Original Article

AI DECISION SUPPORT SYSTEM ADOPTION IN DENTAL EDUCATION: AN EMPIRICAL PLS-SEM STUDY

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ABSTRACT

Despite their potential to enhance evidence-based clinical decision-making, adoption among dental students remains limited because of insufficient trust in AI-assisted diagnosis and inadequate understanding of the economic value of AI-supported dental care. This study investigated the effects of perceived diagnostic usefulness, trust, and digital financial literacy on behavioural intention and AI-CDSS adoption among dental students. A cross-sectional survey was conducted with 350 dental students, and the data were analysed using partial least squares structural equation modelling (PLS-SEM). The results showed that perceived diagnostic usefulness (β = 0.356) and trust (β = 0.321) significantly enhanced behavioural intention, whereas digital financial literacy positively influenced trust (β = 0.287) and indirectly promoted AI-CDSS adoption. Behavioural intention was the strongest predictor of AI-CDSS adoption (β = 0.612) and partially mediated the relationships between the antecedent variables and adoption behaviour. The model explained 64.8% of the variance in behavioural intention and 37.4% of AI-CDSS adoption. These findings highlight the importance of integrating AI-assisted diagnostic training, clinical decision-support competencies, and cost-effectiveness evaluation into dental curricula to prepare future dentists for evidence-based, patient-centred, and technology-enabled oral healthcare.

Key words: AI-CDSS, Dental education, Caries detection, Radiographic diagnosis, Financial literacy.

Introduction

The application of artificial intelligence (AI) in healthcare has expanded rapidly, particularly in clinical decision support systems (CDSS) that assist healthcare professionals in selecting optimal treatment options. AI-CDSS can improve diagnostic accuracy, reduce medical errors, and optimise the allocation of clinical resources [1-3]. In dentistry specifically, AI tools support radiographic caries detection, periapical lesion identification, periodontal bone-loss assessment, and orthodontic treatment planning, aligning with the goals of precision diagnostics and evidence-based oral healthcare [4, 5]. Despite these benefits, the adoption of AI technologies among future dentists remains inconsistent.

A significant barrier remains the scepticism surrounding AI-integrated platforms. Given the high-stakes nature of clinical outcomes, stakeholders are often hesitant to embrace algorithmic guidance absent demonstrable evidence of safety, precision, and reliability [1, 2, 6, 7]. Furthermore, financial literacy represents an understudied facet of this integration. Understanding the cost-effectiveness of AI-assisted diagnostics, the economics of preventive versus restorative treatment, and the pricing of digital dental technologies necessitates economic acumen; consequently, dental students possessing greater financial competency may be better equipped to evaluate the fiscal implications of AI-driven diagnostic recommendations [8-10]. Current literature suggests that while dental students and professionals are broadly receptive to AI applications in oral diagnostics, their adoption is tempered by limited formal AI training, knowledge gaps, and variable institutional trust [4, 11-13].

Previous research has predominantly investigated AI implementation among broad medical practitioners, often utilising frameworks like the Technology Acceptance Model [14, 15]. Nevertheless, there is a shortage of literature synthesising AI integration, financial literacy, and dental education into a unified paradigm. Furthermore, the synergistic influence of trust, perceived utility, and financial acumen on AI adoption remains insufficiently examined. This deficiency is particularly significant for developing economies like Vietnam, where AI applications in oral health are progressing rapidly, yet the financial expertise of students entering the dental profession is currently in its formative, developmental stage [16, 17].

Dental students are a strategically important population for this question. As future dentists, they will routinely interpret radiographic images, formulate treatment plans, and manage the economic aspects of dental care delivery. Their willingness to adopt AI-CDSS for caries detection, lesion identification, and treatment planning, and their capacity to interpret the economic dimensions of AI-generated diagnostic recommendations, will shape the quality and cost-effectiveness of oral healthcare. Yet international evidence suggests that, while dental students are broadly receptive to AI, their adoption is constrained by limited curricular exposure, inconsistent trust in AI-generated diagnoses, and concerns about diagnostic liability and the

appropriate role of AI in clinical judgement [4, 11, 12, 18]. Examining how usefulness, trust and financial literacy jointly drive adoption among this group can therefore inform both curriculum design and the responsible deployment of AI in dental practice.

