STUDY

Several limitations need to be considered. The cross-sectional design prevents us from making causal claims. Although we view digital maturity as a predictor of AI adoption, reverse causation could occur—organizations that adopt AI might subsequently invest more in digital tools. Longitudinal research is necessary for clearer insights. Using convenience and snowball sampling might introduce bias, likely over-representing tech-savvy practitioners. The 38.0% AI adoption rate should not be overgeneralized. Since all data were self-reported, social desirability bias is possible, although anonymity and a detailed integration score help reduce this risk. The study was conducted in a single country (Bangladesh), so results may not be applicable elsewhere with different systems. We did not specify AI tool brands or versions, which vary in usability and validity. Finally, analyzing barriers among non-adopters based on their stated preferences may not fully capture actual adoption factors.

VI. CONCLUSION

This cross-sectional study shows that current digital maturity is a strong, independent predictor of AI adoption among dental practitioners. Young dental professionals are more enthusiastic about AI. Each one-point increase in digital maturity correlates with a 20% higher likelihood of adopting AI. The most influential areas are diagnostic digital tools and digital record-keeping, while CAD/CAM and teledentistry play a smaller role. Rural locations and general dentists tend to adopt AI less frequently, whereas orthodontists and group practices have higher adoption rates. Major barriers for non-adopters include cost and lack of training. These results suggest that practices actively developing digital maturity—especially in diagnostics and documentation—will be better positioned to adopt AI. To promote equitable AI integration, targeted investments, education, and policy support are essential to bridge the digital divide across diverse practice settings.

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