This research investigates the determinants of AI-CDSS adoption among dental students, evaluating how financial literacy impacts clinical decision-making. By utilising a PLS-SEM approach that merges trust theory with the Technology Acceptance Model, the study identifies perceived diagnostic utility, trust, and digital financial literacy as key drivers of behavioural intention and subsequent adoption. With behavioural intention serving as a mediator, this work bridges oral health AI and dental practice economics. Consequently, it provides a comprehensive integrative model, validates the mediating influence of intention, and offers actionable strategies for incorporating both artificial intelligence proficiency and financial acumen into the contemporary dental education curriculum for future practitioners.

Literature review and hypothesis development

Technology acceptance model and perceived diagnostic usefulness

The Technology Acceptance Model holds that perceived usefulness is a primary determinant of technology adoption [14, 15, 19]. In healthcare, perceived diagnostic usefulness refers to the extent to which AI enhances clinical decision-making—improving diagnostic accuracy in radiographic interpretation and caries detection, and supporting better treatment-planning decisions. When dental students perceive AI-CDSS as clinically useful, they are more likely to form favourable intentions to use it, and this perceived value can also reinforce trust in the system [11, 20]. On this basis, the following hypotheses are proposed.

H1. Perceived diagnostic usefulness positively influences behavioural intention.

H2. Perceived diagnostic usefulness positively influences trust.

Trust in AI systems

Trust is a critical factor in healthcare technology adoption: users must believe that AI systems are reliable, accurate and safe for clinical use [1, 21, 22]. Because clinical decisions involve risk, trust reduces the uncertainty associated with relying on algorithmic recommendations and is repeatedly identified as a decisive determinant of AI-CDSS acceptance among healthcare workers [1, 2, 23, 24]. Trust is therefore expected to strengthen behavioural intention.

H3. Trust positively influences behavioural intention.

Digital financial literacy in healthcare

Financial literacy enables individuals to understand and evaluate cost-effectiveness in medical decision-making, including knowledge of dental treatment costs, preventive versus restorative economics, and economic evaluation of AI-assisted diagnostics [9, 25]. Financially literate dental students can better appraise the economic value of AI-supported recommendations, which may strengthen both their intention to adopt AI-CDSS and their trust in such systems since they are better equipped to judge the credibility of cost-related outputs [8, 26]. The following hypotheses are proposed.

H4. Digital financial literacy positively influences behavioural intention.

H5. Digital financial literacy positively influences trust.

Behavioural intention and adoption

Behavioural intention is the most proximal predictor of actual system usage in technology-acceptance models [14, 15]. Dental students who form stronger intentions to use AI-CDSS are more likely to adopt it in practice and during clinical rotations and preclinical training. Behavioural intention is therefore positioned as the proximal driver of adoption and as the mechanism through which the three antecedents exert much of their influence.

H6. Behavioural intention positively influences AI-CDSS adoption.

Mediating effects of behavioural intention

Integrating the above, behavioural intention is expected to mediate the effects of perceived diagnostic usefulness, trust and financial literacy on AI-CDSS adoption. Each antecedent strengthens intention, which then converts into adoption behaviour, implying three indirect effects whose significance, alongside the direct paths, distinguishes partial from full mediation [27]. The conceptual model is shown in **Figure 1**.

H7. Behavioural intention mediates the effect of perceived diagnostic usefulness on adoption.

H8. Behavioural intention mediates the effect of trust on adoption.

H9. Behavioural intention mediates the effect of financial literacy on adoption.

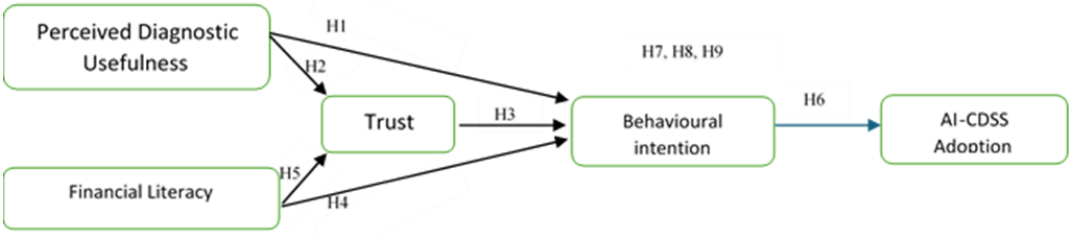

Figure 1. Proposed research model

Materials and Methods

Research design and sample

A quantitative, cross-sectional survey design was adopted to test the hypothesised model. The target population comprised dental students, recruited through convenience sampling. A total of 350 valid responses were obtained, which exceeds the recommended minimum for PLS-SEM and provides adequate statistical power to detect small-to-medium effects [27]. (**Table 1)** presents the demographic profile of the sample.

Table 1. Demographic profile of respondents (n = 350)

Characteristic / Category	Frequency	Percentage (%)
Gender: Male	128	36.6
Gender: Female	222	63.4
Age: 18–20	96	27.4
Age: 21–23	198	56.6
Age: > 23	56	16.0
Year of study: Year 1	72	20.6
Year of study: Year 2	85	24.3
Year of study: Year 3	97	27.7
Year of study: Year 4+	96	27.4
AI experience: None	74	21.1
AI experience: Basic	156	44.6
AI experience: Moderate	88	25.1
AI experience: Advanced	32	9.1
Use of digital tools: Rarely	52	14.9
Use of digital tools: Occasionally	138	39.4
Use of digital tools: Frequently	**160**	**45.7**

Measurement scales

All constructs were measured reflectively using multi-item scales rated on a five-point Likert scale (1 = strongly disagree to 5 = strongly agree). Perceived diagnostic usefulness (4 items) captured the belief that AI improves diagnostic accuracy in radiographic interpretation, caries detection, and dental treatment planning, adapted from TAM [14]. Trust (3 items) reflected the reliability and trustworthiness of AI recommendations, adapted from trust theory and AI-CDSS trust research [1, 21]. Digital financial literacy (3 items) covered the ability to evaluate dental treatment costs and understand the cost-effectiveness of preventive versus restorative care [9]. Behavioural intention (3 items) and AI-CDSS adoption (3 items) were adapted from technology-acceptance and AI-acceptance studies [12, 15]. **(Table 2)** summarises the constructs and items.

Table 2. Constructs and measurement items

Construct	Indicative content	Items
Perceived Diagnostic Usefulness (PU)	AI improves radiographic diagnostic accuracy; enhances dental treatment planning	4
Trust (TR)	AI systems are reliable; AI recommendations are trustworthy	3
Financial Literacy (FL)	Ability to evaluate treatment costs; understanding of cost-effectiveness	3

Behavioural Intention (BI)	Intention to use AI in future; willingness to rely on AI	3
AI-CDSS Adoption (AD)	Actual/intended use; use during internship	3

Data analysis

Partial least squares structural equation modelling (PLS-SEM) was used because it suits prediction-oriented research, models with mediating chains, and data that may depart from multivariate normality [27]. The measurement model was assessed for indicator reliability, internal consistency (Cronbach's alpha and composite reliability), convergent validity (average variance extracted, AVE) [28], and discriminant validity via the heterotrait-monotrait ratio (HTMT) [29]. The structural model was evaluated through path coefficients with bootstrapped significance (5,000 resamples), the coefficient of determination (R^2), effect sizes (f^2), and predictive relevance (Q^2). Mediation was assessed through the significance of indirect effects, with the direct effect distinguishing partial from full mediation.

Results and Discussion

Measurement model

The measurement-model results **(Table 3)** confirm satisfactory reliability and validity. All standardised loadings exceed 0.79, Cronbach's alpha values range from 0.854 to 0.893, composite reliability ranges from 0.898 to 0.926, and AVE ranges from 0.677 to 0.758 — each exceeding the recommended thresholds of 0.70 for reliability and 0.50 for AVE [27, 28].

Table 3. Measurement model: reliability and convergent validity

Construct (Item)	Loading	α	CR	AVE
Perceived Diagnostic Usefulness – PU1	0.812	0.882	0.913	0.677
PU2	0.845			
PU3	0.823			
PU4	0.804			
Trust – TR1	0.836	0.871	0.907	0.709
TR2	0.842			
TR3	0.854			
Financial Literacy – FL1	0.792	0.854	0.898	0.687
FL2	0.826			
FL3	0.861			
Behavioural Intention – BI1	0.871	0.893	0.926	0.758
BI2	0.882			
BI3	0.859			
AI-CDSS Adoption – AD1	0.835	0.869	0.909	0.714
AD2	0.847			
AD3	0.853			

Note. α = Cronbach's alpha; CR = composite reliability; AVE = average variance extracted.

Discriminant validity was assessed using the HTMT criterion **(Table 4)**. All HTMT ratios fall below the 0.85 threshold, confirming that the five constructs are empirically distinct [29].

Table 4. Discriminant validity (HTMT ratios)

Construct	PU	TR	FL	BI	AD
PU	—				
TR	0.721	—			
FL	0.654	0.707	—		
BI	0.768	0.742	0.689	—	
AD	0.701	0.732	0.665	0.812	—

Note. All HTMT values < 0.85, supporting discriminant validity.Structural model and hypothesis tests

The structural-model results **(Table 5)** show that all six direct paths are positive and statistically significant. Perceived diagnostic usefulness (β = 0.356, t = 6.245) and trust (β = 0.321, t = 5.874) are the strongest predictors of behavioural intention, followed by financial literacy (β = 0.182, t = 3.221). Behavioural intention strongly predicts AI-CDSS adoption (β = 0.612, t = 11.742). Perceived usefulness (β = 0.418) and financial literacy (β = 0.287) both significantly influence trust.

Table 5. Structural model results: direct paths

H	Path	β	t-value	p-value	Result
H1	PU → BI	0.356	6.245	<0.001	Supported
H2	TR → BI	0.321	5.874	<0.001	Supported
H3	FL → BI	0.182	3.221	0.001	Supported
H4	BI → AD	0.612	11.742	<0.001	Supported
H5	PU → TR	0.418	7.102	<0.001	Supported
H6	FL → TR	0.287	4.998	<0.001	Supported

The mediation analysis **(Table 6)** confirms that behavioural intention significantly mediates all three antecedent–adoption relationships. The indirect effects of perceived usefulness (β = 0.218, t = 5.990), trust (β = 0.196, t = 5.221) and financial literacy (β = 0.112, t = 3.005) on adoption are all significant, indicating partial mediation in each case.

Table 6. Mediation effects, R^2, f^2, Q^2 and model fit

H	Indirect path	β	t-value	Result
H7	PU → BI → AD	0.218	5.990	Partial mediation
H8	TR → BI → AD	0.196	5.221	Partial mediation
H9	FL → BI → AD	0.112	3.005	Partial mediation

R^2: Trust = 0.512 (moderate); Behavioural Intention = 0.648 (substantial); AI Adoption = 0.374 (moderate)
f^2: PU→BI = 0.214 (medium); TR→BI = 0.182 (medium); FL→BI = 0.067 (small); BI→AD = 0.471 (large)
Q^2: Trust = 0.312; Behavioural Intention = 0.441; AI Adoption = 0.276 (all > 0, predictive relevance)
Model fit: SRMR = 0.058 (< 0.08, acceptable fit)

The model demonstrates strong explanatory and predictive power. It accounts for 64.8% of the variance in behavioural intention (R^2 = 0.648, substantial), 51.2% in trust and 37.4% in adoption, with all Q^2 values above zero, confirming predictive relevance [27]. The standardised root mean square residual (SRMR = 0.058) indicates acceptable model fit. Among the determinants of behavioural intention, perceived diagnostic usefulness has the largest effect, consistent with TAM's central proposition that perceived utility is the dominant driver of adoption [14, 15]; behavioural intention, in turn, exerts a large effect on adoption (f^2 = 0.471).

The findings indicate that perceived diagnostic usefulness remains a central determinant of technology adoption, consistent with TAM and with recent evidence on dental students' attitudes toward AI [11, 12, 14]. Trust plays a vital role in reducing the uncertainty associated with AI systems in high-stakes healthcare environments; its strong effect on behavioural intention and the significant mediated path from trust to adoption, align with systematic-review evidence that trust is decisive for AI-CDSS acceptance among healthcare workers [1, 2]. The prominence of trust underscores that technical usefulness alone is insufficient: students must also believe that AI recommendations are reliable and safe.

Financial literacy contributes both directly to behavioural intention and indirectly through trust, supporting the study's central argument that economic competencies matter for AI adoption in dental. Although its direct effect on intention is the smallest of the three antecedents (f^2 = 0.067, small), its significant influence on trust (β = 0.287) suggests that financially literate students are better able to appraise the cost-related outputs of AI-CDSS and therefore trust them more readily [8, 9]. This highlights the value of integrating financial education into dental curricula, equipping future dentists to evaluate the cost-effectiveness of AI-assisted caries management, the economics of preventive versus restorative treatment pathways, and the return on investment of digital dental technologies.

The hierarchical order of these variables holds significant practical importance. Given that perceived utility and trust serve as the primary drivers of behavioural intent, and considering that intent itself is the most substantial predictor of adoption (f^2 = 0.471), there is an evident pathway for intervention: AI-CDSS must prove its clinical effectiveness and reliability to foster user intent, as solidified commitment is a prerequisite for actual adoption. This mediated framework indicates that enhancing utility, confidence, or financial acumen will most significantly drive adoption by bolstering behavioural intention. For emerging markets like Vietnam, where student exposure to AI and financial expertise fluctuates, a synchronised approach targeting diagnostic utility, trust, and financial literacy concurrently is likely to prove far more impactful than focusing on any individual variable on its own merits [16, 30].

Implications

Theoretically, this study expands the Technology Acceptance Model by integrating digital financial literacy with perceived utility and trust, establishing a novel connection between healthcare AI adoption and dental practice economics within dental education. By utilising behavioural intention as a mediator, the research illustrates how clinical relevance, trust, and financial acumen drive the implementation of AI-CDSS. Practically, dental curricula should incorporate both AI-driven diagnostic software, such as caries-detection and radiographic-interpretation tools, and financial training to cultivate dual competencies for evidence-based, cost-effective decision-making. Furthermore, healthcare organisations and technology developers must prioritise transparency, explainability, and proven reliability in AI-CDSS design to foster the essential trust required for widespread institutional adoption and long-term user engagement.

Conclusion

This research develops an integrative model to analyse AI-CDSS adoption among dental students by merging perceived diagnostic utility, trust, and digital financial literacy within a PLS-SEM framework rooted in TAM and trust theory. Findings reveal that perceived usefulness and trust serve as primary catalysts for behavioural intention, while financial literacy exerts both direct and trust-mediated influences. Behavioural intention acts as the core proximal predictor of adoption, partially mediating all three antecedents, with the model demonstrating robust explanatory power and adequate fit. These results highlight the necessity of interdisciplinary training blending AI proficiency with financial acumen to enhance healthcare decision-making. Consequently, this study provides practical recommendations for dental curricula, medical institutions, and developers aiming to promote the widespread, cost-effective, and reliable integration of clinical decision support systems within modern professional dental practice.

Limitations and future research

Several limitations should be acknowledged. The cross-sectional design precludes causal inference, so longitudinal or experimental designs would more convincingly establish the temporal ordering of the antecedents–intention–adoption chain. The data are self-reported and drawn from a convenience sample of students, which may limit generalisability and introduce common-method and selection concerns; future work should incorporate

procedural and statistical remedies and probability sampling. The focus on dental students means findings may not transfer to practising dentists, who face different incentives and constraints. Future research could include practising dentists, expand to multiple countries, and integrate AI explainability and perceived risk as additional constructs to capture the evolving landscape of AI-supported clinical decision-making.

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Ethics statement: Participation in this study was voluntary. All respondents were informed about the purpose of the research, and their anonymity and confidentiality were guaranteed. Informed consent was obtained from all participants prior to data collection.

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